# How Power Shapes Behavior: Evidence from Physicians


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March 20, 2023

(The most updated version of this paper can be found HERE.)


**Abstract**

Power, defined as the asymmetric control of valued resources, affects most human interactions. Yet there is little observational evidence on how power affects real-world 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 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. Furthermore, within-physician effort is higher for patients recently promoted than those about to be promoted. We document negative spillovers from a physician's high-power patients to their concurrently seen low-power patients, as well as predictable interactions of such power dynamics with 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.'*

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# 1 Introduction

Power is generally defined as the asymmetric control of valued resources – such as 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. In 2017, the #MeToo movement forced the issue of workplace gender equality into the spotlight by highlighting the uncomfortable link between power dynamics in the workplace and sexual harassment (Jodi Kantor and Twohey, 2017; Ryzik et al., 2018).[1] Similarly, there has been a growing recognition of the pervasiveness of power and its potential distortions in modern society – how billionaires are able to convert their immense wealth into political and social influence (Krugman, 2020; Neate, 2022; Faccio, Masulis, and McConnell, 2006), how institutional structures (such as law enforcement, housing policy, etc) may, intentionally or not, grant power to one class of individuals at the expense of another (Darity Jr, 2022; Aaronson, Hartley, and Mazumder, 2021; Goncalves and Mello, 2021), and even in academia, how power can serve to uphold the status quo (Schultz, Stansbury, et al., 2022; Carrell, Figlio, and Lusher, 2022).

Given the significant impact that power has on society, it is not surprising that it has received substantial attention across the social sciences. The literature shows that possessing power changes the way individuals perceive information and behave, sometimes sub-optimally.[2] However, much of the current knowledge on power and individual behavior comes from stylized laboratory games with low 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 rigorously evaluate the real-world effects of power on individual behavior. Power is an abstract concept that is dependent on both the individual and the context and is often inextricably linked with other social factors, making its precise identification and measurement difficult. Therefore, in most settings, it is impossible to distinguish the effects of power from the direct effects of the valued resource that confers that power on an outcome. In this paper, we bypass this empirical difficulty by studying how power affects medical care in the doctor-patient encounter within the US Military Health System (MHS).

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

[1] One of the women in the New York Times article that ignited the 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; Grossman and O. D. Hart, 1986; O. Hart and J. Moore, 1990; G. Baker, Gibbons, and Murphy, 1999) or empirically using stylized economic games in laboratory settings (Moxnes and Van der Heijden, 2003; Kumru and Vesterlund, 2010; Fehr, Herz, and Wilkening, 2013; Bartling, Fehr, and Herz, 2014; Sivanathan, Pillutla, and Murnighan, 2008; Van Dijk, De Dreu, and Gross, 2020; Mallucci, Wu, and Cui, 2019; Burdin, Halliday, and Landini, 2018; Pikulina and Tergiman, 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).

the physician, 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 their own 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), workplaces (Bartolome and Laurent, 1986; Mortensen and Haas, 2021) and law (Glaberson, 2006)) 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 (Li, Dow, and Kariv, 2017; Clemens and Gottlieb, 2014) and non-pecuniary (Kolstad, 2013).

This extreme power differential can have unintended consequences, particularly when scarce resources are distributed in an unequal society. For instance, patients with less power may have their preferences discounted or ignored by providers, resulting in poorer care quality and outcomes. This may be due to patients' inability to advocate for themselves effectively or providers' biases. Although the power differential between doctors and patients may always exist and even be necessary, *variation* in this power differential may lead to inefficient and inequitable variations in care across patients.

We examine the power dynamic between doctors and patients in the US Military Health System (MHS), utilizing a straightforward model that defines power as a product of the individual and context. To overcome the primary empirical challenge of precisely measuring power, we leverage a unique feature of the MHS. The majority of physicians and patients in this system are active duty military, which means they hold observable military ranks. Hierarchy, or rank, is one of the most common ways to establish and reinforce power in society (Magee and A. D. Galinsky, 2008). Therefore, we can utilize the difference in military ranks between physicians and patients as a proxy to gauge the magnitude of the power differential between them.

While the doctor always has more control over valued resources in the medical context, such as access to information, clinical services, decision-making rights, and medical authority, higher-ranking patients will have greater control over resources *outside* the medical context, such as status, networks, and military authority. Therefore, we hypothesize that the power differential between the doctor and patient in the clinical encounter decreases as the patient's rank approaches or surpasses the physician's rank, which can affect medical care and patient outcomes. We provide support for this hypothesis through qualitative data obtained from interviews with military physicians.

Finally, to identify causal estimates of the effect of power on behavior and resource allocation, we use a feature of 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.

