# How Power Shapes Behavior: Evidence from Physicians

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**Abstract**

Power, defined as the asymmetric control of valued resources, affects most human interactions. Yet there is little observational evidence on how power affects behavior and resource allocation. We examine this question using the power differential in the doctor-patient encounter: while it favors the physician in the clinical setting, powerful patients may be able to reduce this asymmetry and so influence physician behavior. We exploit the quasi-exogenous assignment of 1.5 million patients to physicians in US military emergency departments, using the difference in their military ranks to measure their power differential. We find that power confers nontrivial advantage to its possessor: "high-power" patients (those who outrank their physician) receive greater physician effort and have better outcomes than equivalently-ranked "low-power" patients. We document other suggestive results: (i) within-physician effort is higher for patients recently promoted than those about to be promoted, (ii) low-power patients suffer when their physician concurrently cares for a high-power patient, and (iii) rank-based power dynamics vary predictably by doctor-patient concordance on race and sex. While power-driven variation in behavior is often undesirable, it is especially concerning in healthcare where it can harm society's most vulnerable patients.

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*Bertrand Russell (1938): "The fundamental concept in social science is Power, in the same sense in which Energy is the fundamental concept in physics."*

# 1 Introduction

Power is generally defined as the asymmetric control of valued resources – wealth, information, networks, etc – that allow an individual to influence outcomes for themselves and others (Smith and Hofmann, 2016). It is fundamental to economic exchange, the evolution of social norms, and daily interactions between individuals. As such, it has been central to several paradigm-shifting discussions on important societal issues in recent years. For example, there is a growing recognition of how power dynamics drive sex-based harassment in the workplace (Adams-Prassl et al., 2022; Kantor and Twohey, 2017; Ryzik et al., 2018)[1], how billionaires are able to wield immense power by converting wealth into political and social influence (Faccio, Masulis, and McConnell, 2006; Krugman, 2020; Neate, 2022), how institutional structures (such as law enforcement, housing policy, etc), intentionally or not, grant power to one class of individuals at the expense of others (Aaronson, Hartley, and Mazumder, 2021; Darity Jr, 2022; Goncalves and Mello, 2021), and even in academia, how power (that derives from networks and exclusivity) can serve to uphold the status quo (Carrell, Figlio, and Lusher, 2022; Schultz, Stansbury, et al., 2022). In this paper, we examine how power affects decision-making and resource allocation in one such consequential setting, namely, the doctor-patient encounter.

Power has received substantial attention in social science research. We know that power confers some non-pecuniary utility to individuals, such that the simple act of possessing power affects the way people process information and make decisions, sometimes even against their own interests.[2] However, much of this has been found from stylized laboratory games with small payouts. While these games allow for the careful testing of theory, they do not allow researchers to quantify the real-world, high-stakes consequences of power and its full scope of policy implications. This creates a gap between academic knowledge on the topic and the gravity with which power is discussed in society.

This gap exists because it is empirically challenging to evaluate the real-world effects of power on individual behavior. Power is an abstract concept that is a function of both individual and context, and is often inextricably linked with other social factors, making its precise identification and measurement difficult. In most settings, it is impossible to distinguish the effects of power on an outcome from the direct effects of the valued resource that confers that power on that outcome. (For example, do wealthy individuals achieve better health outcomes in society because of their power, or because wealthy people differ from the non-wealthy in unobservable ways?) In this paper, we bypass this empirical difficulty by examining how power affects medical care within the US Military Health System (MHS).

The doctor-patient relationship is arguably one of the most impactful and complex social relationships legally codified by a power differential. This power differential, which favors the physician,

[1] One of the women in the New York Times article that ignited the #MeToo movement was famously quoted as saying "I am a 28 year old woman trying to make a living and a career. Harvey Weinstein is a 64 year old, world famous man and this is his company. The balance of power is me: 0, Harvey Weinstein: 10."

[2] In economics, though studies of power generally pertain to economic markets (e.g., how power effects prices and efficiency) (Ball et al., 2001; Bulte et al., 2012), power in individual decisions have been studied either purely theoretically (Aghion and Tirole, 1997; Baker, Gibbons, and Murphy, 1999; Grossman and Hart, 1986; Hart and Moore, 1990) or empirically using stylized economic games in laboratory settings (Bartling, Fehr, and Herz, 2014; Burdin, Halliday, and Landini, 2018; Fehr, Herz, and Wilkening, 2013; Kumru and Vesterlund, 2010; Mallucci, Wu, and Cui, 2019; Moxnes and Van der Heijden, 2003; Pikulina and Tergiman, 2020; Sivanathan, Pillutla, and Murnighan, 2008; Van Dijk, De Dreu, and Gross, 2020). In the social psychology literature, power has been shown to affect an array of individual behavior and decision-making outcomes using surveys, observation, and laboratory experiments (with popular psychology techniques such as priming, episodic recall, nonverbal cues etc). For a broad review of the social psychology literature, refer to Chapter 15 and 16 of APA Handbook of Personality and Social Psychology (Mikulincer et al., 2015).

is driven by multiple factors: all individuals require the services of a physician in their lives, at which point they surrender some or all decision rights over their health to the physician, at times without knowledge or consent, and often without a way to assess decision quality ex-ante or ex-post because of large information asymmetries. Moreover, while other social contracts with similar power imbalances (such as in policing (Chevigny, 1969; Meko, 2022; Turner, 1992), workplaces (Bartolome and Laurent, 1986; Kray, Kennedy, and Rosenblum, 2022; Mortensen and Haas, 2021; Reskin and McBrier, 2000) and law (Caryn Devins, January 22, 2013; Glaberson, 2006; Levinson, 2016)) often come under scrutiny, the power imbalance in the doctor-patient relationship has largely evaded focus due to a feature unique to medicine: the expectation that the physician is a perfectly altruistic agent for the patient (Arrow, 1963) and will thus be resistant to any distortionary effects of power. This expectation persists despite overwhelming evidence that the healthcare setting is susceptible to principal-agent problems: physicians, like all humans, have biases (Singh, 2021; Singh and Venkataramani, 2022), and respond to incentives both pecuniary (Alexander, 2020; Alexander and Schnell, 2019; Clemens and Gottlieb, 2014; Li, Dow, and Kariv, 2017) and non-pecuniary (Kolstad, 2013).

As a society, we care about extreme power differentials because they have unintended consequences, particularly when scarce resources are allocated in an unequal society. For instance, patients with less power may have their preferences discounted or ignored by physicians (due to patients' inability to advocate for themselves effectively or physicians' biases), resulting in worse care quality and outcomes. Although the power differential between doctors and patients will likely always exist and may even be necessary, *variation* in this power differential may lead to inefficient and inequitable variation in care across patients. Thus, in this study, we examine how variation in the power dynamic between doctor and patient affects patient care and outcomes in the MHS.

We face two empirical challenges to answering this research question: (i) measurement, and (ii) identification. To overcome the first challenge, namely, how to precisely measure power, we leverage a feature unique to the MHS: the majority of physicians and patients in this system are active duty military, and thus hold clear and observable military ranks. Hierarchy, or rank, is one of the most common ways that power is established and reinforced in society (Magee and Galinsky, 2008). Therefore, we can use the difference in military ranks between physicians and patients as a proxy for the magnitude of the power differential between them.

While the doctor always has more control over "valued resources" within the medical context, such as access to information, clinical services, decision-making rights, and medical authority, increasing rank of the patient will correlate with greater control of resources *outside* the medical context, such as status, networks, and military authority. Therefore, the total power differential between the doctor and patient in the clinical encounter should decrease as the patient's rank approaches or surpasses the physician's rank, which in turn may affect medical care and patient outcomes. We provide support for this hypothesis through qualitative data obtained from interviews with military physicians.

To overcome the second challenge, namely, how to identify causal estimates of the effect of power on behavior and resource allocation, we use a feature unique to the emergency department (ED) setting. Patients are assigned to physicians on a queuing basis, which ensures the quasi-exogenous matching of patient to physician. We provide evidence for this assumption and check for violations in robustness checks.

We motivate our research question using a simple model in which power is a function of the individual and context. In our baseline specification, we compare for example, the care provided to Lieutenant A when they are assigned to a physician lower-ranked than them (making Lieutenant A a "high-power" patient in that encounter) to the care provided to Lieutenant B when they are assigned to a physician weakly higher-ranked than them (making Lieutenant B a "low-power" patient in that encounter), while accounting for the average care provided by physicians of each rank. We do this by using fixed effects for patient rank and physician rank. We must emphasize – here and many times over the course of the paper – that we always compare patients of the *same rank* who happen to be, due to random assignment, relatively more or less powerful than their physician. (That is, we never compare outcomes for patients of different ranks.)

In this baseline analysis, we find that physician effort and resource use increases as the power differential in the clinical encounter decreases. Specifically, high-power patients experience about 2.5% more physician effort (measured using relative value units, RVUs) and a 0.14 SD increase in resource use (such as more tests, more procedures, more time with the physicians, and more opioids) than equivalently-ranked low-power patients. Furthermore, high-power patients also have better health outcomes than equivalently-ranked low-power patients, i.e., a 15% decrease in their likelihood of being admitted to the hospital within 30 days. Quick back-of-the-envelope calculations show that if low-power patients in our sample had been treated like high-power patients –keeping all else constant – the MHS would have saved about a third of what they spend on low-power patients.

We then substitute physician fixed effects in place of physician rank fixed effects in our baseline specification, such that variation in the power differential stems from the promotion of the physician to a higher rank while simultaneously accounting for unobserved heterogeneity in practice styles across physicians. Our results become more precise, suggesting that unobservable differences in practice styles across different physicians are not driving our results.

We perform several robustness checks to shore up confidence in our estimates. First, to ensure our estimates are not driven by a small subset of patient or physician ranks, we re-run our analysis on an a propensity-matched sample limited to patients who are capable of both being out-ranked and under-ranked by their physician. Our results still hold. Second, we run 3,072 different regressions based on various combinations of fixed effects and covariates, and the specification curve of these estimates never overlaps 0. Third, we assuage concerns regarding the assumption of quasi-random assignment of physicians to patients in the ED. For instance there may be sorting when more than one physician is available for patient assignment (such as at times of low patient demand). Thus, we re-run our analysis on the subset of patient encounters that occur at times of high demand (i.e, the highest quartile of ED capacity, when sorting is known to be at a minimum) and find that our effect sizes become even larger, suggesting that being a high-power patients is most protective at times of capacity strain (when care quality may deteriorate most).

We perform an additional analysis – referred to as the "promotion bonus" analysis – to examine our question using a different research design. If rank is a marker of power, then a promotion should increase an individual's power. Hence, examining within-physician effort during a narrow window of time around patient promotion to a new rank should isolate the effect of a changing power differential between doctor and patient from other factors usually correlated with rank. Importantly, since the physician is unaware of the date of the patient's promotion, proximity of the encounter to the date of patient's promotion should not affect their clinical care in any way. Results from this event study are suggestive: within-physician effort is significantly higher for patients recently promoted to a given rank than for those about to be promoted to that rank, a result that is robust to a placebo tests with 250 "fake" promotion dates.

Next, we perform three supplemental analyses which show patterns consistent with our hypotheses while using different research designs and testing different parts of our theory. First, we document evidence of the "power spillover". On days the physician attends to a high-power patient, they decrease effort for their concurrently seen lower-ranked patients (whose health outcomes suffer in turn), suggesting suboptimal effort re-allocations by the physician from their relatively less powerful to more powerful patients.

Second, we provide evidence for the generalizeability of our results beyond just military healthcare settings. The power differential between any two people – within the military and without – is a complex amalgam of many different social, economic, and demographic factors (such as age, race, sex, etc), though rank is likely the most salient marker of power in the military. We provide suggestive evidence of this in our data: the effect of being a high-power patient on patient care – while always significant – depends to a large extent on the racial and gender concordance between doctor and patient. For example, outranking their White physician allows Black patients of a given rank to overcome the lower effort they normally receive when being outranked.

Third and finally, we provide evidence of a "power mechanism". Being assigned to a lower-ranked physician is beneficial for the patient even after retirement – when authority is lost but status is kept – suggesting that status ("respect") rather than authority ("fear") drives the effect of patient power in our setting. Taken together, our main analyses, the promotion bonus analysis, and these supplemental analyses paint a more convincing picture of the effects of power on behavior than any one single analysis can by itself.

Our study rigorously confirms what has long been intuitively known: that the powerful are able to enjoy better outcomes in life by way of simply possessing power. More concretely, our paper makes three novel contributions to the literature on power in dyadic encounters. First and foremost, this study may be the first to use real-world data to provide evidence of the "long shadow of power": the idea that power in one domain of life can spill over to unrelated domains (for example, from the military to the clinical in this study), causing distortions in behavior and resource allocation in both. While the porosity of domains to an individual's power is problematic from an equity viewpoint, it becomes especially concerning when it allows scarce resources to be "stolen" from others, a phenomenon that we show in this study to impose substantial and tangible harms to unsuspecting, less powerful individuals. Importantly, while this topic has been explored to some extent in contractual relationships where power differentials are both an intentional feature and an expected norm (such as between employee-employer (Caldwell and Harmon, 2019; Dahl and Knepper, 2021)), we show effects in a setting where it normatively ought *not* to matter, such as the doctor-patient relationship.

Second, our estimates likely provide a lower bound for how variation in patient power may distort processes and outcomes in healthcare, for many reasons. First, active-duty military patients tend to be healthier than patients in civilian settings, which may limit the harm from any physician neglect as well as the benefits of any extra effort. Second, power differentials between patients and physicians in civilian settings may be more extreme and therefore more consequential than in the military, where members often share a sense of deep kinship due to a common mission and similar core (and frequently traumatic) experiences. Third, MHS facilities and beneficiaries may be better resourced than their civilian counterparts on average[3], and the greater scarcity in some civilian healthcare settings may further penalize the least powerful patients. Fourth and finally, we only examine the "hard" benefits of power (such as better health outcomes), while being unable to measure and therefore understating

[3]In 2023, the DoD requested $55.8 billion for the MHS, about 7.2% of its total budget request (Mendez, 2022). Moreover, most MHS facilities reported above average patient experience star ratings, and the DoD obtained above the National Committee for Quality Assurance's seventy-fifth percentile benchmark for 9 out of 14 quality measures tracked (Tanielian and Farmer, 2019).

some of its more obvious benefits (such as being treated with dignity, or satisfaction with care). Thus, taken together, our results hint towards more egregious violations of the doctor-patient contract than we can document in this setting. For example, our findings can speak to the rise of "VIP patients", and "concierge" or "red-carpet" medical care for individuals who are wealthy, famous, influential, or well-connected (Kliff and Silver-Greenberg, 2022)[4].

Third, our results expand a large, more general literature on discrimination (Foels and Pratto, 2015). Power dynamics between individuals from high-power (or dominant) groups and low-power (or marginalized) groups may determine the allocation of resources and opportunities in firms, governments, and societies. That in turn dictates how equitably and efficiently they function. Furthermore, our results allow us to offer a new and cohesive theory for why homophily between individuals on social markers of power (such as race and sex) matters for outcomes in consequential settings such as education, law, and of course, healthcare. In an unequal society, being a part of a privileged sociodemographic group can be a valuable resource; thus, homophily can help rebalance the power differential created by the asymmetries in this resource. For instance, concordance in race and gender between educator and student affects learning outcomes (Gershenson et al., 2022); between judge and defendant affects trial outcomes (Knepper, 2018; Weinberg and Nielsen, 2011); and between doctors and patients affects health outcomes.(Alsan, Garrick, and Graziani, 2019; Cabral and Dillender, 2021; Frakes and Gruber, 2022; Greenwood et al., 2020). Our findings can also account for the protective effects of occupational homophily: patients who are physicians themselves receive a different level of care (Frakes, Gruber, and Jena, 2021; Johnson and Rehavi, 2016) due to their greater access to medical information, a resource that is highly valued in clinical settings. To summarize: the MHS only offers us a convenient setting to investigate an empirically challenging research question, but it does not preclude us from drawing more general conclusions.

In Section 2, we describe the background and our conceptual framework. In Section 3, we describe our data. In Section 4, we present our empirical section and results, and in Section 5, we present our supplemental analyses. In Section 6, we discuss policy implications (such as the relevance of our results to the practice of Shared Decision-Making) and conclude.

# 2 Background and Conceptual Framework

## 2.1 Defining the power differential between two individuals

Power, broadly defined, is the asymmetric control over valued resources in a relationship – resources such as wealth, information, networks, decision rights, authority and status[5] – that allows an individual to affect outcomes for themselves and others (Smith and Hofmann, 2016). An individual's power in a specific setting depends on the individual (i.e., the control they can exert over resources) as well as the specific context (which dictates the value of the resources). We formalize this intuition by creating

[4]For example, here is an excerpt from a New York Times exposé on how NYU's emergency department pressured physicians to give preferential treatment to a certain class of patients: "On hospital computers, electronic medical charts sometimes specify whether patients have donated to the hospital or how they are connected to executives, according to screenshots taken by frustrated doctors in recent years and shared with The Times. "Major trustee, please prioritize," said one from July 2020." (Kliff and Silver-Greenberg, 2022)

[5]The psychology literature generally differentiates between power, authority, and status as being slightly distinct yet heavily related constructs. According to this literature, power is characterized by control of tangible resources, authority is power based on perceived formal or legal legitimacy (Thompson, 1956), and status is power conferred on an individual perceived to have social value by others (Blader and Chen, 2012). However, this distinction seems unnecessary and confusing for the purposes of our paper and we thus discard it. Instead, we conceptualize authority and status as *valued resources* themselves (similar to wealth, information, etc), whose asymmetric control allows individuals to accumulate power and affect outcomes. For example, an individual with greater authority or status can exert more influence over their or others' outcomes than individuals with less.

a simple model to (i) connect the idea of "control of valued resources" to the realization of the power differential in an interaction between two individuals, and (ii) formally define what effect we are trying to identify in this paper and how.