In our main specification, we examine the effect of the power differential between doctor and patient on physician effort and resource use for the patient. In this analysis, all variation in the power differential stems from changing the physician rank relative to a *fixed* patient rank (i.e., keeping patient rank constant). For example, we compare the effort provided by physician of rank $R_j = R^+$ on a patient of rank $R_i = R^*$ to the effort provided by a physician of rank $R_j \neq R^+$ on a patient of the same rank $R_i = R^*$. We use patient rank instead of, or in combination with, physician rank because: i) using fixed effects for both patient and physician rank would leave no variation in the power differential, and ii) because patient rank is far more predictive of patient care (due to being strongly correlated with factors such as age) than is physician rank. Even still, comparing patient care by physicians of different ranks has its own issues; we provide a secondary empirical strategy after our main analysis as an alternative way to test our theory.

In our main analysis, we find that – keeping patient rank constant – physician effort and resource use increases as the power differential in the clinical encounter is reduced. "High-power" patients, who are defined as patients as-randomly assigned to strictly lower-ranked physicians, experience about 2.6% more physician effort (measured using relative value units, RVUs) and a 0.15 SD increase in resource use (such as more tests, more procedures, more time with the physicians, and more opioids) than equivalently-ranked "low-power", who are defined as patients that are as-randomly assigned to weakly higher-ranked physicians in the ED. Furthermore, high-power patients also have better health outcomes than equivalently-ranked low-power patients (e.g., a 14% decrease in their likelihood of being admitted to the hospital within 30 days). Importantly, our estimates become even more precise when adding in physician fixed effects, when the variation in the power differential between a given physician and a given patient rank stems from the promotion of the physician from lower to higher ranks[3] – suggesting that it is not unobservable differences in practice styles across different physicians that are driving our results. Quick back-of-the-envelope calculations reveal 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 $36.4 million, which is nearly a third of what they spent on low-power patients.

We perform several robustness checks to shore up confidence in our estimates. First, we create a specification curve using about 1200 combinations of various fixed effects and covariates and find that our coefficient on high-power patients never overlaps zero. Second, we assuage concerns regarding the assumption of quasi-random assignment of physicians to patients in the ED (e.g., there might be sorting if there is more than one physician available when the patient comes into the ED) by re-running our analysis on the subset of patient encounters that occur at the highest quartile of ED capacity when sorting is known to be at a minimum and find that our estimates remain the same or become larger.[4] Third, to ensure our estimates are not being 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 theoretically capable of both being out-ranked and under-ranked by their physician. Our results still hold.

Of course, there are drawbacks to varying physician rank while keeping patient rank constant in order to identify variation in the doctor-patient power differential (for instance, we may simply pick up differences in care patterns between older and young physicians). While we try to control for physician experience using physician age in all our specifications, we also perform a secondary analysis – what we call the "promotion bonus" analysis – where this is not a concern. If rank is a marker of power, then 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. Results from this event study are highly 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"

[3] In other words, when using physician FEs and patient rank FEs, we compare the effort provided by physician X of rank $R_j = R^1$ on a patient of rank $R_i = R^*$, to the effort provided by same physician X (when they were/when they become) of rank $R_j \neq R^1$ on a patient of the same rank $R_i = R^*$.

[4] This makes sense: if a high-ranking patient comes in, they could exert pressure on which ED physician they get assigned to (e.g., they might request to be assigned to a high-ranking physician), but this selection biases our estimates towards the null as high-ranking patients are less likely to be identified as high-power in such encounters. Also, that high-ranking patients can event exert pressure on which physician they see is itself an effect of power on patient care!

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 present "power heterogeneities" in which we show that power stemming from military rank interacts with doctor-patient race and gender concordance in interesting and predictable ways, suggesting that power dynamics are indeed an amalgam of several factors even beyond military rank. For example, being high-power allows Black patients to overcome the lower effort they normally receive from higher-ranking White physicians. Finally, we provide evidence of a "power mechanism": being assigned to a lower-ranking physician is beneficial for the patient even after retirement, suggesting that status ("respect"), rather than authority ("fear"), drives greater physician effort in this setting. Taken together, our main analyses, the promotion bonus analysis, and these supplemental tests paint a more convincing picture of the effects of power on behavior than any one single analysis can by itself.

These results are applicable not only to non-military healthcare settings but also to non-healthcare settings. Our findings have implications for the rise of "VIP patients" and the concerning increase in "concierge" and "red-carpet" medical care for individuals who are wealthy, famous, influential, or well-connected (Kliff and Silver-Greenberg, 2022)[5]. Although the MHS offered us a convenient opportunity to investigate an empirically challenging research question in a specific context, we can still draw more general conclusions. Rank serves as a clear and salient indicator of power in the MHS, but outside the military, power differentials may depend on various resources, including wealth, race, status, networks, class, socioeconomic background, sexual orientation, and disability status. Our results indicate that any power differential between two people, regardless of the ease with which researchers can measure it, can have nontrivial and potentially suboptimal effects on decisions and resource allocations. In high-stakes settings, such as healthcare, the implications of these effects may be of even greater concern from a societal welfare perspective. It is worth noting that our estimates may represent a lower bound for several reasons, including the fact that active-duty military patients tend to be healthier than non-military patients in civilian settings, which likely limits the harm from physician neglect. Additionally, 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 kinship and experiences.

Our study may be the first to confirm, using real-world data, what has long been uncertainly extrapolated from small-scale, stylized laboratory experiments: that the powerful can enjoy better outcomes in society by way of simply possessing power. Importantly, we also offer a cohesive theory for why homophily between two individuals matters for outcomes in massively consequential settings such as healthcare, education, and law. For instance, concordance in sociodemographic factors like race and gender between doctors and patients affects health outcomes.(Alsan, Garrick, and Graziani, 2019; Greenwood et al., 2020; Cabral and Dillender, 2021; M. D. Frakes and Gruber, 2022); that between educator and student affects learning outcomes (S. Gershenson et al., 2022); that between judge and

[5]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." (2022)

defendant affects trial outcomes (Knepper, 2018; Weinberg and Nielsen, 2011). Our study sheds light on one reason behind this phenomenon. In an unequal society, being a part of a privileged race or gender can be a valuable resource, and homophily helps to rebalance the power differential created by the asymmetries in this resource. Furthermore, our findings can also account for the protective effects of occupational homophily. Patients who are physicians themselves receive a different level of care (Johnson and Rehavi, 2016; M. Frakes, Gruber, and Jena, 2021) due to their greater access to medical information, a resource that is highly valued in clinical settings.

In Section 2, we describe the background and our conceptual framework. In Section 3, we describe our data. In Section 4, we present out 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[6] – 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 a simple model to connect the idea of "control of valued resources" to the realization of the power differential in an interaction between two individuals.

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 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

[6] 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 Y.-R. 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.

from power differentials in secondary contexts[7]:

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

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 where the interaction is not occuring). 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 affectd 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. 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 $\phi_{iC}$.

## 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 (Frosch et al., 2012; Berry et al., 2017), while physicians admit to using strategies to "handle" being more powerful than their patients (Nimmon and Stenfors-Hayes, 2016; Fochsen, Deshpande, and Thorson, 2006).

[7]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).

However, we hypothesize that the *realized* power differential between the doctor and patient in a clinical encounter ($\Pi_{(j-i)c^+}$) depends on the expected power differential between them outside the clinical setting as well, i.e., 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 – ultimately changing the realized power differential between them *within* the clinical encounter.

But how does one test this? Power differentials outside the medical setting are difficult to measure or observe, as they depend on a complex amalgam of observable and unobservable factors unique to the doctor and patient. A feature unique to the Military Health System makes the examination of this research question possible. In the MHS, both the doctor and patient are active duty military, and thus, are both part of a rigid and clear rank-based hierarchy. Critically for our paper, hierarchical differentiation has long been considered one of the fundamental ways that power is established and reinforced (Magee and A. D. Galinsky, 2008).

#### *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 The impacts 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 (A. 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 (A. Galinsky, Rucker, and Magee, 2015; Alexander et al., 2012). 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.

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. Keeping patient rank constant and varying physician rank, or vice versa, allows for variation in this power differential $\Pi_{(j-i)c^+}$. In the main analysis of this paper, we use the former (i.e., keep patient rank constant), while conducting a separate analysis using a different research design to circumvent the issues stemming from varying physician rank while keeping patient rank constant (discussed in greater detail in the empirical section). We cannot quantify the extent to which each of these changes in behavior – either from the physician and patient – would predominate in this setting.[8] However, 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.

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; 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.

[8] 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.

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, which predicts the 10-year mortality for patients with multiple comorbidities).[9]

## 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 one of the most commonly used when examining within- and across- physician variation in practice patterns in the healthcare setting (Gowrisankaran, Joiner, and Léger, 2018; Y. Chen, 2021; Greenwood et al., 2020; Chan, 2018). It is based on a critical, institutional feature of 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 (i..e, considered a "high-power" patient). On average, high-power patients are of course higher-ranked

[9] 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.

than low-power patients and thus observably different: high-power patients are on average 17 years older, 48% less likely to be Black, and 28% less likely to be female than low-power patients (Table 2 Col 2). However, adding patient-rank fixed effects (Col 3) eliminates all these differences, with economically trivial differences remaining in the Charleson Score. Adding in hospital FEs (Col 4) and month-year FEs (Col 5) results in a balanced sample where, *within* a patient rank, high-power patients (i.e., those assigned to strictly lower-ranked physicians) and low-power patients (i.e., those assigned to weakly higher-ranked physicians) are observably similarly.