Assume, for simplicity, two individuals $I \in [i, j]$ and two contexts $C \in [c^+, c^-]$. An individual's control over resources – represented by $\phi \in [0, 1]$ – is indexed by the individual and the context. For example, individual $i$ has $\phi_{ic^+}$ control of resources in context $c^+$, where $\phi_{ic^+} = 1$ implies total control over the resources in that context. If each context (and the interactions within it) were independent of other contexts, then the *expected* power differential ($\Pi^*$) in an encounter between the individuals i and j in a given context would simply be the difference between each individual's control of resources in that context, like so:

$$\Pi^*_{(j-i)c^+} = \phi_{jc^+} - \phi_{ic^+} \tag{1}$$

In this case, context $c^+$ is referred to as the primary context, i.e., the setting where the interaction between i and j is taking place, or the context in which most of the interactions between them take place. However, the *realized* power differential ($\Pi$) between two people in the primary context $c^+$ may be different than the *expected* power differential ($\Pi^*$) due to information spillovers from secondary contexts such as $c^-$. Spillovers may occur if $i$ and/or $j$ have repeated interactions, care about outcomes outside the primary context $c^+$, or if certain resources are not easily confined to a specific context (such as status, since if an individual has status in one context, they likely have status in others as well). Thus, we re-write Equation (1) in a more general format, where the *realized* power differential for an encounter between individuals i and j in primary context $c^+$ ($\Pi_{(j-i)c^+}$) can be affected by spillovers from power differentials in secondary contexts such as $c^-$:[6]

$$\begin{aligned}
\Pi_{(j-i)c^+} &= \Pi^*_{(j-i)c^+} + w_{c^-} \cdot \Pi^*_{(j-i)c^-} \\
\Pi_{(j-i)c^+} &= \underbrace{\left[\phi_{jc^+} - \phi_{ic^+}\right]}_{\text{Term I}} + w_{c^-} \cdot \underbrace{\left[\phi_{jc^-} - \phi_{ic^-}\right]}_{\text{Term II}}
\end{aligned} \tag{2}$$

In this more general Equation (2), we introduce a term $w_c \in [0, 1]$, which is essentially a salience weight assigned to a secondary context (i.e., the context outside the one where the interaction is actually occurring). If $w_{c^-} = 0$, it means that the interaction in the primary context $c^+$ is unaffected by the power differential in the secondary context $c^-$ (and Equation (2) collapses into Equation (1)); if $w_{c^-} = 1$, it means that the interaction in context $c^+$ is affected equally by the power differential in context $c^-$ as it is by the expected power differential in context $c^+$. In this paper, we hypothesize that as humans, we are unable to compartmentalize power dynamics so stringently by context, and thus interactions in one context are likely to be affected by power differentials in other contexts. In other words, we hypothesize that $w_{c^-} \neq 0$.

In most settings, it is difficult to measure the sign on either Term I (the difference in control of resources in the primary context where the encounter occurs), Term II (the difference in control of resources in other secondary contexts), or both – making the study of power dynamics difficult.

[6] Consider a professor and her student. In the classroom context (i.e., the primary context), the power differential clearly favors the professor as she controls the valued resources in the classroom: decision-rights (e.g., the ability to decide student's grades, what material is to be covered, what classroom policies are etc), and authority (e.g., having the university formally recognize the aforementioned decision rights). However, there may be spillovers onto this context from the non-classroom context: privileged students may control more resources than the professor outside the classroom – such as wealth, access to university administration, etc – all of which could affect the realized power differential between them and the professor in the classroom context. Celebrity students and children of important university donors may be treated differently in the classroom (as may be, on the other end of this example, low-income or disabled students), though the *actual* control of valued resources in the primary classroom context does not change (in that the student does not have the power to give themselves a favorable grade).

This is because most commonly, there are several valued resources that can be controlled in a given context (e.g., wealth, status, information) and each resource is controlled to varying degrees by an individual. An individual's control in one context ($\phi_{IC}$) is the sum of their control over each distinct resource ($r$) available in that context (i.e., $\phi_{IC} = \sum^{r} \phi_{ICR}$), and normally, it is not always evident how $\phi_{jC}$ relates to $\phi_{iC}$. However, in our study, due to the nature of the doctor-patient relationship, the clear and unyielding hierarchy that defines every military organization in the world, as well as the quasi-exogenous matching of physician to patient in EDs, we are able to hypothesize about the signs of Term I and Term II with some confidence.

## 2.2 Measuring the doctor-patient power differential in the Military Health System

In this section, we apply the model from the prior section to our specific setting: healthcare. In the specific case of the doctor-patient interaction, we know the sign on Term I in Equation (2). The doctor will always have greater control than the patient over a range of valued resources within the clinical context, specifically, the decision-rights over the patient's health, legal authority to make life-or-death decisions, information (both ex-ante and ex-post, about the diagnosis, treatment, and quality of care), clinical resources (such as equipment, beds, medicines, etc), and the status associated with being a physician. Using the notation above, if the clinical context is represented by $c^+$, then for physician $j$ taking care of patient $i$, $\phi_{jc^+} > \phi_{ic^+}$. Therefore, Term I in Equation (2) is positive. There is some qualitative evidence that both doctors and patients are cognizant of this power differential: in interviews, patients admit to conforming to socially sanctioned roles such as being compliant, avoiding confrontation etc to avoid alienating their physicians (Berry et al., 2017; Frosch et al., 2012), while physicians admit to using strategies to "handle" being more powerful than their patients (Fochsen, Deshpande, and Thorson, 2006; Nimmon and Stenfors-Hayes, 2016).

However, we hypothesize that the *realized* power differential between the doctor and patient in a clinical encounter ($\Pi_{(j-i)c^+}$) also depends on the expected power differential between them outside the clinical setting. That is, we hypothesize that the salience weight $w_{c^-}$ on Term II is non-zero. This is a reasonable hypothesis: doctors and patients are human, and human are rarely able to segment information into distinct, vacuum-sealed categories (such as the context). As such, we expect either or both to be influenced by their expected power differential *outside* the clinical setting, especially if it is large in magnitude or highly salient, which would ultimately change the realized power differential between them *within* the clinical encounter.

### *2.2.1 Using Military Rank To Measure Power*

The military is one of the oldest and most classical examples of hierarchical organizations in the world, where hierarchy is formalized via a strict and clear ranking system. Military rank is always observable via uniform and denotes formal authority: for example, disrespecting a more senior officer and failing to follow orders are against military regulations and can result in administrative or judicial punishment. Increasing military rank usually leads to greater control over a range of resources in the military setting as well: higher salary, access to equipment and infrastructure, greater status, more decision-rights (i.e., regarding both the military's overall function more broadly, as well as narrower lower-level decisions such as whom to promote etc), and greater generalized legal authority.

This rigid military code of power and hierarchy collides with the existing power dynamics inherent to the healthcare context. The majority of patients and physicians in the MHS are active duty military and are assigned a military rank. In the healthcare setting (represented by $c^+$), generalized military power is limited as the legal and context-specific power of the physician takes precedence. For instance, a patient can request but cannot require a physician to prescribe them a certain drug or order a certain treatment, no matter how high-ranking the patient might be in the military. However, in the military context (represented by $c^-$) , any non-clinical interaction between an MHS doctor and their patient is influenced by their relative military ranks. That is, an interaction in the military between two individuals i and j where $Rank_i > Rank_j$, is characterized by $\phi_{ic^-} > \phi_{jc^-}$ on average. A patient higher-ranked than the physician can use either their higher status in the military or greater formal authority over the physician to influence the physician's outcomes in the military.

In this paper, we examine how the total power differential between doctor and patient in a clinical encounter changes with the rank of the physician (keeping patient military rank constant) in Equation (2):

$$\frac{d\Pi_{(j-i)c^+}}{d\phi_{jc^-}} = \frac{d}{d\phi_{jc^-}}\left(\underbrace{[\phi_{jc^+} - \phi_{ic^+}]}_{\text{Term I}} + w_{c^-} \cdot \underbrace{[\phi_{jc^-} - \phi_{ic^-}]}_{\text{Term II}}\right) = w_{c^-} \tag{3}$$

Since we hypothesize that the salience weight associated with the secondary context, $w_{c^-}$, is positive, the realized power differential in a doctor-patient clinical encounter is positively related to the doctor's military rank (keeping the patient's military rank constant). In other words, as doctor rank decreases, the realized power differential in a doctor-patient clinical encounter decreases. As Term I is always positive in the clinical setting (since military rank does not affect control over clinical resources), this can be intuited from the equation itself: the realized power differential is largest when the doctor outranks the patient (Term II is positive) and smallest when the patient outranks the doctor (Term II is negative).

### 2.3 Estimating the impact of the doctor-patient power differential on patient care

In the previous section, we highlighted the relationship between military rank and the power differential between doctor and patient in the MHS. In this section, we walk through the relationship between this power differential and the outcomes that we examine in this paper. Laboratory experiments show us that power affects the way individuals search for, perceive, and incorporate information, thereby affecting subsequent decisions and behavior (Galinsky, Rucker, and Magee, 2015; Simpson et al., 2015). We use this literature to inform our understanding of how the power imbalance in the doctor-patient relationship can affect the physician's treatment of the patient either through changes in physician behavior or changes in patient behavior.

For example, reducing a physician's (real or perceived) power in a clinical encounter with a patient may change how physicians *provide* care. Reducing an individual's power causes them to act in a more other-regarding manner, be more empathetic of others' suffering, be less likely to rely on stereotypes when evaluating others, engage in longer and higher-quality information search, be more likely to pay attention to the needs, beliefs, and advice of others, and be less likely to rely only on their own subjective experiences when making decisions (refer to Galinsky, Rucker, and Magee (2015) for a detailed review of the primary literature). Thus, when the realized power differential in a doctor-patient encounter is smaller than usual (such as when caring for a high-power patient), the physicians may consciously or subconsciously spend more time, effort, and resources in an attempt to provide – or at least *signal* that they are trying to provide, quality clinical care. For example, they may take a more thorough clinical history, be more likely to elicit patient preferences, order more tests to diagnose the problem, be more likely to take patient symptoms seriously, and in general less likely to make off-the-cuff judgements based on stereotypes or first impressions. (It is important to clarify that such changes in physician behavior cannot necessarily be considered behavioral distortions; for example, there may be strong organizational or personal incentives for physicians to treat high-power patients better.)

In our setting, qualitative evidence supports the hypothesis that high-ranking patients cause changes in physician behavior, as noted by some direct quotes from interviews with military physicians:

> You're supposed to be blind to [the military rank of the patient], but human nature takes over ... you're just a little bit more careful when the stakes are higher.
>
> – Chief of military ED

> ... know that [the Colonel] is coming in and to not have him wait ... could you help facilitate getting [a specialist] involved if he needs something ...
>
> – Text message received by ED physician

Similarly, increasing the patient's (real or perceived) power in a clinical encounter may also change how patients *demand* care from their physicians. Power makes an individual more confident in their knowledge and experiences, more optimistic about their outcomes in the future, more resistant to social pressures to conform, more likely to express their opinions in negotiations, more persuasive, more assertive and action-oriented, and more focused on pursuing and accomplishing goals (Alexander et al., 2012; Galinsky, Rucker, and Magee, 2015). The relevance of these effects to patient behavior in the clinical setting is clear: high-power patients may demand both more and higher-quality care, be more likely to advocate for themselves, and be more able to convince the physician to provide care they believe is appropriate for their symptoms.

Based on this literature, we can safely hypothesize that reducing the power imbalance between the doctor and patient will observably change the type of care the physician provides to the patient. However, we cannot predict who – physician or patient – will drive these changes. That said, in one interview a physician hypothesized that changes in medical care may be physician-driven because physicians know patient rank and can thus respond to power differentials, while patients may not always know physician rank as physicians may be in scrubs.

We define the medical care provided by physician j to a patient i as a function of the realized power differential between them and, of course, patient and physician characteristics that affect outcomes directly outside of affecting the power differential, such as patient clinical characteristics and physician ability. That is, the medical care function is

$$M_{ijc^+} = f(\Pi_{(j-i)c^+}) \cdot g(i) \cdot h(j) \tag{4}$$

The primary focus of this paper is estimating $\frac{dM_{ijc^+}}{d\Pi_{(j-i)c^+}}$, i.e., how medical care changes with respect to power differentials in the doctor-patient clinical encounter.

This model is useful because it accomplishes two things. First, it can reconcile some of the prior literature that hints at – but never explicitly mentions or tests – the effects of power in the doctor-patient relationship. For example, improvements in patient care and health outcomes associated with doctor-patient concordance on race and sex (Alsan, Garrick, and Graziani, 2019; Frakes and Gruber, 2022; Greenwood et al., 2020) can be attributed to a decrease in the magnitude of Term II. White physicians may treat Black patients worse and male physicians may do the same to female patients, both because Black/female patients hold less power outside the clinical context than White/male patients (i.e., in our model, Term II is more positive for Black/female patients than it is for White/male patients), making the realized power differential in the clinical setting $\Pi_{(j-i)c^+}$ larger in favor of the physician. This is because in a society where institutionalized sex- or race-based discrimination is prevalent, being of the privileged race or sex may itself be a valued resource. Thus, when the physician shares the same race or sex as the patient, the power differential in the secondary context between the doctor-patient becomes smaller, as the control of resources in society becomes more equal. A different but related vein of literature also shows that physicians treat patients who are themselves physicians differently than other patients. Once again, this can be easily explained by our model. In the primary clinical context, information is one of the most valued resources available. A patient who is also a physician has greater control of information than the average patient, making Term I – and thus also the realized power differential – smaller in magnitude.

Second, our framework can be applied to other settings, as well as adapted flexibly for alternative definitions of power. For example, this model can be used in a variety of primary contexts and relationships, such as employer-employee relations in workplaces, educator-student in classrooms, even two countries in negotiations. Moreover, researchers wishing to define important constructs differently can easily do so; instead of modeling status and authority as valued resources (as we currently do), they could model them as constructs that increase the salience term for the secondary context ($w_{c^-}$), (e.g., a high-status patient may be more likely to bring attention to their power outside the clinical setting than a low-status patient). Alternatively, since status is not always specific to contexts, patient status can be modeled as a valued resource *within* the primary clinical setting. If so, status will simply shrink the size of Term I and thus ultimately the realized power differential in the clinical encounter, as the difference in status between a physician and a high-status patient is smaller than that between a physician and a low-status patient. That is to say, our model can be used flexibly in future research to understand the effects of power on behavior.

# 3 Data

## 3.1 The Military Health System (MHS)

We run our analyses using data from the Military Health System (MHS). The MHS is an integrated delivery network encompassing both a payer and provider of health care services. As a payer, The MHS manages TRICARE, an insurance benefit for active duty and retired military and their families. As a provider, the MHS runs one of the largest health care systems in the United States with 51 hospitals and nearly 400 outpatient clinics. Hospitals range from small community hospitals to large academic medical centers. This system is augmented by an expansive network of civilian hospitals, physicians, and other health care providers known as the "purchased care" system. These providers bill a third-party carrier (e.g. Humana or Healthnet) for services provided to Tricare beneficiaries and are paid similar rates as Medicare pays for their beneficiaries. For this study we focus on patients using an emergency department in the direct care system, but use claims from both the direct care and purchased care system to construct utilization outcomes that extend beyond the index visit (e.g. 30 day readmissions).

The direct care system includes several features that are critical for our identification. First, Active Duty Service Members are all on the same insurance plan – Tricare Prime ruling out differences in care based upon coverage difference. Second, they are required to receive care in the direct care system unless they receive special permission – for instance if they are stationed in a remote area that does not have a direct-care hospital within an hour drive – and face zero out of pocket costs. This allows us to observe the universe of all ED use by our patient sample, limiting attrition to civilian facilities. Third, employees in the direct care system including physicians are paid via a fixed salary. Physicians do not receive additional compensation based on the quality or quantity of care provided, ruling out a direct financial incentive to provide more care to high-power patients.

Military emergency departments are predominantly manned by active-duty military doctors augmented by civilian physicians. Patients are assigned to beds in a similar manner as civilian hospitals. Patients are first triaged so that the most critically ill patient receives care first, and are then assigned to an open bed on a first-come first-served basis. At no time can a patient request a specific physician. Physician schedules and bed-assignments are decided weeks in advance likewise limiting any capacity for physicians to select specific patients, though we test this assumption in robustness checks.