There may be the concern that this 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 (Chang and Obermeyer, 2020; Chan, 2018), violating the identification assumption. Thus, in robustness checks later, 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 Dependent Variables*

*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, and (ii) by constructing a Resource Index which collectively captures clear and tangible instances of effort and resource use.

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). 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." 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. 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 create a composite index to capture physician effort in a more granular fashion, i.e., by using clear and 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: (i) 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; (ii) 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; (iii) the number of procedures on the record (using Current Procedural Terminology (CPT) codes, which are used by physicians for documenting procedures and medical services); (iv) the probability of ordering any test, (v) probability of ordering any image, and (vi) probability of performing any procedure. This type of collapsed index has been used in other papers to avoid issues arising from multiple hypothesis-testings (Currie, Mueller-Smith, and Rossin-Slater, 2020; Singh, 2021), but we also show our main results broken up into 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 low in this sample, we re-ran Equation (5) using patient outcomes such as hospital admission on index visit, hospital admission within 30 days of index visit, and return to ED within 30 days (ED bounceback). We remain uncertain about whether increased physician effort and resources improve patient health, 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, depending on where the patient lies on the "returns to care" curve.

#### *4.3.2 Independent Variables*

We create two measures – categorical and dichotomous – of the power differential between doctor and patient. An active duty military patient of rank $R_p$ enters the ED and can be assigned to 4 possible clinical encounter types: I) the patient outranks the physician; II) the patient has the same rank as the physician; III) the patient is lower-ranked than the physician; and IV) with a civilian physician.

In our discrete, categorical measure of the power imbalance, we are interested in the magnitude of the power differential between doctor and patient. Hence, the value of this categorical variable is simply the difference between the rank of the patient minus the rank of the physician, allowing for nonlinearities in the effect of the power differential. As civilian physicians do not have a military rank, Type IV clinical encounters are excluded from this measure and analysis. Note that, using this measure, all physician ranks can provide variation in the independent variable in the form of multiple values (e.g., the highest ranking physician, an O-6, can have an independent variable value of anywhere from 4 to -14).

In our dichotomous measure of the power imbalance, we are interested in comparing encounters with *reduced* power differentials (i.e., with high-power patients) to those with the *standard* power differential (i.e., with low-power patients), keeping constant patient rank. Thus, we include all clinical encounter types, though only one clinical encounter type – i.e., Type I, where the patient outranks the physician – is identified as having a reduced power imbalance. As a result, the value of this dichotomous variable is equal to 1 only when the patient is assigned to a physician who is strictly lower-ranked to them, and 0 otherwise. We use this dichotomous 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 dichotomous measure allows us the easier display and interpretation of the range of outcomes studied than the categorical measure, which has 20 separate categories.

Note that, in this 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 thus included to more precisely estimate the nuisance parameters in the model (e.g., diagnosis FEs). All the variation in the independent variable primarily comes from the officer patient X officer physician encounters. This is not a concern as we first present results excluding these civilian physicians when using the categorical version of the independent variable. Moreover, in robustness checks, we create a propensity-matched sample limited to only those patients who can theoretically be assigned to both higher- and lower-ranked physicians (our results still hold, suggesting that our result are not driven by a small subset of patient ranks).

### 4.4 Empirical Specification

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

$$DepVar_{ij} = \beta \underbrace{IndVar_{ij}}_{\substack{\text{Categorical or dichot}\\ \text{measure of power imbalance}}} + \overbrace{\phi_{r(i)}}^{\substack{\text{Pat-rank}\\ \text{FE}}} + \underbrace{\mathbf{X}_{i/j}}_{\substack{\text{Pat/Doc}\\ \text{chars}}} + + \overbrace{\delta_{d(i)}}^{\text{Diag FE}} + \underbrace{\eta_{h(i)}}_{\substack{\text{Hospital}\\ \text{FE}}} + \overbrace{\tau_{t(i)}}^{\text{Time FE}} + \epsilon_{ij} \tag{5}$$

where $DepVar$ measures physician effort and resource use (using the dependent variables we outline in the previous section); $\beta$ measures either (i) (using the categorical measure) the marginal effect of the difference in ranks between doctor and patient compared to when they are equally ranked, keeping constant patient rank (this measure allows us to look at non-linearities in the effect of power differentials); or ii) (using the dichotomous measure) the marginal effect of a reduced power differential in the clinical encounter, or differently put, the marginal effect of being a high-power patient, keeping constant patient rank. $\phi_{r(i)}$ is a fixed effect for patient rank; $X_i$ is a vector of patient covariates (linear and quadratic terms for age, sex, race, and Charleson Score), $X_j$ is a vector of doctor covariates (age, sex, and race), $\delta_{d(i)}$ signifies fixed effects for the first 3 digits of 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 1204 different combinations of these covariates to show remarkable robustness of our estimates to covariate selection.