Our data includes all claims from both the direct and purchased care system from 2008-2017. Additionally, we match this data with administrative records on both patient and physicians that include their military ranks and other demographic variables.

### 3.2 Military ranks

The military uses 24 unique ranks across three broad categories - Warrant Officers, Enlisted, and Officers. Warrant Officers are somewhat rare and have a unique power structure so we focus our analysis on enlisted and officers. Enlisted service members are the broad labor force and make up about 90% of the military. They generally have a specific specialty such as "infantry", "truck driver", or "medic". Higher ranking enlisted are supervisors and technical experts, broadly responsible for first-line leadership and training of enlisted troops. Officers serve as supervisors, planners, and organizational leaders within the military. While the military services label these ranks differently (e.g. an Army Major is equivalent to a Navy Lieutenant Commander), they use a common alphanumeric code. For instance, an E-5 is the fifth enlisted rank regardless of service and an O-3 is the third officer rank regardless of service. An important note is that officers are always senior to enlisted in formal authority, although the highest ranking enlisted will often have informal authority due to respect for their position and tenure. The distribution of these officers in our sample - both patients and physicians, are shown in Table 1.

The promotion process varies starkly based on rank. The initial ranks for both officers and enlisted (E-1 to E-3 and O-1 to O-2) are promoted automatically based on time in service, unless they fail to pass physical fitness tests, or get into some disciplinary trouble. More senior ranks vary in their process, but limit promotions based on some measures of performance and potential.

### 3.3 Military physicians

The military primarily recruits physicians through one of three programs. For physicians that have already completed medical school, the military offers the Active-Duty Health Professions Loan Repayment Program. This program repays up to $120,000 in medical student loan debt in exchange for 1 year of active-duty service for each 40K in repaid student loan debt (Casscells, 2008). The military has two programs for students that have not yet attended medical school. First, the military runs its own medical school - the Uniformed Services University (USU). Students at USU do not pay any tuition. Additionally, these students are commissioned as active-duty officers and receive full pay and benefits, initially at the O-1 rank (Clarke, 2021). USU graduates are obligated to serve in the military for seven years. Finally, the military offers medical school scholarships through the Health Professions Scholarship Program (HPSP) (Stortz et al., 2021). Students in the HPSP receive a full scholarship to attend medical school. Like USU, these students are commissioned at the O-1 level, but are considered in a reserve status. They receive a monthly stipend of about $2,200, but not the full pay and benefits that USU students receive (U.S. Army, n.d.). HPSP graduates are obligated to serve in the military for four years. Regardless of the recruitment program, military physicians may remain on active-duty beyond their initial obligation at their own discretion. The data does not allow us to distinguish between these recruiting sources.

After Medical School, both USU and HPSP students are promoted to O-3 and matched with a residency site. Physicians that have completed medical school and/or residency prior to recruitment are given a rank consistent with their level of experience, but never lower than O-3. Physicians are then managed under a separate promotion process from the rest of the military. Promotions through O-6 are generally time-driven with promotions occurring at six, twelve and eighteen years of service (Headquarters, Department of the Army, 2020). Qualitative conversations revealed that physician promotion rates to O-6 are higher than operational military promotion rates to O-3.

# 4 Empirical Strategy and Results

In our main analysis, we exploit the quasi-random assignment of patients to physicians in the ED setting in Military Health System hospitals to examine how the power differential between the doctor and patient affects patient care and outcomes. Then later in a secondary analysis, we exploit the timing of patient promotion in an event study design to examine how within-physician effort changes for patients recently promoted vs those about to be promoted to a given rank.

## 4.1 Sample construction

We limit our sample to active duty patients between the ages of 18 and 64, seen in an emergency room by an ED physician with an Evaluation & Management (E/M) code between 99281 and 99285 or 99291 (to ensure it is an ED visit). Providers are civilians and active-duty military. We call this sample the *main sample*. Table 2 presents patient characteristics for this sample: on average, this sample is quite young (28 years), 23% female, 30% Black, and fairly healthy (mean Charleson score of 0.018, a validated scale that ranges from 0 to 6 and predicts the 10-year mortality for patients with multiple comorbidities).[7]

## 4.2 Identification Strategy

We exploit the quasi-random assignment of patient to physician in the ED for identification of causal estimates. This identification strategy is most commonly used when examining within- and across- physician variation in practice patterns in the healthcare setting (Chan, 2018; Chen, 2021; Gowrisankaran, Joiner, and Léger, 2018; Greenwood et al., 2020). It is based on a critical, institutional feature of

[7]The Charleson score can range from 0 to 6, with 6 being the highest 10-year mortality risk for patients based on comorbidities such as myocardial infarction, CHF, PVD, CVA or TIA, dementia, COPD, connective tissue disease, peptic ulcer disease, liver disease, diabetes mellitus, hemiplegia, moderate to severe CKD, solid tumor, leukemia, lymphoma, and AIDS. A CC score of less than 1 identifies the most healthy individuals, i.e., those with the lowest probability of death. In our sample, the average CC score of 0.018, which suggests an unusually healthy population, both by nature of being young as well as being active duty military.

the ED: physician schedules in an ED are set in advance, patient arrival to the ED is unanticipated, and patient assignment occurs sequentially to physicians that are available on duty. This feature essentially ensures the random assignment of patient rank to physician rank, which is our identifying assumption.

We show that this assumption holds in Figure A.1, which plots the relative likelihood of a physician rank being matched to patients of a specific rank relative to the bottom-most patient rank group (i.e., $\leq$ E-4). It would be concerning if – within a physician rank – the red dots were increasingly further away from the central vertical line as patient rank increases (i.e., moving up the Y-axis), as this would suggest that increasing patient rank is systematically correlated with a certain physician rank. However, this does not seem to be the case. All the red dots cluster around the central vertical line and are not systematically on one side or the other – suggesting that the matching of patient and physician rank is as-random.

Only in about 1.4% of the 1.5 million encounters is the patient higher-ranked than the physician (Table 2). This is primarily because, by definition, enlisted patients – who make up 91% of the patient sample – cannot outrank their physician. They are included in the analysis to estimate a variety of nuisance parameters (such as fixed effects for 14,650 diagnosis codes). However, we also re-run our main analysis using only the officers in the sample to show that our results – though more imprecisely estimated because of the drastically smaller sample (N=110,525) – remain robust.

We refer to patients who strictly outrank their physician in a given encounter as "high-power" patients. (Note that a patient cannot be high-power in absolute terms, only in relation to the physician assigned to them in the ED encounter.) On average, high-power patients are observably and mechanistically different from low-power patients. For example, high-power patients are from more senior ranks in the military, and senior military are by definition older than junior military. However, after adjusting for the rank of patient, high-power patients (those assigned to physicians of lower rank) and low-power patients (those assigned to physicians of the same or equal rank) are observably similar (Table 2).[8]

There may also be the concern that the assumption of quasi-random assignment fails when the hospital has low patient demand. For example, when the ED has empty beds, physicians may be able to sort into, or select, different patients based on unobservable characteristics (Chan, 2018; Chang and Obermeyer, 2020), violating the identification assumption. For example, patients who are senior military members may request senior physician for their experience or familiarity. Though this would just bias our results towards the null, nevertheless, in robustness checks we address this issue by re-running our main analyses limited to encounters that occur when the ED is at its busiest. We show that, at the fourth quartile of ED capacity, the identification assumption still holds and our main results remain robust.

## 4.3 Construction of Variables

### *4.3.1 Outcomes*

*Physician effort and resource use*: We measure physician time, effort, and resources expended on a patient: (i) by using total Relative Value Units (RVUs), a standardized and widely used measure of physician productivity and resource use, in both standard and logged form, and (ii) by constructing a Resource Index which collectively captures six clear and tangible instances of effort and resource use.

[8] High-power and low-power patients are observably similar even after controlling only for patient rank, but we include physician rank controls in Table 2 to mirror our main empirical strategy.

Physician effort is measured via logged RVUs (Relative Value Units). RVUs are used to determine reimbursement levels for physician services, and are commonly used as a proxy for physician effort, performance, and productivity (Jacobs et al., 2017; Proctor, 2012; Satiani, 2012). For example, Nurok and Gewertz (2019) state that RVUs are "based on the time it takes to perform the service, the technical skill and physical effort, the required mental effort and judgment, and the stress caused by the potential risk to the patient."[9] We present results using RVUs and Logged RVUs, though we primarily use the latter in this paper as RVUs are heavily skewed.

RVUs are an *aggregate* measure of physician effort. We also wish to capture physician effort in a more granular fashion, so we create a composite index based on tangible measures of time and resource use by the physician. This index is the sum of six separate standardized measures, all coded such that higher values represent higher time and/or resource use:

1. The dispensing of an opioid prescription. Prescribing opioids is an especially important and pertinent measure to this setting. Pain is one of the most common reasons active duty military come to the ED, and the act of prescribing opioids implies that the physician not only believes the patient's symptoms but also trusts them to not abuse the opioids. This trust in the patient is likely to be higher when the patient is a high-power patient.;
2. The final digit in the evaluation and management code where the higher number signifies more effort and resource use by the physician. There are 6 emergency department E&M codes (99281 – 99285 and 99291), each representing an increasing intensity of service provided to the patient based on the level of medical decision-making, patient history, and examination needed;
3. The number of procedures on the record (using Current Procedural Terminology (CPT) codes, which are used by physicians for documenting procedures and medical services);
4. Any test ordered;
5. Any imaging procedure ordered; and
6. Any procedure ordered

This type of collapsed index has been used in other papers to avoid issues arising from multiple hypothesis-testing (Currie, Mueller-Smith, and Rossin-Slater, 2020; Singh, 2021), but we also show our main results broken up by each individual measure as well.

*Patient Outcomes:* Does providing increased effort and resources to high-power patients result in better health outcomes? The additional time spent on clinical history and detailed examinations, extra tests and procedures, and additional effort in diagnosing patients may lead to better outcomes both in the index encounter and later. For instance, timely care may increase the chance of a correct diagnosis or reduce the likelihood of hospital admission during the index visit. Additional effort or care may also decrease the possibility of the patient returning to the ED untreated, dissatisfied, or in need of more serious medical care. As mortality rates are extremely low in this sample, we re-ran Equation (5) using the following three patient outcomes:

1. Hospital admission on index visit
2. Hospital admission within 30 days of index visit; and
3. Return to ED within 30 days (ED bounceback)

We remain agnostic about whether increased physician effort and resources will improve patient health,

[9] Outside of the physician effort ("work") component, RVUs are also meant to capture two other components – specifically, practice expenses and malpractice expenses – that are not relevant in this setting. In our primary analyses, we use ED fixed effects and patient-diagnosis fixed effects, with the goal of reducing variation in practice expenses across patients. Moreover, as the MHS is self-insured, it does not have malpractice expense. Thus, while other factors go into determining the total RVUs associated with an encounter, it is a valid and reliable metric for estimating physician effort in our setting, especially within-facility and within-diagnosis.

as the marginal return to care curve is typically concave, and in some contexts, may even be an inverted U-shape. Therefore, the effect of increased medical care on health outcomes can be positive, economically nonsignificant, or negative (least likely), depending on where the patient lies on the "returns to care" curve.

#### *4.3.2 Treatment*

In the MHS, an active duty military patient of rank $R_i$ can enter the ED and can be assigned to 4 mutually exclusive and exhaustive types of clinical encounters: I) the physician is lower-ranked; II) the physician is equally ranked; III) the physician is higher; and IV) the physician is unranked (civilian physician).

We wish to compare encounters with a *reduced* power differential to those with the *standard* power differential, accounting for average differences in how patients of different ranks are treated and how physicians of different ranks treat patients. Thus, for our main analysis, only one encounter type – Type I, where the patient outranks the physician – is considered "treated", while the other three types are used as controls in a model with fixed effects for physician rank and patient rank. Though we rely on this binary measure as our treatment for the majority of this paper, we also present results using the (discrete) difference in patient ranks (for which we necessarily exclude civilian physicians given their lack of rank).[10,11]

### 4.4 Empirical Specification and Results

Our baseline specification uses the following linear regression model, where patient $i$ is as-randomly assigned to doctor $j$:

$$Y_{ij} = \beta \underbrace{D_{ij}}_{\text{Treatment}} + \overbrace{\phi_{r(i)}}^{\substack{\text{Pat-rank}\\ \text{FE}}} + \underbrace{\phi_{r(j)}}_{\substack{\text{Phys-rank}\\ \text{FE}}} + \overbrace{\mathbf{X}_i}^{\substack{\text{Pat}\\ \text{chars}}} + \underbrace{\mathbf{X}_j}_{\substack{\text{Phys}\\ \text{chars}}} + \overbrace{\delta_{d(i)}}^{\text{Diag FE}} + \underbrace{\eta_{h(i)}}_{\substack{\text{Hospital}\\ \text{FE}}} + \overbrace{\tau_{t(i)}}^{\text{Time FE}} + \epsilon_{ij} \tag{5}$$

where $Y_{ij}$ measures physician effort and resource use (using the outcomes we outline in the previous section); $\beta$ measures the marginal effect of the treatment $D_{ij}$, i.e., an indicator for a high-power patient encounter where the patient strictly outranks the physician ; $\phi_{r(i)}$ is a fixed effect for rank of the patient; $\phi_{r(j)}$ is a fixed effect for rank of the physician; $X_i$ is a vector of patient covariates (linear and quadratic terms for age, sex, race, and Charlson Score), $X_j$ is a vector of physician covariates (linear and quadratic terms for age, sex, and race); $\delta_{d(i)}$ signifies fixed effects for the first 3 digits of

[10] We prefer this binary measure for several reasons. First, in such ED encounters, Term II in Equation (2), which measures the power differential between the doctor and patient outside the clinical context, can be most clearly assumed to be negative (as $\phi_{jc-} < \phi_{ic-}$), making the realized power differential in a clinical encounter the smallest in magnitude it can be amongst the 4 encounter types. Second, it is possible that $w_{c-}$ might actually be a non-linear function of the rank of the patient: it may be 0 when the patient is weakly lower-ranked to the physician, and become positive and non-zero when the patient outranks the physician. In other words, in a clinical encounter, the physician may not be influenced (or be influenced to a lesser extent) by patient military rank unless the patient outranks them – in which case, the power differential outside the clinical context suddenly becomes salient and reduces the magnitude of the realized power differential within the primary context of the clinical encounter. Third, and finally, using a binary measure allows us the easier display and interpretation of the range of outcomes studied than the categorical measure, which has 20 separate categories.

[11] Note that, in this binary measure, civilian physicians and enlisted patients are not providing any variation in the independent variable as they cannot, by definition, experience an encounter with a reduced power differential. However, they comprise a non-trivial portion of the sample (enlisted are about 91% of the patient sample and civilians are about 18.5% of the physician sample) and are included solely to more precisely estimate the high dimensional nuisance parameters we use in our baseline model (for example, there are 14,650 diagnosis fixed effects). All the variation in the independent variable primarily comes from the officer patient X officer physician encounters. This is not a concern as later in robustness check, we restrict our analysis to only officer patients and physicians, and our results still hold (suggesting that our result are not driven by a small subset of patient ranks).

patient's ICD-9/10 diagnosis codes, $\eta_{h(i)}$ is hospital fixed effects, and $\tau_{t(i)}$ is a vector of time-related fixed effects (year-month and day-of-week). However, given concerns about LATE interpretations in presence of covariates (Blandhol et al., 2022), in robustness checks, we also present a specification curve using 3,072 different combinations of these covariates to show remarkable robustness of our estimates to covariate selection.

Conditional fixed effects are difficult to understand intuitively; nevertheless, we need to emphasize the correct interpretation of $\beta$ before diving into the results. First, the patient rank FEs allows us to make all comparisons in the RVUs *between patients of the same rank*. We never compare outcomes between, for example, a Lieutenant and a Private, because this comparison would simply pick up differences due to age or other unobservables that differentiate patients of higher ranks from those of lower ranks. Second, the physician rank FEs allow us to de-mean the RVUs by the average RVUs provided by physicians of different ranks, as an O-3 physicians might practice differently from an O-4 physician due to, say, differences in experience. (We also add controls for physician characteristics like age, race, and sex to account for additional differences in practice style.)

Thus, $\beta$ estimates the difference in RVUs between, for example:

(i) a "low-power "Lieutenant A who is as-randomly assigned to a physician same or higher-ranked than him (de-meaned of the average RVUs provided by a physician of that rank), and

(ii) a "high-power "Lieutenant B who is as-randomly assigned to a physician lower-ranked than him (also de-meaned of the average RVUs provided by a physician of that rank).

In essence, this empirical approach allows us to isolate discordance in rank between doctor and patient, such that the only difference between two doctor-patient pairs is that in one, the patient outranks the physician and in the other, the patient does not. (In the next analysis, we drop physician rank fixed effects to include physician fixed effects to further account for differences in practice style across physicians).

We first present results using the discrete difference in ranks between the doctor and patient. We use Equation 5 with two changes: we exclude civilians physicians as they do not have a rank, and omit physician rank fixed effects as they would be collinear with the difference. There is a clear positive effect in Figure I: as the patient gains power relative to the physician (moving right on the X-axis), physician effort on the patient, measured by Logged RVUs, increases (keeping patient rank constant). The figure also suggests a subtle non-linearity: patient rank does not affect patient care much when the patient is lower-ranked than the physician, but there is an observable increase in effort when the patient is similarly-ranked, and then an even larger jump when the patient outranks the physician.

Next, Figure II presents marginal effects of being a high-power patient from Equation 5 for all standardized outcomes (so that estimates can be presented in a single figure): physicians exert 0.036 SDs more RVUs (an increase of 2.5%) and 0.045 SDs more logged RVUs, and are 0.054 SDs higher on the Resource Index with high-power patients than they are with low-power patients of the same rank. When examining the components of the Resource Index individually, physicians are also significantly more likely to prescribe opioids, use a greater intensity evaluation and management code, perform more procedures, order any test, and order any image in encounters with a high-power patient. Estimates for non-standardized outcomes and their summary statistics are presented in Table A.1.

The bottom-most panel in Figure II suggests that patient outcomes may be better for high-power patients as well. Most notably, keeping patient rank constant, high-power patients experience a 0.019 SD reduction in their likelihood of hospital admission within 30 days of the index encounter, a 15% reduction in risk. Thus, the return on the increased effort provided to high-power patients may be nontrivial. Were the MHS to treat all their low-power patients like high-power patients (keeping all else constant), they would recoup nearly a third of what they currently spend on low-power patients.[12]

Figures I and II both suggest that – in line with our hypothesis – there is a positive relationship between patient power and physician effort on that patient. High-power patients enjoy more effort and resources than low-power patients, after accounting for differences in care patterns across patient and physician ranks. Importantly, these increased resources appear to have tangible and positive effects on patient health outcomes.

Next, we substitute physician FEs to Equation 5 in place of physician rank fixed effects (while retaining patient rank FEs) to control for physician ability and/or practice style. This specification, presents a more stringent test of our theory, as it forces all the variation in our treatment (i.e., being a high-power patient in the clinical encounter) to stem from physician promotion. Essentially, the $\beta$ parameter now compares, for example, RVUs spent on a (low-power) Lieutenant A assigned to a physician who is weakly higher-ranked than a Lieutenant, to RVUs spent on a (high-power) Lieutenant B by the *same* physician when that physician was lower-ranked than a Lieutenant.

This test uses a smaller sample (only physicians who are promoted and see patients at differing rank) and is more demanding on the data. Despite this, the estimates from this analysis (Figure A.3) become larger for some outcomes, and universally more precise. This suggests that between-physician variation in care practices are not driving our results, and in line with our overarching hypothesis, being a high-power patient increases physician effort and resource use, and improves patient outcomes, keeping constant patient rank *and the physician*.

## 4.5 Robustness Checks

### *4.5.1 Concerns about small proportion of "treated" patients*

There may be concerns that our estimates may be biased due to the small proportion of all patient encounters who are classified as high-power. This occurs because enlisted patients cannot by definition be high-power patients as physicians are always officers, and enlisted are always junior to officers. Thus, we re-run our main analysis by limiting our analysis to encounters occurring only between patients and physicians *who are officers* (N=110,525), a mere 7% of our main sample. Given the smaller sample size, we only drop diagnoses code FEs (recall there are 14,650 FEs) from Equation 5. Figure A.2 presents the results: estimates are similar for RVUs, smaller in magnitude (i.e., less positive) for the resource index, more protective (i.e., more negative) for health outcomes, and less precise for all estimates. Overall, a high-power patient still receives greater effort and has better outcomes than an equivalently-ranked low-power patient.

[12]For a 2.5% increase in RVUs (i.e., an increase of 0.07 RVUs), a high-power patient experiences a 15% decrease (i.e., a decrease of 0.3 pp) in their likelihood of subsequent hospitalization. Medicare reimburses RVUs at the rate of \$33.59 per RVU (Medicare Medicaid Services, 2022), and a hospitalization costs \$11,700 on average (Torio and Moore, 2016). A high-power patient has \$2.35 more resources spent on them than a low-power patient, and saves \$35.1 in hospitalization costs, leading to a total savings of \$32.75 per patient. Low power patients consume 2.77 RVUs on average, i.e., \$93.04 per patient (note: this is the professional portion of the cost and does not include any facility charges). Savings of \$32.75 per patient imply that nearly a third of physician expenses could be recouped if low-power patients were treated like high-power patients, all else equal.

#### *4.5.2 Concerns about variation in characteristics even within patient rank*

There may still be concerns about whether appropriate comparisons are being drawn due to variation in patient characteristics even within a rank (for example, are we comparing a high-power 60 year old Lieutenant to a low-power 55 year old Lieutenant?). Thus, we first drop all patient ranks that can provide no variation in power differentials, which drops all enlisted as well as a the lowest and highest officer patient groups (resulting in an N = 52,154, which is 3% of the main sample). Then, we re-run our analysis on a propensity score matched sample on the remaining patient sample, but between matched patients who theoretically only differ in whether they are high-power or low-power, to further limit differences in our treated and comparison group.

The propensity score is derived by a logistic regression of an indicator for whether the patient is high-power on covariates such as patient rank, patient and physician characteristics (age, race, sex), quarter-year, hospital, and diagnosis group. After deriving the propensity score, each treated observation is matched with its K "nearest neighbor" - the control observation that has the closest propensity score. Finally, the average treatment effect is estimated as the difference between the treated observations and the matched controls. Standard errors are estimated using the methods developed by (Abadie, Diamond, and Hainmueller, 2010; Abadie and Imbens, 2006, 2012). Table A.2 presents results using 1 nearest neighbor (Col 1), 2 NN (Col2), 5 NN (Col 3) and 10 NN (Col 4). Our overall results are robust to this approach and similar in magnitude to our main results.

#### *4.5.3 Sensitivity of estimates to choice of covariates*

We show that our results are not driven by our choice of covariates. Figure A.4 displays the distribution of the $\beta$ estimate from running 3,072 regressions of Equation (5), with various combinations of covariates and fixed effects (always including fixed effects for patient rank and hospital). None of the 3,072 estimates overlap zero, suggesting that our parameter of interest – i.e., the marginal effect of being a high-power patient on physician effort and resource use – is remarkably robust to covariate specification.

#### *4.5.4 Concerns regarding violation of the identifying assumption*

In our main analysis, we rely on the quasi-exogenous assignment of patient rank to physician rank to estimate the effect of reducing the power imbalance on physician effort. However, evidence suggests that ED physicians may exert preferences over patient selection when given the opportunity (Chan, 2018; Chang and Obermeyer, 2020), such as during periods of low patient demand or when multiple physicians are available for waiting patients. If this occurs, the identification assumption would be violated, although the bias would likely lean towards the null. Senior-ranked patients, receiving more care due to their age, would also likely request or be assigned senior-ranked physicians (which is itself an effect of the power of high-ranking patients), making it less likely that they are classified as "high-power" patients. Our setting does not appear to show evidence of any such violation (Figure A.1). Nevertheless, we exploit a crucial observation made by Chan (2018) and Chang and Obermeyer (2020) to support our main results: selection based on physician preferences is largely eliminated when ED physicians have limited opportunities to choose between incoming patients, such as when the ED is operating at capacity. Thus, we re-perform our analyses, restricting them to encounters that occur only in the fourth quartile of daily ED strain (daily ED strain is calculated by counting the number of occupied beds on each date in our 10-year sample) – a sample we refer to as the *constrained sample*.

Figure A.5 shows that, the evidence upholding the identifying assumption in the constrained sample is even more robust compared to the same figure plotted for the main sample (in Figure A.1). That is, the red dots – which estimate how much more likely a given physician rank is to be paired with the specific patient rank relative to the lowest patient rank – are even closer and more uniformly located around the central vertical line. On average then, there are no systematic patterns of matching between patient and physician rank at the highest quartile of ED strain.

Figure A.6 shows that on almost every measure, the magnitude of the effect of being a high-power patient is larger using this subset of the sample – where the identifying assumption can be assumed to hold most certainly – than when using the main sample. Most strikingly, the protective effect of the being a high-power patient on patient outcomes increases substantially in the hypothesized direction. For example, the effect of reduced power is about 0.03 SDs more negative (i.e., more protective) on all three patient outcomes: hospital admission (-.027 SD in the constrained sample vs -.0005 SD in the Whole sample), 30-day inpatient admission (-.051 SD in the constrained sample vs -0.019 SD in the Whole sample), and 30-day ED bounceback (-.02 SD in the constrained sample vs 0.01 SD in the Whole sample). Put differently, when we are most confident that patient-physician assignment is random, high-power patients enjoy even more effort and better outcomes in the clinical encounter than low-power patients. This makes sense: when the ED is at capacity, care quality decreases and health outcomes worsen for all patients but especially so for vulnerable patients (Singh and Venkataramani, 2022). Thus, being a high-power patient (under quasi-exogenous doctor-patient assignment) has the most beneficial effects when the ED is at capacity, possibly because the reduced power differential allows for a high standard of care to be maintained at a time when care quality for all patients is generally worse.

### 4.6 Secondary Analysis: The "Promotion Bonus"

In this section, we perform a secondary analysis – the "promotion bonus" analysis – that examines our research question using a different research design. We exploit a unique feature of the military setting – the time of patient's promotion to the next rank – to estimate the effect of patient's relative power to the physician on within-physician effort. If military rank confers power to an individual, then a promotion to a higher rank should increase that power. Thus, for example, we compare within-physician effort provided to patients who visit the ED within a year after promotion to the rank of Lieutenant, to patients who visit the ED within a year prior to promotion to the rank of Lieutenant. Keeping the physician constant at a given rank, the promotion of the patient should only change the power differential between the physician and the patient without changing other factors correlated with rank. Moreover, since i) a physician does not know whether a patient has just recently been promoted or is about to be promoted, and ii) patient rank is easily observed in the EMR, the proximity of the patient encounter to the date of patient's promotion should have no effect on physician effort outside of changing the power differential between the doctor and patient.

Promotions occur in several manners. For more junior ranks (E1-E6) they are "semi-centralized", meaning that there is input from the service member's unit along with broad cut-offs from the military's centralized human resources. For more senior ranks, a centralized board meets and reviews all service members eligible for promotion to the next rank. The board is generally made up of individuals that have never met the service member and base their decisions primarily on annual reviews. Service Members become eligible for promotion after serving in a rank for a pre-specified amount of time. This time varies by rank.

(It should be noted that promotions do not occur randomly, patients usually know of their impending promotion, and the promotion may affect their care-seeking behavior. As a result, patients who go to the ED prior to promotion might differ from those who wait to go afterwards. For these reasons, and because the size of this sample is a fraction of our main sample, we consider this analysis to be secondary to our main empirical strategy.)

#### *4.6.1 Empirics and Results*

We limit our main sample to only those patients – both enlisted and officer – who experience a promotion during our sample period. Then we drop all ED encounters that occur beyond a ± 1 year period around the time of promotion, which yields a sample of 419,878 patients. We also drop all encounters that occur within 45 days of the patient's promotion date, as the patient's new rank may be not be updated in MHS systems (such as the eletronic medical record systems) at the same time as the actual promotion. We drop all civilian physicians. We call this sample the *promotion sample.*

Table A.4 presents the summary characteristics of patients just recently promoted and just about to be promoted to a given rank. Patients are more likely to visit in the year after promotion than they do in the year prior. On average, patients visiting the ED within a a year of promotion are about 1 year older, about 0.4 pp (1.8% ) less likely to be Black, 1.7 pp (5.4%) less likely to be female and have 0.1 points (7%) higher Charleson comorbidity scores than patients visiting the ED within a year prior to promotion. The age difference makes sense: if patients are promoted on average about the same age, then patients within ± 1 year of the date of promotion will be about a year apart in age. These differences, while statistically significant, are not clinically meaningful. We provide evidence in support of this assumption by showing no pre-trend using an event study design.

We estimate the following model:

$$Y_{ijt} = \beta Post_{it} + PromotionRank_{it} + \mathbf{X}_i + \gamma_{j\times r(j)t} + \eta_{h(i)} + \tau_t + \epsilon_{ijt} \tag{6}$$

where $Y_{ijt}$ capture logged RVUs and Resource Index expended by physician $j$ on patient $i$; $Post_{it}$ is 1 if the patient encounter occurs after the promotion date, 0 otherwise. $PromotionRank_i$ captures fixed effects for the rank a patient was either promoted to, or is about to be promoted to; $\gamma_{j\times r(j)t}$ is a fixed effect for physician $j$ × physician $j$'s rank at time $t$ (as physician $j$ may be in the data at more than one rank). $\beta$ estimates physician $j$'s effort for patients recently promoted to a given rank vs those just about to be promoted to that same rank, while keeping both the physician and the physician's rank constant.

On average, a physician exerts 1% more logged RVUs ($p<0.001$), and uses 0.039 higher resources on the Resource Index for patients post-promotion compared to those pre-promotion to a given rank (Table A.5 Panel A). Figure III plots the event study to graphically depict how promotion affects physician effort (with -1 being the omitted category): there is no significant trend in physician effort a year prior to the "event" (i.e., the promotion date), but immediately following the event, there is a large and sustained increase in within-physician effort.

*Robustness Check*: We also run a placebo test to ensure that our results are not picking up spurious estimates. We create 250 random dates of promotion for each patient in the promotion sample, and re-run Equation (6) for each placebo promotion date. Results are presented in A.7: the "true" estimate (represented by the vertical black line) was well beyond the top 5% of extreme values , suggesting that there is less than a 5% chance that such extreme results would be observed if the null hypothesis

– i.e., that patient promotion, which increases patient power, does *not* affect physician effort – were true.

Overall, this secondary analysis provides further support to the hypothesis that a higher patient rank decreases the power differential between doctor and patient in the clinical encounter, and as a result, directly increases physician effort and resource use on the patient. Importantly, any limitations of this secondary analysis are not shared with our main empirical strategy; together, these analyses provide a stronger test than either can on its own.

# 5 Supplemental Analyses

In supplemental analyses, we document several interesting phenomena, all of which serve to support our main results, provide them further nuance, and contextualize them within the broader literature. In (1), we examine whether there are spillovers from a physician's high-power patients to their concurrently seen low-power patients. In (2), we show that our results are generalizeable to civilian health settings by examining the extent to which the effect of patient power depends on doctor-patient concordance on other sociodemographic factors (such as race and sex) which may be more salient markers of power in civilian settings. Finally in (3), we try to triangulate on a mechanism. While physicians might provide greater effort to high-power patients for a number of reasons, we try to examine two potential ones: the patient's status, vs their authority. We use the patient's time of retirement in an event study to do so (as presumably after a patient retires, they keep their status, but lose their authority, especially as time goes on).

## 5.1 Supplemental Analysis 1: Spillovers from high- to low- power patients

So far, we only examine the effect of a patient's power on physician effort for *that* patient itself. In this section, we examine the effect of patient power on physician effort for their *other*, concurrently seen patients. This is interesting to consider given the scarcity of physician attention. When a physician is assigned to a high-power patient, it may cause the physician i) to increase effort only for that patient (no effect on their other patients), ii) to reallocate effort towards the high-power patient from their other low-power patients (negative effect on other patients), or iii) to increase effort for all patients (positive effect on other patients, i.e., the "if I'm ordering tests for this patient, I might as well order tests for my other patients too" line of reasoning).

### *5.1.1 Empirics and Results:*

We collapse our main sample into a provider-date-level dataset, where each row represents each date $t$ that each physician $j$ saw a patient in the ED. It gives us a dataset with approximately 315,921 provider-dates, with 1214 unique physicians working on average 248 days and each seeing on average 4.2 active duty patients per day.

We estimate the following model:

$$Y_{jt}^{LowPower} = \beta \cdot \mathbb{I}[HighPower_{jt}] + \delta_j + \phi_{r(j)t} + \mathbf{X}_{jt} + \tau_t + \epsilon_{jt} \tag{7}$$

$Y_{jt}^{LowPower}$ is one of the two aggregate outcomes calculated for physician $j$'s low-power patients seen on date $t$: (i) averaged logged RVUs exerted by physician $j$ per per physician $j$'s low-power patients in the ED on date $t$, and (ii) average negative outcomes (30-day ED bounceback or 30-day hospital admission) per physician $j$'s low-power patients in the ED on date t. $\mathbb{I}[HighPower_{jt}]$ is an indicator for whether physician j saw any high-power patients on date $t$. $\delta_j$ is physician fixed effect; $\phi_{r(j)t}$ is a physician rank (on date of encounter) fixed effect; $X_{jt}$ is a vector of physician-date controls, such as average age of patients, proportion Black patients, proportion female patients, average rank for low-power patients seen, total number of patients seen by physician $j$ on date $t$, and total number of patients in the ED on date $t$. These last two are measures of capacity strain and likely exert influence on the outcome of interest. $\tau_t$ is a vector of time-related fixed effects (specifically year-month and day-of-week).