The most important point to note in our analysis is this: unless specified, we always compare outcomes within a patient rank, never across patient ranks. All variation in our independent variables, i.e. the power differential, stems from varying the physician rank while keeping the patient rank constant. So we basically compare outcomes for a patient of a specific rank (say $R_i = R^*$) assigned to a doctor of any rank (say, $R_j = R^+$) to outcomes for a patient of the *same* specific rank (i.e., $R_i = R^*$) assigned to a doctor of a different rank (say, $R_j \neq R^+$). Comparing outcomes between patients of different ranks may provide biased estimates as patients of different ranks may be observably and unobservably different in ways that directly affect patient care. For example, patient rank is correlated with patient age, race, sex (i.e., $g(i)$ in Equation 4), all of which have large direct effects on our outcome of interest.

However, there is a clear drawback to using patient rank fixed effects instead of physician rank fixed effects (we cannot use both without losing all variation in the power differential): physician attributes correlated with physician rank, which may directly affect care (i.e., $h(j)$ from Equation (4)), such as ability and experience, are not accounted for. We opt for this approach because patient rank will undoubtedly have more significant and direct effects on medical care than physician rank; for instance, the impacts of patient age, race, and sex (characteristics correlated with patient rank) on patient care are first-order effects, whereas the effects of physician ability or experience (characteristics potentially correlated with physician rank) are less so. Nevertheless, we address this concern in three ways. First, in all specifications, we incorporate physician characteristics such as age (physician age serves as a proxy for physician experience), sex, and race to control for variations in physician practice style.

Second, in a separate analysis, we add physician FEs to Equation (5) (while retaining patient rank FEs) to control for physician ability and/or practice style. This specification, which keeps the physician constant *and* the patient rank constant, presents a more stringent test of our theory, as it forces all the variation in our dichotomous independent variable (i.e., being a high-power patient in the clinical encounter) to stem from physician promotion. Essentially, the $\beta$ parameter now compares how a patient of rank $R_i = R^*$ is treated by a physician of rank $R_j = R^+$, to how a patient of the same rank $R_i = R^*$ is treated by the *same* physician when that physician held a rank $R_j \neq R^+$.

Third, following the robustness checks for our main analysis, we introduce and present results from a "secondary empirical strategy" where we exploit a narrow window of time around patient promotions to control for factors that typically co-occur with (patient and physician) rank while varying the power differential between doctor and patient. Specifically, we compare within-physician effort for patients *just* promoted to rank $R_i = R^*$ versus those *about* to be promoted to rank $R_i = R^*$ using an event study design.

### 4.5 Results

Using the categorical measure of the power imbalance between doctor and patient, we see a clear negative relationship between the size of the power differential and the effort provided by the physician in Figure I. That is, as the patients 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 supports our hypothesis of 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.

We next present results using the dichotomous independent variable. Figure II presents results for all standardized outcomes (so that estimates can be presented in a single figure): keeping constant patient rank, physicians exert nearly 0.037 SDs more RVUs (an increase of 2.6%) and 0.048 SDs more logged RVUs, and consume 0.058 SDs more on the Resource Index in encounters with high-power patients than they do with low-power patients. 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 (as well as their summary statistics) are also presented in Table A.1.

Figures I and II both suggest that – in line with our hypothesis – there is a positive relationship between the patient power and physician effort on that patient. High-power patient enjoy more effort and resources than low-power patients, keeping constant patient rank. As the difference in rank between patient and physician should not clinically affect patient care, we interpret this result as: decreasing the power differential between doctor and patients causes the physician to increase their effort and resource use on the patient.

Next, we examine the effect of reduced power differentials in the clinical encounter on patient outcomes. The bottom-most panel in Figure II shows that – by and large – patient outcomes are better for patients in encounters with a smaller power differential. Most notably, keeping patient rank constant, high-power patients experience a 0.02 SD reduction in their likelihood of hospital admission within 30 days of the index encounter, which is a 14.2% reduction.

Figure A.2 then presents our main results adding in physician fixed effects to our main specification, Equation (5). Though the estimates are slightly smaller in magnitude with the physician fixed effects, they become more precise and remain entirely in line with our overarching hypothesis: that being a high-power patient increases physician effort and resource use, and improves patient outcomes, keeping constant patient rank and the physician.