Table 3 presents results from Equation 7. Columns (1) and (2) presents results when the outcome is, respectively, the average Logged RVU per low-power patient, and the average 30-day ED bounceback or 30-day hospital admission likelihood per low-power patient, seen by physician $j$ on date $t$. We find that – controlling for total number of patients seen by the physician and the total number of patients in the ED on a given day – attending to a high-power patient reduces the average effort exerted on the physician's concurrently seen low-power patients by about 1.9% (Col 1). We also find about a 0.3 pp (3.4%) increase in the average likelihood of a low-power patient being returned to the ED or admitted to the hospital within 30 days of the index encounter (Col 2). In Cols 3 and 4 we break apart the combined negative outcome measure used in Col (2) and find that both 30-day hospital admission increases (by 0.15 pp, $p = 0.127$) as well as 30-day ED bounceback (0.28 pp, $p = 0.068$).

Overall, this is suggestive evidence that physicians reallocate resources from their low-power patients to their concurrently cared-for high-power patients, with observable harm for low-power patients. The results from this supplemental analysis also align with the results from our main analysis, which shows that high-power patients enjoy increased physician effort and resource use with associated reductions in the likelihood of hospital admission within 30-days of the index ED visit.

## 5.2 Supplemental Analysis 2: Generalizability of results to non-military healthcare settings

The ranking structure in the military may not have a direct parallel in civilian healthcare settings. Thus, there may be concerns that results from our paper may not be applicable to healthcare settings more broadly. We believe these concerns are misplaced: while rank is an extremely (and possibly the most) salient indicator of power in the military, it is unlikely to be the only one. As in civilian settings, the power differential between two military members likely also depends on factors other than rank, such as the individuals' age, race, sex, etc. We expect power dynamics in the military to be thus affected by such sociodemographic factors – factors that are both present and may be even more influential in non-military settings.

Tn this section, we examine how two such factors – race and sex – interplay with the rank-based power dynamics we have documented thus far. More specifically, we examine how the race and sex of *both patient and physician* affects physician effort in high-power patient encounters.

### *5.2.1 Empirics and Results*

We amend Equation (5) to include interactions of the treatment with $PatChar_i$, which captures either patient race (=1 if patient is Black) or patient sex (= 1 if patient is female), and with $ProvChar_j$

which similarly captures physician race or sex:

$$\begin{aligned}
Y_{ij} &= D_{ij} + PatChar_i + ProvChar_j \\
&+ D_{ij} \cdot PatChar_i + D_{ij} \cdot ProvChar_j + PatChar_i \cdot ProvChar_j \\
&+ D_{ij} \cdot PatChar_i \cdot ProvChar_j \\
&+ \phi_{r(i)} + \phi_{r(j)} + \mathbf{X}_i + \mathbf{X}_j + +\delta_{d(i)} + \eta_{h(i)} + \tau_{t(i)} + \epsilon_{ij} \qquad (8)
\end{aligned}$$

$Y_{ij}$ measures RVUs spent on patient $i$ by physician $j$. (When examining heterogeneities by patient race, we limit the sample to only Black or White patients). Table A.3 Panel A presents regression coefficients from this analysis; Panel B presents the marginal effect of being a high-power patient for four types of matches based on race (physician Black/White $\times$ patient Black/White, Col 1) or sex (physician male/female $\times$ patient male/female, Col 2); and Panel C presents the marginal effect of the patient being Black or female for four types of matches based on patient power and race (patient high-power/low-power $\times$ physician Black/ White, Col 1), or sex (patient high-power/low-power $\times$ physician male/ female, Col 2). We also present predictive margins (at means of control variables) of RVUs from this model – disaggregated by patient power, patient race/sex, and physician race/sex, in Figure IV so the results from this regression are easier to interpret.

Results from both the race and sex concordance analyses reveal remarkably similar results, which we discuss separately below. Three things to note beforehand: (i) Predictive margins is Figure IV should be interpreted as keeping all else constant except the variables being manipulated, specifically, patient race or sex, physician race or sex, and patient power; (ii) Estimates for Black or female physicians are necessarily imprecise because only 3% of physicians in our sample are Black and only 19% are female, and thus should be interpreted with caution; and (iii) There is no biological reason for there to be differences in the care provided to Black vs White patients who are otherwise identical, but there may a biological reason why female patients are treated differently than the male patients (for example, women require reproductive care and men do not). For this reason, we are more limited in what we can extrapolate from the sex concordance analysis than from the race concordance analysis.

*Race:* Results from the race concordance analysis are presented in Table A.3 Col (1) and Figure IV top row. Four important results stand out.

First, physicians give significantly more effort on average to high-power patients than low-power patients of both races (Panel B Col 1, and IV top row, left).

Second, White physicians respond to patient power equally for both Black patients (an increase of 0.065 RVUs, $p < 0.05$) and for White patients (an increase of 0.07 RVUs, $p < 0.05$) (Table A.3 Panel B Col (1) and Figure IV top row, middle). However, Black physicians increase effort significantly more for high-power Black patients (by 0.52 RVUs, $p < 0.1$) than they do for high-power White patients (by 0.03 RVUs, n.s) (Panel B Col (1) and Figure IV top row, right). It is unclear why this occurs; it is possible when representation of a group in powerful positions is low, the group may be more sensitive to markers of power for members of the underrepresented group (Tajfel et al., 1979).

Third, the moderating effect of patient race on physician response to patient power is concerning amongst White physicians. Simply being Black significantly reduces the effort provided by White physicians (Panel C Col (1) and Figure IV top row, middle): they give 0.06 fewer RVUs to both high-power ($p < 0.05$) and low-power ($p < 0.001$) Black patients than they do to equivalently powered White patients. However, being high-power allows Black patients to overcome the lower effort they receive from White physicians when they are low-power. This is in line with prior research on the "power shield" (Pike and Galinsky, 2021), a phenomenon where being in a powerful role has been observed to attenuate demographic disparities. (Even still, a point to note is that high-power Black patients receive the same average effort from White physicians as low-power White patients receive from White physicians.)

Fourth, the moderating effect of patient race on physician response to patient power is more complex amongst Black physicians (Panel C Col (1) and Figure IV top row, right). To begin with, Black physicians provide non-significantly less effort (0.03 fewer RVUs, n.s.) to Black low-power patients than they do to White low-power patients. This lower effort is both non-significant and half the size of the effort deficit faced by low-power Black patients when seen by White physicians. In essence, this suggests that White physicians differentiate more between low-power patients on the basis of race that do Black physicians. On the other hand, Black physicians provide quite literally "off-the-charts" more effort to Black high-power patients than they do to White high-power patients (0.45 more RVUs, $p < 0.1$), suggesting that unlike White physicians who differentiate based on race equally for low-power and high-power patients (by penalizing Black patients), Black physicians differentiate based on race only for high-power patients (by rewarding Black patients).

To summarize: both Black and White physicians give more effort to high-power patients than equivalently-ranked low-power patients. However, White physicians give lower effort to Black patients than White patients regardless of their power, while Black physicians treat low-power Black and White patients similarly yet provide vastly more effort to high-power Black patients than they do to high-power White patients.

*Sex:* Results for women patients tell a similarly interesting story. Results from the sex concordance analysis are presented in Table A.3 Col (2) and Figure IV bottom row. As mentioned previously, unlike the effort comparisons between Black and White patients (which should not differ, all else equal), we cannot compare effort provided to male vs. female patients, as there are biological reasons for their care to be different.

Table A.3 Panel B Col (2) and Figure IV (bottom row, left) show that, once again, the power effect predominates regardless of patient sex: on average, physician effort is greater for high-power patients than for low-power patients of either sex (always accounting for patient and physician rank).

Decomposing the result by physician sex, we find three prominent differences in how male physicians (Figure IV bottom row, middle) and female physicians (Figure IV bottom row, right) respond to patient power (Panel B Col 2). First, male physicians respond far more to patient power than female physicians do. That is, male physician increase effort by 0.051 RVUs ($p < .05$) for male patient power, and by 0.182 ($p < 0.001$) for female patient power. Female physicians however, increase effort by 0.022 RVUs (n.s.) for male patient power, and by 0.089 (n.s.) for female patient power.

Second, male physicians also discriminate on the basis of sex much more than female physicians do (Panel C, Col (2) and Fig IV bottom row, middle and right). For example, male physicians provide much more effort on average to female patients than male patients, of both high-power status (0.169, $p < .001$) and low-power status (0.037, $p < 0.001$) than do female physicians (0.069, and 0.002 resp, both n.s.). It is unclear why this occurs; one might speculate that male physicians are providing nonspecific and nontargeted "female care" (i.e., kitchen-sink care that is specific to women, such as pregnancy tests, pelvic exams etc) regardless of clinical condition, when taking care of female patients.

Third, and finally, male physicians are much more responsive to the power of female patients than they are to the power of male patients (Panel B, Col 2 and Fig IV bottom row, middle). They increase effort by 0.182 RVUs ($p < .001$) for high-power female patients, but only by 0.051 ($p < 0.05$) for high-power male patients. In fact, the effort that female high-power patients receive from male physicians (2.96 RVUs) dwarfs the effort provided by male physicians to all other patient types. It is unclear why physicians respond this strongly to high-power female patients; we speculate that this may be because representation of powerful women in the military is low, and being higher-ranked may be a stronger signal of quality for women, and may thus elicit more respect by physicians.

To summarize: high-power patients get more care than low-power patients, whether or not they are male or female. However, male physicians both (i) respond more strongly to patient power and (ii) differentiate care based on patient sex more than female physicians do.

Overall, the results from this supplemental analysis suggest that patient power stemming from military rank leads to increased physician effort, regardless of patient sex and race – presumably because rank is an unusually clear and inflexible indicator of power in this setting. Even still, patient -physician concordance on race or sex leads to interesting interactions with such rank-based power dynamics, providing credible evidence to the hypothesis that the power differential between two individuals is a weighted combination of many different individual characteristics. While it just so happens that in the military context, an individual's rank likely gets the largest weight, factors such as race and sex may be weighted differently in civilian contexts.

### 5.3 Supplemental Analysis 3: Understanding the mechanism behind the power effect (Authority vs Status)

So far, we have remained circumspect regarding the exact mechanism through which high-power patients command better care. Why does a physician behave differently towards a patient who outranks them? In this section, we test two potential reasons that could explain our results: either (i) higher relative rank commands higher status, or (ii) higher relative rank commands greater authority.

In the first mechanism, the physician expends more effort because they respect the high-power patient (due to the greater status commanded by their relatively higher rank). This increased effort may be because the physician seeks the approval of the patient, they may trust the patient more, and/or may be more empathetic to their condition, etc. In the second mechanism, however, deference to authority plays a larger role in physician behavior. The physician exerts more effort because they fear reprisal if the patient leaves dissatisfied; for example, the relatively higher-ranking patient may complain directly or indirectly to the physician's commanding officer, which could affect the physician's professional development (such as promotions etc).

We use the dates of the patient's retirement from the military to examine how retirement affects physician effort. After retirement, a patient assigned to a lower-ranking physician should still have status, but little to no authority (especially the further after retirement the patient visits the ED).

#### *5.3.1 Empirics and Results*

We limit the main sample to only those patients who retired – what we refer to as the *retiree sample* – giving us a sample of 238,100 patient encounters. To examine whether the effect of being a high-power patient changes after retirement, we run the following linear regression model where $PostRet_{it} = 1$ if the patient is retired at the time of encounter:

$$\begin{aligned} Y_{ij} = D_{ij} + PostRet_{it} + \beta D_{ij} \cdot PostRet_{it} \\ + \phi_{r(i)} + \phi_{r(j)} + \mathbf{X}_i + \mathbf{X}_j + \delta_{d(i)} + \eta_{h(i)} + \tau_{t(i)} + \epsilon_{ij} \end{aligned} \tag{9}$$

$\beta$ is the extent to which the effect of the patient being high-power on physician effort depends on the patient being retired. We then plot the results as an event study, plotting the effect of being a high-power patient $\pm 5$ years from the "event" (i.e., the date of retirement). We include five years pre- and post- retirement as a high-ranking military official may retain important connections and networks after retirement such that authority may still play a role in the doctor-patient encounter. However, these networks are likely to weaken the further away the encounter is post-retirement.[13]

Table A.6 presents the demographics and the break-down of the various ranks that comprise the retiree sample. About 6.9% of the encounters prior to retirement are with high-power patients, as opposed to 8.6% of encounters post-retirement. There are statistically significant differences in patients pre- and post- retirement; however, these differences are largely irrelevant for the purposes of our analysis are we are interested in the interaction between being a high-power patient and being retired, keeping patient rank constant.

Table A.5 Panel B presents the regression coefficients from estimating Equation (9). The interaction term between high-power and post-retirement is small in magnitude and statistically non-significant, meaning that being retired does not change the effort bonus awarded to high-power patients. This is confirmed by the event study (Figure A.8): the effect of being a high-power patient is the same in the 5 years leading up to, and 5 years after the date of retirement. This suggests that status is likely playing a significant role in the effort bonus provided by physicians to high-power patients. However, since we do not have the entire sample of retireds (as many go to the VA after retirement) we cannot rule out authority as a mechanism entirely.

# 6 Conclusion

We investigate how the power differential between two people affects behavior and outcomes by exploiting the military ranking system and the employment of active duty members as physicians in military hospitals. Our findings indicate that physicians exert more effort and use more resources when they are assigned to high-power patients (i.e., patients who outrank them) than low-power patients of the same rank. Additionally, high-power patients experience better health outcomes, with a lower likelihood of being admitted to the hospital within 30 days of the index ED visit. These results are echoed in a secondary analysis where we find that within-physician effort is greater for patients recently promoted than those about to be promoted.

We also document several other interesting phenomena: (i) attending to high-power patients harmfully diverts physician effort and resources away from concurrently seen low-power patients; (ii) power dynamics based on rank interact with patient and physician sex and race in predictable ways; (iii) and retired military members still enjoy greater effort when assigned to lower-ranking physicians, suggesting that status is more likely than authority to drive the observed changes in physician behavior. Our results and conceptualization of the power differential between the doctor

[13] It is important to note that military retirees may either visit the VA or the MHS (or purchase commercial insurance), depending on eligibility, and such the retiree sample does not capture the entire population of military retirees in the same way that it does for active duty military members.

and patient explain and reconcile a large literature on the effects of doctor-patient homophily (one age, sex, race, and even occupation!) on patient care. Using several techniques and supplemental analyses, we find overwhelming support for the hypothesis that high-power patients receive greater effort and associated health benefits from their physicians than equivalently-ranked low-power patients.

Although our data comes from the Military Health System, the findings of this study are broadly applicable beyond military healthcare contexts. While rank is a salient and important indicator of power in the military, this phenomenon can be extrapolated to non-military healthcare settings, as well as to entirely non-healthcare settings. In non-military healthcare settings, for instance, physicians may attend more to wealthy patients who can benefit (via donations) or harm (via litigation) them and the organization, or they may provide care that aligns with the preferences of patients who can directly or indirectly communicate their power outside the hospital.

Our analysis may even underestimate the true effect of the power differential in the doctor-patient relationship for several reasons. First, physicians and patients in the MHS share a sense of camaraderie from shared experiences and decisions that is largely absent in non-military clinical settings. As a result, power differentials in civilian clinical settings may be far more extreme, resulting in more significant changes in physician behavior than what we observed in this study. Second, active duty military personnel are generally healthier than the general population, so any power-imbalance-driven neglect or medical mistreatment is unlikely to be as detrimental to health as it can be in civilian clinical settings. Third, our analysis only measures "hard" benefits of being a high-power patient, such as reduced 30-day ED bounceback and hospital admission, and ignores "soft" benefits such as being treated with dignity or satisfaction with healthcare encounters. Finally, MHS hospitals and facilities are well-resourced, which may put them on the "flatter" part of the returns-to-care curve, resulting in smaller benefits from providing additional physician effort than can be expected at other healthcare facilities that are forced to provide lower-quality care due to rationing, congestion-related externalities, etc.

Our results can extend beyond healthcare settings too, as we show that power in one domain of life casts a "long shadow" in other domains as well. In contexts with valued resources and clear power differentials (e.g., classrooms, courtrooms, firms, etc), how individuals are treated within the context can depend on the allocation of resources outside that context. For instance, private firms show preferential treatment in hiring or promotions towards politicians' family members (Gagliarducci and Manacorda, 2020). Educators are more likely to suspend students of color and from low socioeconomic backgrounds, even with all else constant (Barrett et al., 2021). Landlords are more likely to evict tenants who are disadvantaged (those with children, experiencing job loss, black women, and low-income individuals), even keeping constant missed rental payments (Desmond and Gershenson, 2017). These examples can be explained, to some extent, by the pressures that power exerts on behavior. Our results emphasize the significance of tangible policies as safeguards against the distortionary and often invisible effects of power as opposed to relying solely on social norms.[14]

One policy implication is specially relevant for the healthcare setting. In recent years, there has been an increasing push from policy-makers and patient advocates to adopt the process of "Shared Decision-Making" (SDM), which was identified by the landmark 2001 Institute of Medicine report (Baker, 2001) as a fundamental way to improve the quality of care in the US. SDM takes a patient-centered approach to care, whereby both the patient and physician jointly arrive at a clinical decision that is "most consistent with the patient's preferences and values" (Barry and Edgman-Levitan, 2012).

[14]For instance, the #MeToo movement led to an increase in HR oversight over workplace relationships regarding viewing potentially innocuous acts (such as complimenting someone on their looks) through the lens of employee-employer power dynamics.