Now let us put these results in perspective. For a 2.6% increase in RVUs (i.e., an increase of 0.072 RVUs), a high-power patient experiences a 14% decrease (i.e., a decrease of 0.28 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 B. J. Moore, 2016). Thus, comparing across the same patient rank, a high-power patient has \$2.42 more resources spent on them than a low-power patient, and saves \$32.76 in hospitalization costs, leading to a total savings of \$30.34 per patient. If – keeping all else constant – every one of the 1.2 million low-power patients in our sample was treated like a high-power patient, over the period of 10 years, the MHS would have saved \$36.4 million. How substantial are these savings? 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 \$30.34 per patient essentially imply that nearly a third of physician expenses could be recouped if low-power patients were treated like high-power patients.

## 4.6 Robustness Checks

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

We show that our results are not driven by our choice of covariates. Figure A.3 displays the distribution of the $\beta$ estimate from running 1,204 regressions of Equation (5) using the dichotomous measure of our independent variable (i.e., an indicator for a high-power patient), with various combinations of covariates and fixed effects. None of the 1204 estimates overlap zero, suggesting that our parameter of interest – i.e., the marginal effect of the reduced power imbalance on physician effort and resource use – is remarkably robust to covariate specification.

### *4.6.2 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 (Chang and Obermeyer, 2020; Chan, 2018), 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. Higher-ranked patients, receiving more care due to their age, would also likely request or be assigned higher-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. Moreover, our setting does not appear to show evidence of any such violation (Figure A.1). Nevertheless, we exploit a crucial observation made by Chang and Obermeyer (2020) and Chan (2018) 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.4 shows that, the evidence upholding the identifying assumption seems to be even more robust compared to the same figure plotted for the entire 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. This suggests that, on average, there are no systematic patterns of matching between patient and physician rank at the highest quartile of ED strain.

Figure A.5 shows that on almost every measure, the magnitude of the effect of being a high-power patient is slightly larger using this subset of the sample – where the identifying assumption can be assumed to hold most certainly – than when using the Whole sample. Most strikingly, the protective effect of the reduced power imbalance 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 -.0015 SD in the Whole sample), 30-day inpatient admission (-.049 SD in the constrained sample vs -0.02 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.

#### *4.6.3 Concerns of a) patient heterogeneity within a patient-rank and b) subset of patient ranks driving results*

Even though all comparisons in our main analyses occur within a patient-rank, there may still significant heterogeneity in patient characteristics within a rank that may bias our estimates. Moreover, there may be concerns that our estimates are driven by a small segment of high-ranking patients who may not be often assigned to low-power patient status. Thus, we first drop all patient ranks that can provide no variation in power differentials (i.e., those that cannot be assigned to both higher vs lower-ranking physicians). Then, we re-run our analyses on a propensity score matched sample where all comparisons are made between patients who only differ in whether they are high-power or low-power.

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 and Imbens (2006), Abadie and Imbens (2011), and Abadie and Imbens (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.

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

We have already talked extensively about the potential issues with varying physician rank while keeping patient rank constant to provide variation in the power differential. In this section, we perform a secondary analysis – the "promotion bonus" analysis – that circumvents these issues by 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, we compare within-physician effort provided to patients who visit the ED within a year post-promotion to rank $R_i = R^*$, and patients who visit the ED within a year pre-promotion to rank $R_i = R^*$. Keeping the physician constant, 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.

### *4.7.1 Empirics*

We limit our Whole 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 promotion date, to avoid issues with when the updated rank starts showing up in the physician's EMR. 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. We add in, one-by-one, fixed effects for promotion rank (Col 3), physician (Col 4), and month-year (Col 5), and see that, on average, patients visiting the ED within a a year of promotion are about 1 year older, about 0.5 pp (2.3% ) less likely to be Black, 1.8 pp (6%) less likely to be female and have 0.1 points (7%) higher Charleson comorbiditiy 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. However, none of these differences are clinically meaningful and should not affect our outcome of interest, logged RVUs. We provide evidence in support of this assumption using an event study, where we plot the trend in physician event pre- and post- promotion.

We use the following model, including physician fixed effects $\delta_j$:

$$logRVU_{ij} = \beta Post_t + RankPromoted_i + \mathbf{X}_i + \delta_j + \phi_{r(j)} + \eta_{h(i)} + \tau_{t(i)} + \epsilon_{ij} \tag{6}$$

$Post_i$ is equal to 1 if the patient encounter occurs after the promotion date. $RankPromoted_p$, equals the rank a patient was either promoted to, or is about to be promoted to. $\beta$ 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. The primary difference between the two patients should be that the patient promotion changes the power differential between that doctor and their patient.

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.

### *4.7.2 Results*

On average, a physician exerts 0.009 (p<0.001) logged RVUs more, and 0.037 higher (p<0.001) 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.

Results from the placebo check are presented in A.6: 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 result 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; stacked together, these analyses begin to hold water.

# 5 Supplemental Analyses

In these 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 (I), we examine whether there are spillovers from a physician's high-power patients to their concurrently seen low-power patients. In (II), we examine the idea that power is a complex amalgam of many factors, of which rank is a highly salient one in the military. So we examine how the greater effort enjoyed by high-power patients interacts with doctor-patient concordance on race and sex. Finally in (III), 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: The "Power Spillover"

So far, we only examine the effect of patient power on physician effort for the patient in question. In this section, we examine the effect of patient power on physician effort for *other* 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, or iii) to increase effort for all patients (i.e., "if I'm ordering tests for this patient, I might as well order tests for my other patients too"). In this section, we examine whether there are any effort spillover effects from a physician's high-power patients to their concurrently seen low-power patients, and whether there are any associated effects on the outcomes of said low-power patients.

This analysis is another way to combat the limitation of the main analysis, i..e, not being able to keep physician rank constant due to the use of patient rank fixed effects. In this analysis, we examine the allocation of effort across high- and low- power patients within a physician (at a given rank), controlling for both number of patients seen by the physician as well as the total number of patients in the ED on that date. As patient assignment to the physician in the ED is quasi-random, the physician cannot exert pressure on which other patient types they see on days they care for a high-power patient,

### *5.1.1 Empirics*

We collapse our Whole 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 305,668 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:

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

$DepVar_{jt}^{LowPower}$ is one of the two outcomes of interest calculated for physician $j$'s low-power patients seen on date $t$: averaged logged RVUs exerted by physician $j$ on their low-power patients in the ED on date $t$, and average 30-day ED bounceback or 30-day hospital admission for 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 $t$. Theses 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).

#### *5.1.2 Results*

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, $p = 0.068$) as well as 30-day ED bounceback (0.28 pp, $p = 0.127$). The negative effects on health outcomes are particularly important, since if physicians were selecting "easier"/ healthier low-power patients on days they are assigned to a high-power patient, then though being healthier would drive the lower effort, it still does not explain the worse health outcomes.

Overall, this is suggestive evidence that physicians reallocate resources from their low-power patients to their high-power patients when attending to the latter, 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: "Power Heterogeneities" by Race and Sex

In all our analyses thus far, we measure only one dimension of power in the doctor-patient encounter and one that is limited to the military setting: the difference in military ranks between physician and patient. However, beyond the military setting and even in the doctor-patient encounter, the power differential between two people depends on many factors, such as age, race, sex, wealth, class etc. Thus, in this section, we examine how two of these factors – race and sex – interplay with the rank-based power dynamics we have documented thus far. More specifically, we examine how *patient and physician* race/sex affects physician effort in high-power patient encounters.

#### *5.2.1 Empirics*

We amend Equation (5) to include interactions of the dichotomous version of the independent variable ($HighPower_{ij}$, which identifies encounters with high-power patient) with $PatChar_i$, which captures either patient race (=1 if patient is Black) or sex (= 1 if patient is female):

$$RVU_{ij} = HighPower_{ij} + PatChar_i + \beta HighPower_{ij} \cdot PatChar_i + \phi_{r(i)} + \mathbf{X}_{i/j} + +\delta_{d(i)} + \eta_{h(i)} + \tau_{t(i)} + \epsilon_{ij} \tag{8}$$

$\beta$ identifies the joint effect of a patient being high-power and being Black/female on physician effort (RVUs). When examining heterogeneities by race, we limit the sample to only those encounters with Black or White patients, to allow for simpler and more precise interpretation of results.

Table A.3 presents heterogeneities in effect by patient race (Cols 1 - 3) and patient sex (Cols 4 - 6). We also present estimates after limiting encounters by physician race (Cols 2 and 3) and sex (Cols 5 and 6). We then re-run Equation (8) using a fully saturated triple interaction (i.e., including all single, double, and triple interactions) between $HighPower_{ij}$, $PatChar_i$, and $ProvChar_j$, where $ProvChar_j$ now similarly captures *physician* race (Black v White) or sex (male v female). We present predicted effort estimates from this model in Figure IV, keeping patient rank constant.

### *5.2.2 Results I: Race*

The regression coefficients in Table A.3 Col (1) and the predicted physician effort estimates in Figure IV (top row, left) show that physicians on average exert significantly more effort for high-power patients than low-power patients, whether they be Black or White patients. However, decomposing these results by physician race reveals interesting dynamics (we discuss Figure IV as it is easier to interpret).