However, given the significant power differential between physicians and patients and the results of our study suggesting that it nontrivially affects patient care, it is worth considering the limitations of such an endeavor in the absence of resources that explicitly recognize, measure, and attenuate the effects of this power imbalance.

Our concern does not lie with the doctor-patient power imbalance itself, which is likely necessary for effective physician performance and is by and large wielded in a careful and ethical manner. Rather, it lies with the inequitable variation in how that power is exercised, with the most vulnerable patients bearing the burden of this disparity. Thus, we suggest examining the viability of potential tools, such as task-shifting, automation, increasing diversity in the provider workforce, patient advocacy, and shared-decision-making aids that recognize the role of power in medical care, particularly in critical clinical decisions.

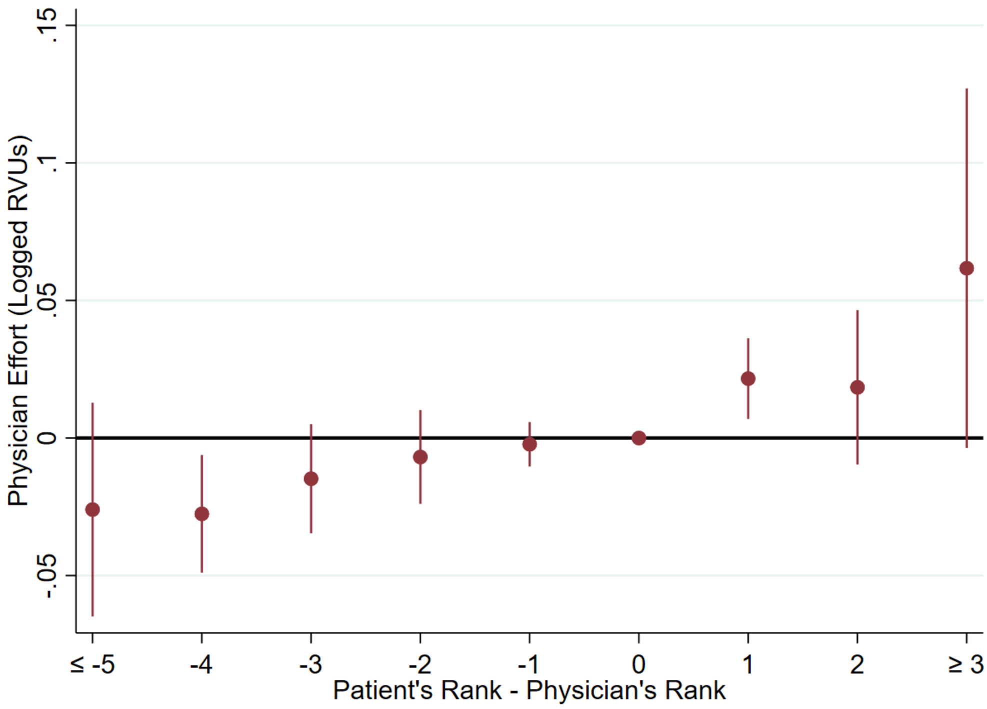


**FIGURE I**

Doctor-Patient Power Differential and Physician Effort

This graph plots physician effort on the Y-axis (i.e., logged RVUs) at each level of the realized power differential between doctor and patient on the X-axis (i.e., difference in military ranks between the patient minus the physician) from Equation 5 (but excluding physician rank). The reference group is when the patient and physician share the same rank, X-axis = 0 . Civilian physicians are excluded. Fixed effects included for: patient-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level.

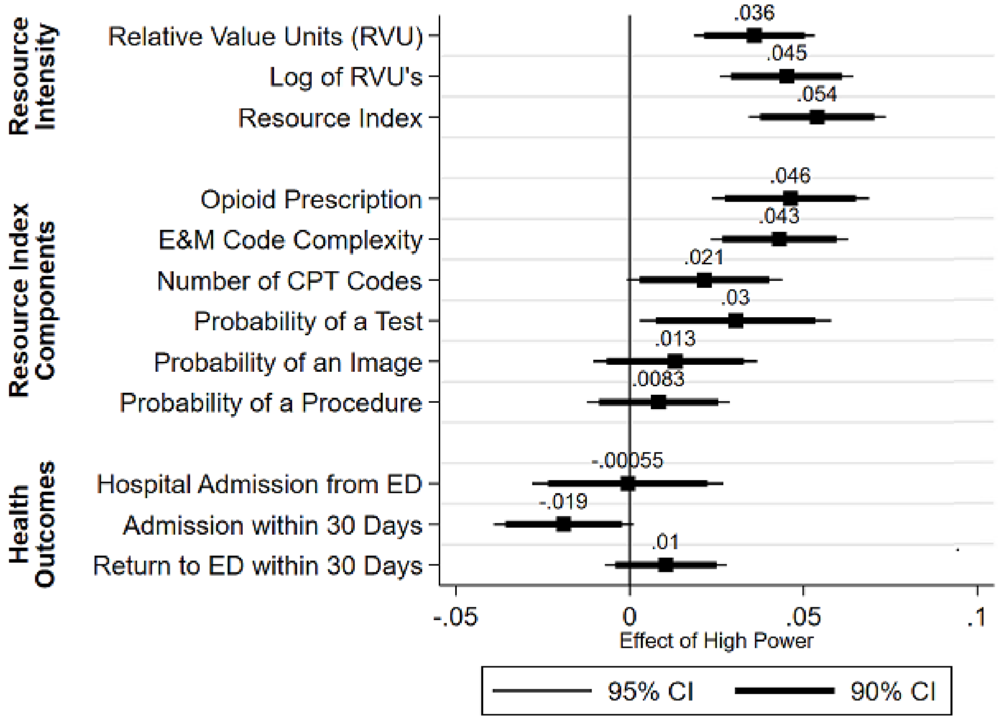


**FIGURE II**

High-Power Patients and (standardized) Physician Effort, Resource Use, and Health Outcomes

This figure plots coefficients from Equation 5. The X-axis plots the marginal effect (with 90% and 95% confidence intervals) of being a high-power patient for each standardized outcome on the Y-axis. Patients are considered "high-power" if they strictly outrank their assigned physicians in the encounter, and "low-power" otherwise. Outcomes are grouped into 3 panels: the top-most panel includes measures of physician effort and resource use (specifically, RVUs and a constructed "Resource Index"), the middle panel includes the individual components of the Resource Index, and the bottom-most panel includes various measures of patient health outcomes. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level. Estimates for non-standardized outcomes are presented in Table A.1.

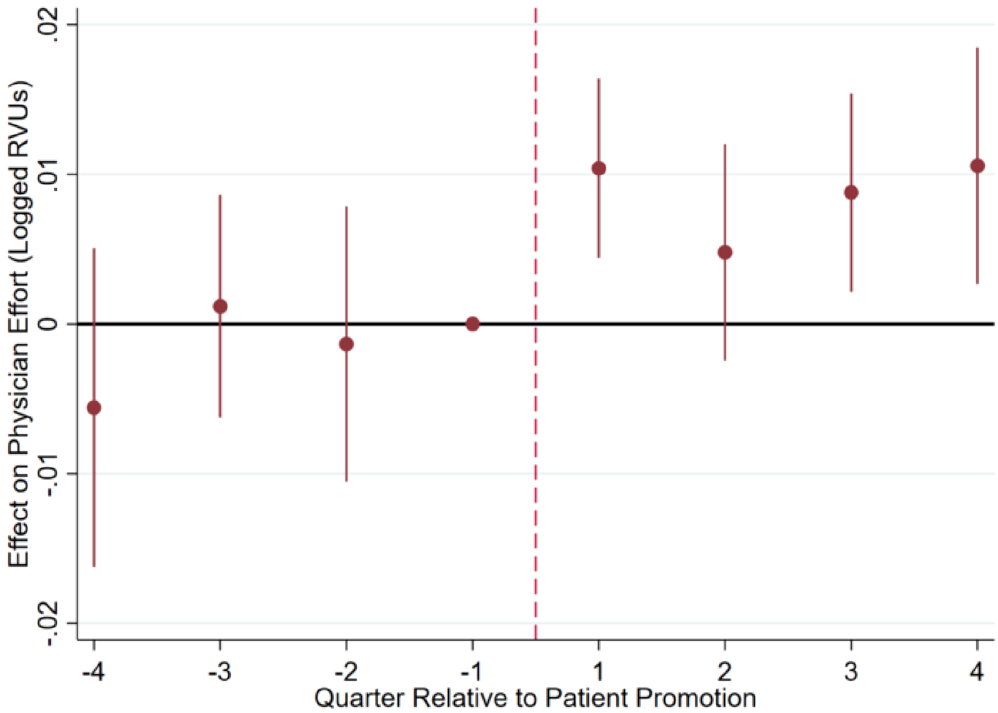


**FIGURE III**

Event Study: Patient Promotion and Within-Physician Effort

This figure plots coefficients from Equation 6. It plots within-physician effort (logged RVUs) on the Y-axis at each quarter pre- and post- the patient's promotion date on the X-axis. The ommitted category is quarter -1. Encounters within 45 days of the promotion date are4 excluded from the analysis. Fixed effects included for: patient promotion rank, physician × physician-rank, hospital, year-month, and day-of-week. Other covariates include: patient age, age-squared, race, sex, and Charleson score. Standard errors are clustered at the hospital-level. Estimates are also presented in Table A.5 Panel A.

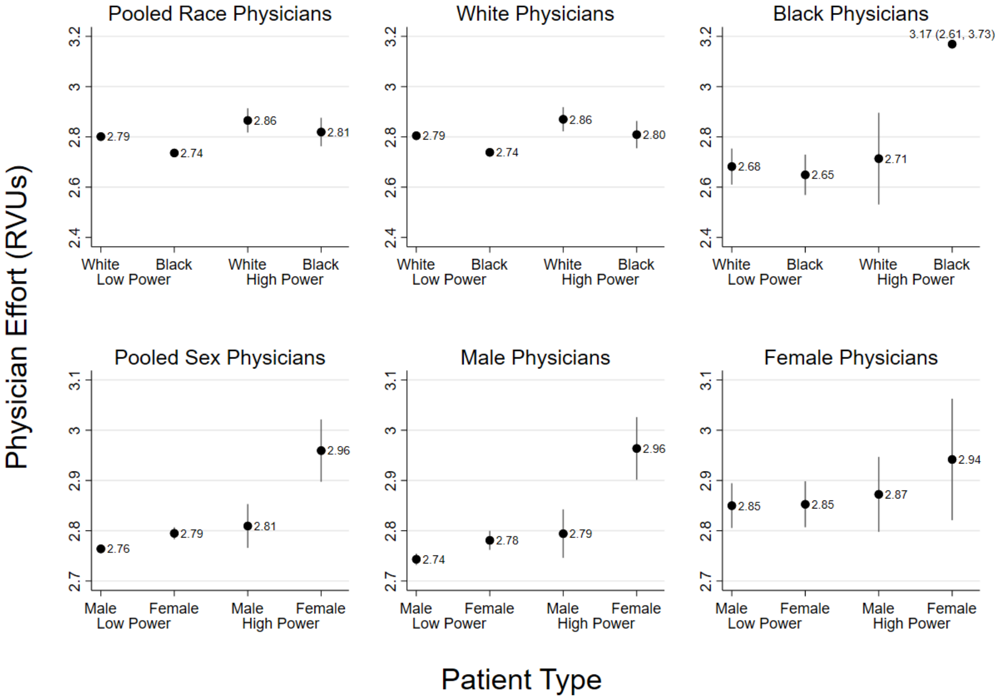


**FIGURE IV**

Heterogeneity in Power Effects by Patient and Physician Race and Sex

This graph plots predictive margins (at the means of all control variables) for physician effort across four patient types: i) White low-power, ii) Black low-power, iii) White high-power, and iv) Black high-power. based on estimates from Equation 8. The leftmost column includes encounters with White and Black physicians (top row) or Male and Female physicians (bottom row). The middle column limits encounters to White physicians (top row) or Male Physicians (bottom row). The rightmost column limits encounters to Black physicians (top row) or female physicians (bottom row). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level. Estimates are also presented in Table A.3.

**TABLE 1**

Frequency Tables: Patient and Physician Ranks

| **Rank** | **Patient** | **Provider** |
|---|---|---|
| Enlisted - Junior | 53.66% | |
| Enlisted - Middle | 29.44% | |
| Enlisted - Senior | 7.92% | |
| Officer - Junior | 2.34% | |
| Officer - 3 | 3.19% | 24.64% |
| Officer - 4 | 1.80% | 35.33% |
| Officer - 5 | 1.25% | 16.84% |
| Officer - 6 | 0.38% | 4.72% |
| General Officer | 0.02% | |
| Civilian | 0 | 18.47% |
| Total Observations | 1,547,851 | |
| Number of Unique Providers | | 1,340 |
| Number of Unique Patients | 856,357 | |

Frequency of each rank group. Enlisted-Junior includes E1-E4 as described in the text. Enlisted Middle includes E5-E6. Enlisted Senior includes E8-E9. Officer junior includes O-1-O2. General Officer includes O-7 and above. Civilian patients are excluded.

**TABLE 2**
Balance Table for Whole Sample

| | Sample Mean<br>Mean | Coefficient on<br>High Power Patient |
|---|---|---|
| Age | 27.816 | -0.23<br>(0.148) |
| Race - Black | 0.232 | -0.004<br>(0.008) |
| Gender - Female | 0.303 | 0.010<br>(0.012) |
| Charlson Score | 0.018 | -0.002<br>(0.002) |
| **Fixed Effects** | | |
| Patient Rank | | Yes |
| Physician Rank | | Yes |
| *N - Observations* | | |
| Low-Power patient encounters | 1,526,525 | 1,526,525 |
| High-Power patient encounters | 21,326 | 21,326 |
| Total patient encounters | 1,547,851 | 1,547,851 |

This table presents balance tests for patient characteristics between high-power and low-power patients. Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Col (1) presents sample means. Col (2) presents unadjusted differences between High- and Low-Power patient encounters, adjusting for patient rank and physician rank fixed effects.$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$t

**TABLE 3**

Spillover Effects

| | $DepVar_{jt}^{LowPower}$: **Average DV per physician** $j$**'s low-power patient on date** $t$ | | | |
|---|---|---|---|---|
| . | (1) | (2) | (3) | (4) |
| | Logged RVU's | Negative Outcome | 30-day hosp adm | 30-Day ED return |
| $\text{HighPower}_{jt}$ | -0.0187*** | 0.0034** | 0.0015 | 0.0028* |
| | (0.0050) | (0.0016) | (0.0010) | (0.0015) |
| Controls | Yes | Yes | Yes | Yes |
| **Fixed Effects** | | | | |
| Physician | Yes | Yes | Yes | Yes |
| Physician Rank | Yes | Yes | Yes | Yes |
| Month-Year | Yes | Yes | Yes | Yew |
| Day of Week | Yes | Yes | Yes | Yes |
| Sample Mean | 2.83 | 0.10 | 0.02 | 0.09 |
| N | 315,921 | 315,921 | 315,921 | 315,921 |

This table presents coefficients from estimating Equation 7. Unit of analysis is the physician-date. The outcome in Col (1) is average effort (logged RVUs) provided by physician $j$ per low-power patient on date $t$. The outcome in Col (2) is the mean likelihood of negative health outcome (30-day admission or 30-day ED bounceback) per physician $j$'s low-power patient on date $t$. Col (3) and (4) break out each negative outcome individually: 30-day hospital admission and 30-day ED bounceback, respectively. The treatment variable, $HighPower_{jt}$, is equal to 1 if physician $j$ cares for a high-power patient on date $t$. Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Physician and physician-rank fixed effects are included. Other control variables include: average age of patients, proportion black patients, proportion female patients, average rank for low-power patients seen on each provider-day, number of patients in the ED on date $t$, and number of patient assigned to physician $j$ on date $t$. Standard errors are clustered at the hospital-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$

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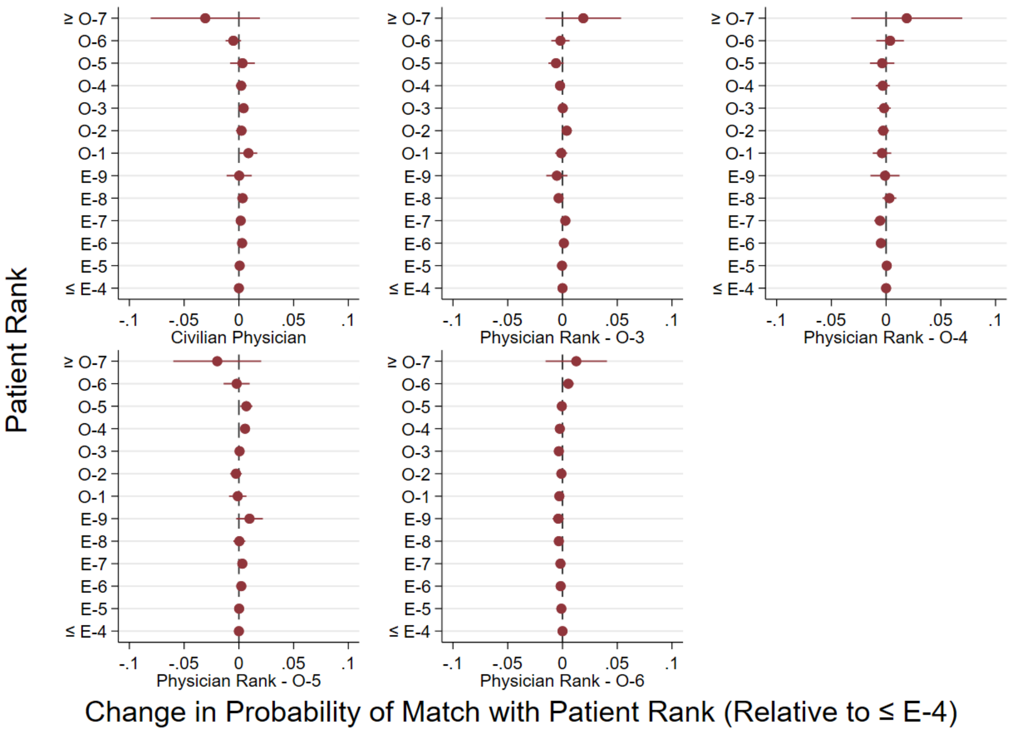


**FIGURE A.1**

Evidence for Identification Assumption: Likelihood of Match Between Patient and Physician Rank

This figure displays the results of separately regressing each physician rank on the vector of patient ranks, patient covariates, and hospital and time fixed effects for all encounters. The Y-axis in all five sub-figures (each representing a different physician rank) represents a patient rank. The X-axis represents the relative likelihood of the specific physician rank being matched to a given patient rank, relative to the bottom-most patient rank, (i.e., E-4 or lower).

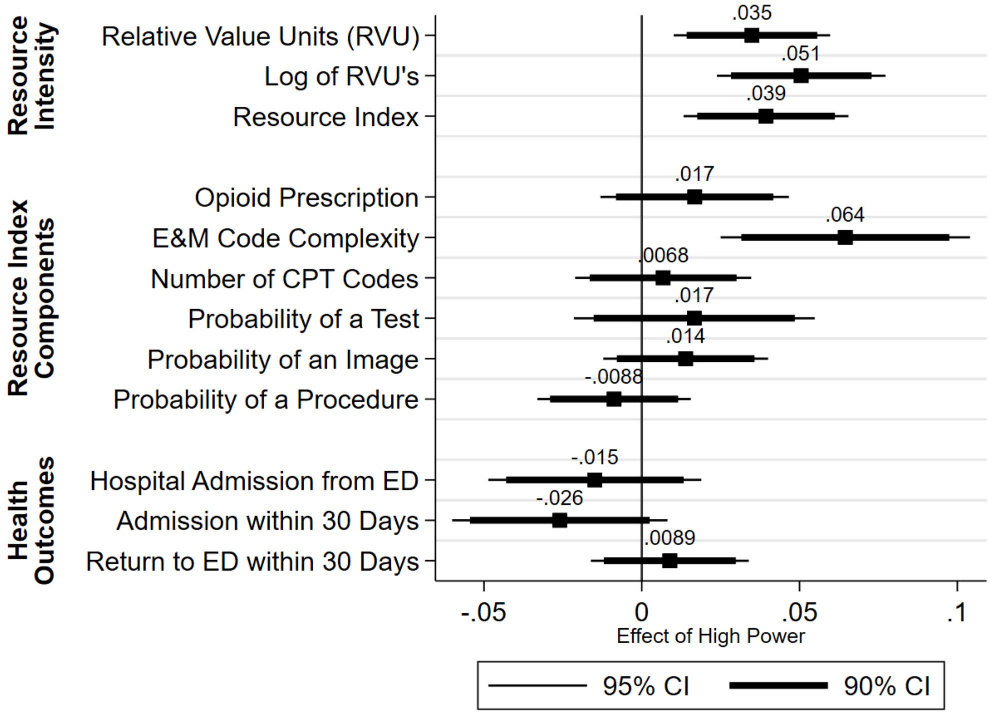


**FIGURE A.2**

Officer-only sample: High Power Patients and (standardized) Physician Effort, Resource Use, and Health Outcomes

This figure plots coefficients from Equation 5 - *but limited to only those encounters that occur between officer patients and physicians.*. The X-axis plots the marginal effect (with 90% and 95% confidence intervals) of being a high-power patient for each standardized outcome on the Y-axis. Patients are considered "high-power" if they strictly outrank their assigned physicians in the encounter, and "low-power" otherwise. Outcomes are grouped into 3 panels: the top-most panel includes measures of physician effort and resource use (specifically, RVUs and a constructed "Resource Index"), the middle panel includes the individual components of the Resource Index, and the bottom-most panel includes various measures of patient health outcomes. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level.

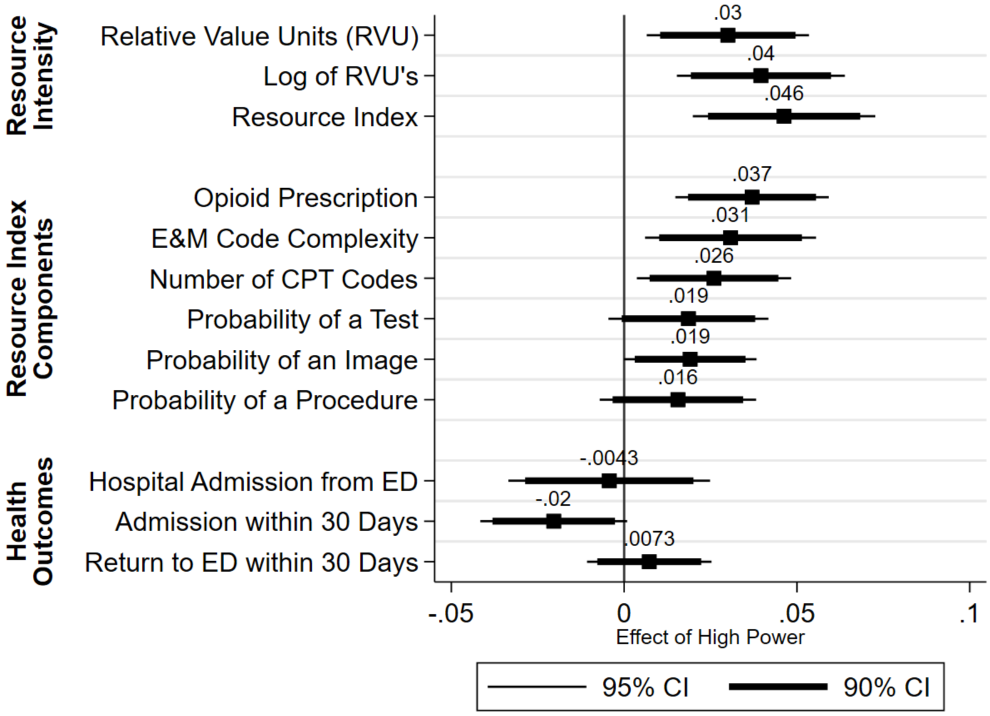


**FIGURE A.3**

With Physician FEs: High Power Patients and (standardized) Physician Effort, Resource Use, and Health Outcomes

This figure plots coefficients from Equation 5 - *with the inclusion of physician fixed effects instead of physician rank fixed effects*. The X-axis plots the marginal effect (with 90% and 95% confidence intervals) of being a high-power patient for each standardized outcome on the Y-axis. Patients are considered "high-power" if they strictly outrank their assigned physicians in the encounter, and "low-power" otherwise. Outcomes are grouped into 3 panels: the top-most panel includes measures of physician effort and resource use (specifically, RVUs and a constructed "Resource Index"), the middle panel includes the individual components of the Resource Index, and the bottom-most panel includes various measures of patient health outcomes. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level.

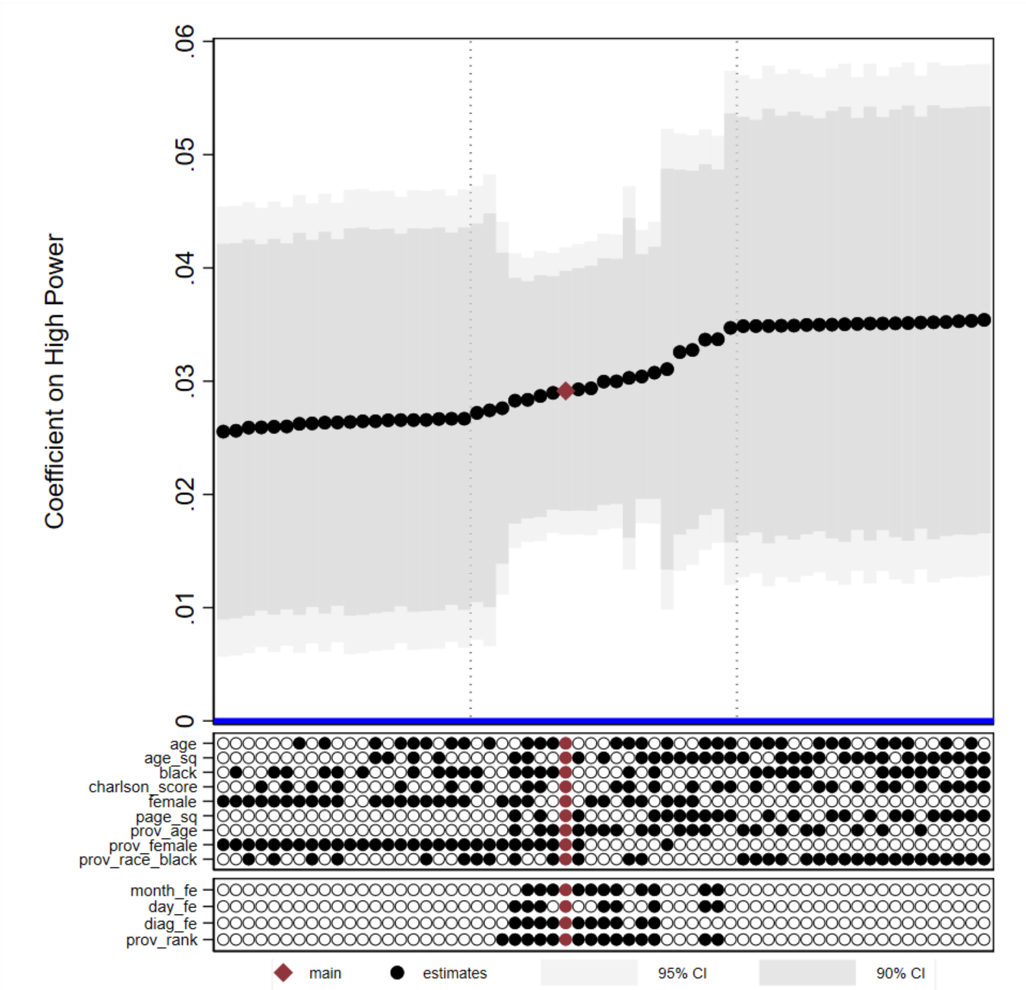


**FIGURE A.4** Specification Curve

This figure plots the distribution of the (20 smallest, 20 largest, and 20 random) $\beta$ coefficients from Equation 5 from approximately 3,072 specifications regressing physician effort (logged RVUs) on an indicator for the patient being high-power, using various combinations of covariates. Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Black dots indicate that a covariate was included in the regression. Red dots indicate the main specification which included all covariates. Patient-rank and hospital fixed effects were included in all specifications. Standard errors are clustered at the hospital-level.

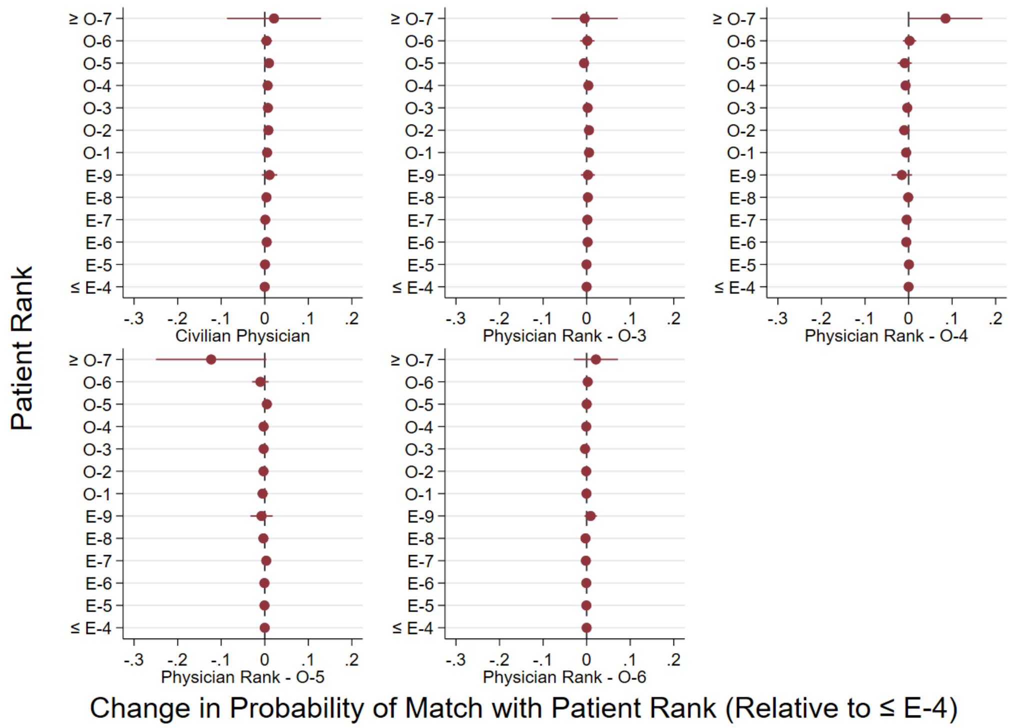


**FIGURE A.5**

(Constrained Sample) Evidence for Identification Assumption: Likelihood of Match Between Patient and Physician Rank

This figure displays the results of separately regressing each physician rank on the vector of patient ranks, patient covariates, and hospital and time fixed effects, limited to only those encounters that occur at the highest quartile of ED capacity. The Y-axis in all five sub-figures (each representing a different physician rank) represents a patient rank. The X-axis represents the likelihood of the specific physician rank being matched to a given patient rank, relative to the bottom-most patient rank, (i.e., E-4 or lower).

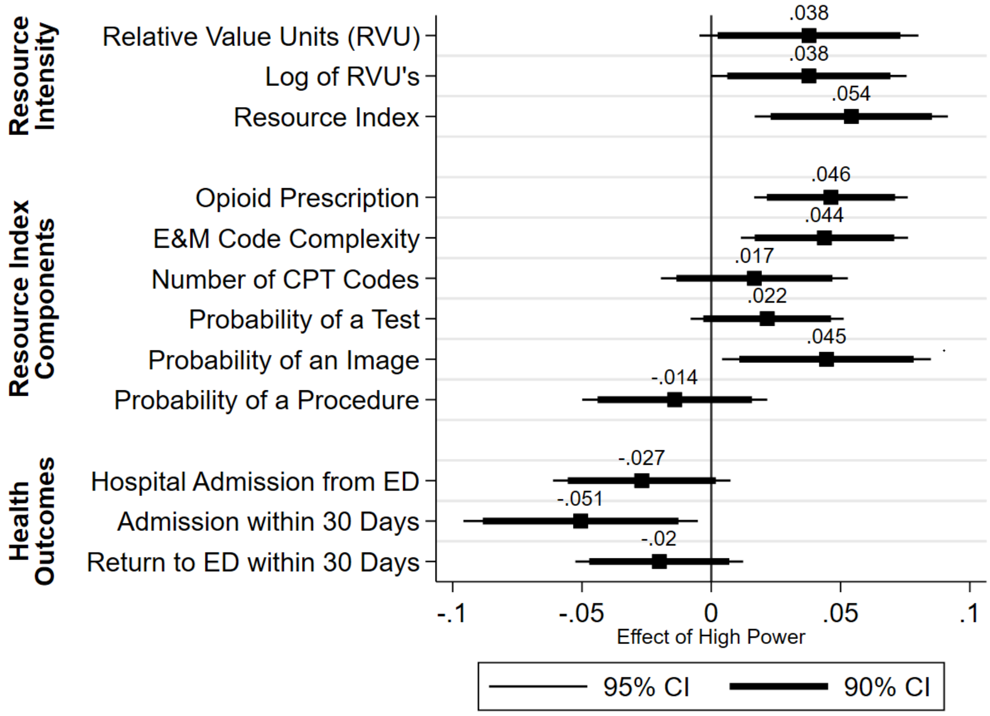


**FIGURE A.6**

Constrained Sample: High Power Patients and (standardized) Physician Effort, Resource Use, and Health Outcomes

This figure plots coefficients from Equation 5 - *but limited to only those encounters that occur at the highest quartile of ED capacity.* The X-axis plots the marginal effect (with 90% and 95% confidence intervals) of being a high-power patient for each standardized outcome on the Y-axis. Patients are considered "high-power" if they strictly outrank their assigned physicians in the encounter, and "low-power" otherwise. Outcomes are grouped into 3 panels: the top-most panel includes measures of physician effort and resource use (specifically, RVUs and a constructed "Resource Index"), the middle panel includes the individual components of the Resource Index, and the bottom-most panel includes various measures of patient health outcomes. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level.

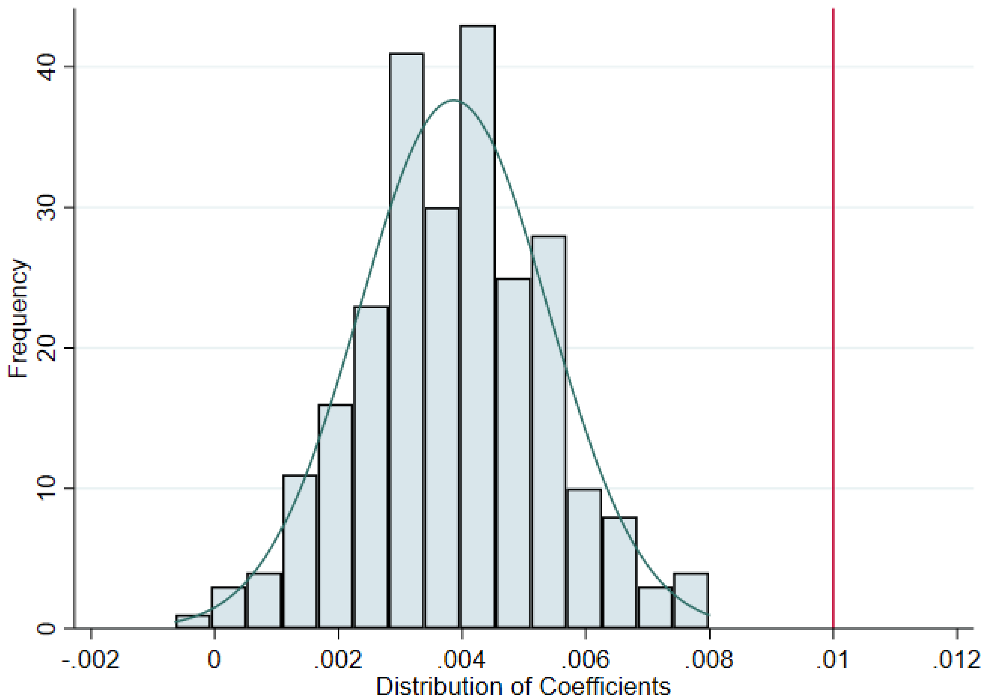


**FIGURE A.7**

Placebo Tests: Effect of Patient Promotion on Within-Physician Effort

This figure displays the histogram of $\beta$ coefficients from regressing physician effort (i.e., logged RVUs) on an indicator for the encounter occurring post-patient promotion (Equation 6) using 250 randomly selected, fake placebo promotion dates for each active duty military promoted during our sample period. The vertical black line represents the "true" regression coefficient using the real dates of promotion. Physician and physician-rank fixed effects are included and civilian physicians are excluded. Patient promotion rank fixed effects are used, allowing all comparisons in physician effort to be made within the rank the patient is about to be/ has recently been promoted to. Other covariates include: patient age, age-squared, race, sex, and Charleson score, fixed effects for hospital, year-month, and day-of-week. Standard errors are clustered at the hospital-level.

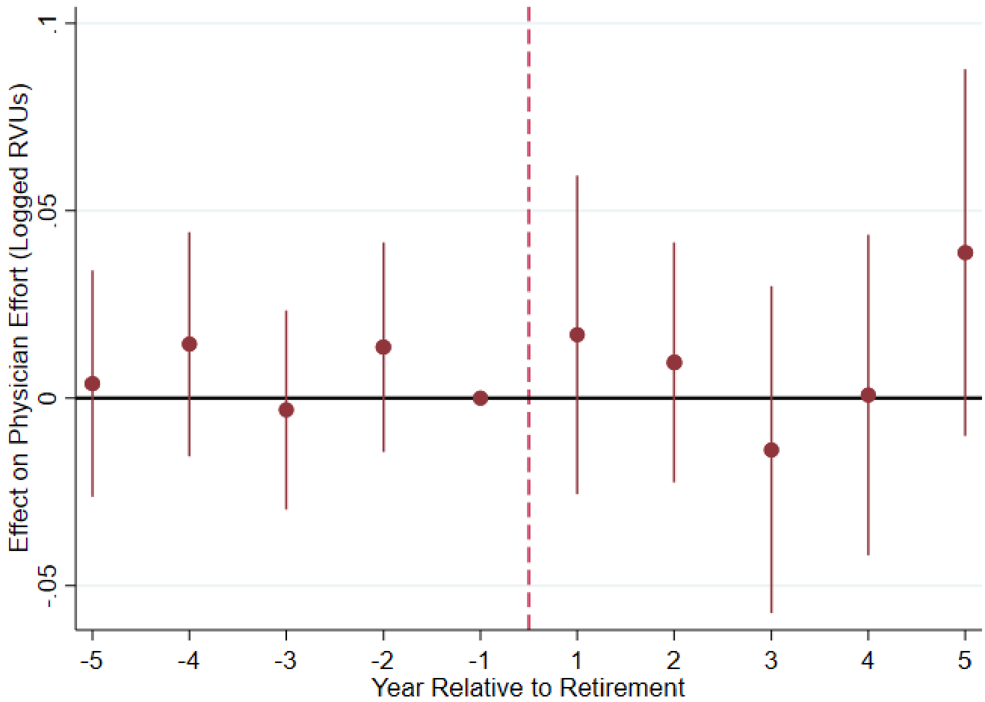


**FIGURE A.8**
Event Study: Effect of Patient Retirement on Physician Effort (Logged RVUs)

This graph plots the interaction coefficient from a linear regression of physician effort (logged RVUs) on an interaction between the patient being high-power and each year pre- and post- the patient's retirement date. The omitted category is -1 (the year prior to retirement). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level. Standard errors are clustered at the hospital-level. Estimates are also presented in Table A.5 Panel B.

## TABLE A.1

High-Power Patients and (non-standardized) Physician Effort, Resource Use, and Health Outcomes

| **Outcome** | **Coefficient on High Power** | **Mean** | **Standard Deviation** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| ***Panel A: Resource Intensity*** | | | | | |
| RVUs | $0.070^{***}$<br>(0.017) | 2.77 | 1.94 | 1 | 82 |
| Log of RVUs | $0.029^{***}$<br>(0.006) | 0.81 | 0.64 | 0 | 4.41 |
| Resource Index | $0.140^{***}$<br>(0.026) | 0 | 2.62 | -3.91 | 12.70 |
| ***Panel B: Resource Index Components*** | | | | | |
| Opioid Prescription | $0.019^{***}$<br>(0.005) | 0.21 | 0.41 | 0 | 1 |
| E&M Complexity | $0.042^{***}$<br>(0.010) | 2.78 | 0.94 | 1 | 6 |
| Number of CPT Codes | $0.041^{*}$<br>(0.023) | 1.53 | 2.00 | 0 | 10 |
| Probability of a Test | $0.012^{**}$<br>(0.006) | 0.23 | 0.42 | 0 | 1 |
| Probability of an Image | 0.003<br>(0.003) | 0.06 | 0.23 | 0 | 1 |
| Probability of a Procedure | 0.003<br>(0.005) | 0.34 | 0.47 | 0 | 1 |
| ***Panel C: Health Outcomes*** | | | | | |
| Admission from ED | -0.000<br>(0.003) | 0.05 | 0.21 | 0 | 1 |
| 30-Day Admission | $-0.003^{*}$<br>(0.001) | 0.02 | 0.14 | 0 | 1 |
| 30-Day Return to ED | 0.003<br>0.003 | 0.09 | 0.29 | 0 | 1 |
| Total Observations | 1,547,851 | | | | |

This table presents the regression coefficients (with standard errors in parenthesis) from regressing each outcome on "High-power patient" using Equation (5). Outcomes are grouped into 3 panels: the top-most panel includes measures of physician effort and resource use (specifically, RVUs and a constructed "Resource Index"), the middle panel includes the individual components of the Resource Index, and the bottom-most panel includes various measures of patient health outcomes. All outcomes are described in greater detail in the text. Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$

**TABLE A.2** Propensity Score Matching

| | (1) Log of RVU's NN1 | (2) Log of RVU's NN2 | (3) Log of RVU's NN5 | (4) Log of RVU's NN10 |
|---|---|---|---|---|
| High Power | 0.042 | 0.101** | 0.091*** | 0.054*** |
| | (0.068) | (0.042) | (0.031) | (0.021) |
| **Matched on:** | | | | |
| Patient Age | Yes | Yes | Yes | Yes |
| Patient Rank | Yes | Yes | Yes | Yes |
| Patient Race | Yes | Yes | Yes | Yes |
| Patient Gender | Yes | Yes | Yes | Yes |
| Physician Age | Yes | Yes | Yes | Yes |
| Physician Race | Yes | Yes | Yes | Yes |
| Physician Gender | Yes | Yes | Yes | Yes |
| Quarter-Year | Yes | Yes | Yes | Yes |
| Hospital | Yes | Yes | Yes | Yes |
| Diagnosis Group | Yes | Yes | Yes | Yes |
| Sample Mean | 2.82 | 2.82 | 2.82 | 2.82 |
| N | 52,154 | 52,154 | 52,154 | 52,154 |

Results of K-nearest neighbor propensity score matching with 1:1 match and oversampling. All patient ranks that do not have variation in the independent variable (i..e, patient ranks who cannot both be a high-power patient and low-power patient) are dropped. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$

**TABLE A.3**

Heterogeneity Analysis

| PANEL A | (1) Black & White Phys | (2) Male & Female Phys |
|---|---|---|
| High Power Patient | 0.065** (0.025) | 0.051** (0.026) |
| Patient Race = Black | -0.067*** (-0.005) | |
| Physician Race = Black | -0.123*** (0.038) | |
| Patient Race = Black × Physician Race = Black | 0.033 (0.026) | |
| High Power Patient × Patient Race = Black | 0.005 (0.030) | |
| High Power Patient × Physician Race = Black | -0.034 (0.103) | |
| High Power Patient × Patient Race = Black × Physician Race = Black | 0.483* (0.265) | |
| Patient Sex= Female | | 0.038*** (0.011) |
| Physician Sex = Female | | 0.107*** (0.0.28) |
| Patient Sex= Female × Physician Sex = Female | | -0.035 (0.021) |
| High Power Patient × Patient Sex= Female | | 0.132*** (0.044) |
| High Power Patient × Physician Sex= Female | | -0.029 (0.041) |
| High Power Patient × Patient Sex= Female × Physician Sex = Female | | -0.065 (-0.052) |
| Observations | 1,148,791 | 1,547,611 |
| Mean RVUs | 2.79 | 2.77 |
| Unique Physicians | 1,099 | 1,340 |
| Percent of Physicians = Black (Col 1) or Female (Col 2) | 2.91% | 19.46% |

| PANEL B | Marginal Effect of Patient= High-power | Marginal Effect of Patient= High-power |
|---|---|---|
| Patient = White (Col 1)/ Male (Col 2) AND Physician = White (Col 1)/ Male (Col 2) | 0.065** (0.025) | 0.051** (0.025) |
| Patient = Black (Col 1)/ Female (Col 2 ) AND Physician = White (Col 1)/ Male (Col 2) | 0.07** (0.028) | 0.182*** (0.033) |
| Patient = White (Col 1)/ Male (Col 2) AND Physician = Black (Col 1)/ Female (Col 2) | 0.031 (0.102) | 0.022 (0.035) |
| Patient = Black (Col 1)/ Female (Col 2) AND Physician = Black(Col 1)/ Female (Col 2) | 0.519* (0.30) | 0.089 (0.057) |

| PANEL C | Marginal Effect of Patient Race= Black | Marginal Effect of Patient Sex= female |
|---|---|---|
| Patient = High Power AND Physician = White (Col 1)/ Male (Col 2) | -0.061** (0.028) | 0.169*** (0.043) |
| Patient = Low Power AND Physician = White (Col 1)/ Male (Col 2) | -0.066*** (0.004) | 0.037*** (0.015) |
| Patient = High Power AND Physician = Black (Col 1)/ Femal (Col 2)e | 0.455* (0.264) | 0.069 (0.055) |
| Patient = Low Power AND Physician = Black (Col 1)/ Female (Col 2) | -0.032 (0.026) | 0.002 (0.016) |

Cols (1) and (2) present estimates from examining doctor-patient concordance on race and sex respectively. Col (1) only includes encounters with Black and White physicians. Using estimates from Equation (8), Panel A presents regression coefficients, Panel B presents marginal effects of being a high-power patient, and Panel C presents marginal effects of the patient being Black (Col 1) or Female (Col 2). Patients are considered "high-power" if they strictly outrank their assigned physicians in the encounter, and "low-power" otherwise. Fixed effects included for: patient-rank, physician-rank, diagnosis (first 3 digits of ICD-9/10 code), hospital, year-month, and day-of-week. Other covariates include: (patient and physician) age, age-squared, race, sex, and (patient) Charleson score. Standard errors are clustered at the hospital-level.

**TABLE A.4**

Characteristics of Encounters Pre- and Post- Patient Promotion

| | Sample Mean<br>Mean | Coefficient on<br>High-power patient |
|---|---|---|
| Age | 25.44 | 0.92*** |
| | | (0.055) |
| Race - Black | 0.215 | -0.004** |
| | | (0.002) |
| Gender - Female | 0.310 | -0.017*** |
| | | (0.003) |
| Charlson Score | 0.014 | 0.001** |
| | | (0.001) |
| **Fixed Effects** | | |
| Promotion Rank | | Yes |
| Physician $\times$ Physician Rank | | Yes |
| *N - Observations* | | |
| Patient Before Promotion | 117,756 | 117,756 |
| Patient After Promotion | 302,122 | 302,122 |
| Total Observations | 419,878 | 419,878 |

This table presents patient characteristics for encounters occurring within 1 year of patient promotion, limited to patients who ever got a promotion in our sample. Col (1) presents sample means. Col (2) presents unadjusted differences. Cols (3), (4), and (5) add in fixed effects for patient ranks, hospital, and month-year, respectively.$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$

**TABLE A.5**

Power and Promotions/ Retirement

| | (1)<br>Log RVUs | (2)<br>Resource Index |
|---|---|---|
| ***Panel A: Promotions Sample*** | | |
| Post-Promotion | 0.010*** | 0.039*** |
| | (0.002) | (0.007) |
| Sample Mean | 2.67 | -0.23 |
| Observations | 419,610 | 419,610 |
| ***Panel B: Retiree Sample*** | | |
| High Power | 0.051** | 0.075** |
| | (0.023) | (0.031) |
| Post-Retirement | -0.189*** | -0.063 |
| | (0.035) | (0.046) |
| High Power * Post-Retirement | -0.02 | 0.050 |
| | (0.028) | (0.053) |
| Sample Mean | 2.93 | -0.00 |
| Observations | 237,926 | 237,926 |

Panel A presents the regression coefficients from regressing physician effort (Logged RVUs, Col 1) and resource use (Resource Index, Col 2) on an indicator for the encounter occurring post-patient promotion, as described in Equation (6). This analysis includes fixed effects for patient promotion rank, physician x physician rank, and hospital. Panel B presents the regression coefficients from regressing physician effort (Logged RVUs, Col 1) and resource use (Resource Index, Col 2) on a saturated interaction between (i) he encounter occurring post-patient retirement and (ii) the patient being high-power, as described in Equation (9). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Fixed effects included for patient-rank, physician-rank, Other covariates in both analyses include: patient and physician age, age-squared, race, sex, and patient Charleson score. Fixed effects for patient rank, physician rank, hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week are included. Standard errors are clustered at the hospital-level.

**TABLE A.6**

Characteristics of Encounters Pre- & Post- Patient Retirement

| | (1) Sample Mean | (2) Prior to Retirement | (3) Post-Retirement |
|---|---|---|---|
| ***Panel A - Patient Demographics*** | | | |
| Age | 40.68 | 39.52 | 46.01 |
| Gender - Female | 0.20 | 0.21 | 0.15 |
| Race - Black | 0.28 | 0.27 | 0.32 |
| Charlson Comborbidity Score | 0.035 | 0.029 | 0.063 |
| ***Panel B - Patient's Retirement Rank*** | | | |
| Enlisted - E6 & E7 | 0.65 | 0.66 | 0.63 |
| Enlisted - E8 & E9 | 0.14 | 0.13 | 0.19 |
| Officer - O1 & O2 | 0.01 | 0.01 | 0.00 |
| Officer - O3 | 0.04 | 0.04 | 0.02 |
| Officer - O4 | 0.07 | 0.07 | 0.06 |
| Officer - O5 | 0.07 | 0.07 | 0.09 |
| Officer $\geq O6$ | 0.02 | 0.03 | 0.02 |
| *N - Observations* | | | |
| Total | 238,100 | 195,394 | 42,706 |
| High-Power Patients | 7.17% | 6.86% | 8.62% |

This table presents patient characteristics for encounters occurring within 5 years of patient retirement, limited to patients who ever retired in our sample. Col (1) presents sample means. Col (2) and (3) presents mean characteristics for encounters up to 5 years prior, and up to 5 years after patient retirement, respectively. All differences are statistically significant at the 0.001 level.