White physicians give low-power White patients significantly more effort (2.80 RVUs) than they give equivalently-ranked low-power Black patients (2.74 RVUs) (Figure IV top row, middle). This persists even for high-power patients: White physicians give high-power White patients more effort (2.87 RVUs) than equivalently-ranked high-power Black patients (2.81 RVUs). In fact, White physicians give high-power Black patients similar levels of effort on average as equivalently-ranked low-power White patients. High-power White patients receive the highest levels of effort amongst the 4 groups (2.87 RVUs), while low-power Black patients receive the lowest levels of effort amongst the 4 groups (2.74 RVUs), keeping patient rank constant. This suggests that being a high-power patient allows Black patients to overcome the low effort they usually receive when being seen by a weakly higher-ranking White physician. This result is in line with prior research on the "power shield" (Pike and A. D. Galinsky, 2021), a phenomenon where being in a powerful role has been observed to eliminate demographic disparities.

Importantly, the disparity in effort faced by low-power Black patients attenuates when the sample is limited to encounters with Black physicians (Figure IV top row, right). While the power effect still persists (i.e., Black physicians exert more effort for high-power than low-power patients, both Black and White), Black physicians provide similar effort for low-power White patients (2.69 RVUs) and low-power Black patients (2.66 RVUs) on average. Column 3 in Table A.3 presents regression coefficients and significance levels for these results.

In addition, an interesting result is worth discussing here. Unlike White physicians who are sensitive to patient power for both Black and White patients, Black physicians are sensitive to patient power only for Black patients and by a lot. White physicians increase effort by 0.07 RVUs for high-power patients, both Black and White (Figure IV top row, middle). On the other hand, while Black physicians provide similar levels of effort for low-power Black and White patients and high-power

White patients (2.69, 2.66, and 2.71, resp.), they provide quite literally "off-the-charts" amount of effort for high-power Black patients (3.17 RVUs, an increase of 0.51 RVUs from low-power Black patients). It is unclear why this occurs; possibly when representation of a group in powerful positions is low, the group may be more sensitive to markers of power for members of its own group.

#### *5.2.3 Results II: Sex*

Results for women patients tell a similarly interesting story. The regression coefficients in Table A.3 Col (4) and the predicted physician effort estimates in Figure IV (bottom row, left) show that, once again, the power effect predominates regardless of sex (as it did regardless of race): on average, physician effort is greater for high-power patients – both male and female – than it is for low-power patients, keeping constant patient rank.

We then decompose these results by physician sex. There are three prominent differences in how male physicians (Figure IV bottom row, middle) and female physicians (Figure IV bottom row, right) respond to patient power. First, female physicians do not appear to respond as much to patient power for male patients, treating low-power and high-power male patients similarly (2.85 and 2.88 RVUs respectively) – yet increasing effort from 2.86 to 2.95 RVUs in response to the power of female patients. Male physicians, in contrast, respond to the power of both male and female patients, though still significantly more for female (an increase of 0.19 RVUs) than for male patients (an increase of 0.06 RVUs). In fact, the effort that female high-power patients receive from both male and female physicians dwarfs the effort provided to other patients. It is unclear why physicians respond this strongly to high-power female patients; 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.

Second, female physicians provide the same level of effort for low-power male and low-power female patients (2.85 and 2.86 RVUs, respectively, unlike male physicians who provide significantly more effort to low-power female patients (2.78 RVus) than low-power male patients (2.74 RVUs). It is unclear why this occurs; one might speculate that male physicians may be 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, female physicians seem to provide more effort overall, because the group they provide the lowest effort to (i.e., male low-power patients) still receive more effort (2.85 RVUs) than the effort provided by male physicians to male low-power patients, female low-power patients, *and* male high-power patients. It is unclear why female physicians' baseline effort is so much higher than male physicians', though this result is in line with studies showing that female physicians spend more time on patient care (Ganguli et al., 2020).

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

### 5.3 Supplemental Analysis 4: Disentangling the "Power Mechanism" (Authority vs Status)

So far, we have remained largely circumspect regarding the exact nature of power that patients command when they are in an encounter where they outrank the physician. In this section, we test two potential mechanisms: outranking the physician may increase physician effort because (i) higher rank commands higher status, or (ii) higher 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 higher rank. This increased effort may be because the physician may seek the approval of the patient, they may trust the patient more, and/or may be more empathetic to their sufferings, etc. In the second mechanism, however, deference to authority plays a larger role in physician behavior. The physician exerts more effort because they fear patient reprisal if the patient leaves dissatisfied; for example, the 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 lower-ranking physician should have greater status, but little to no authority (especially the further after retirement the patient visits the ED).

#### *5.3.1 Empirics*

We limit the Whole sample to only those patients who retired – what we refer to as the *Retiree sample* – giving us a sample of 238,100 patient encounters. We amend Equation (8) to examine whether the effect of being a high-power patient changes after retirement, where $PostRet_{it} = 1$ if the patient is retired at the time of encounter:

$$\begin{aligned} DepVar_{ij} = {} & HighPower_{ij} + PostRet_{it} + \beta HighPower_{ij} \cdot PostRet_i \\ & + \phi_{r(i)} + \mathbf{X}_{i/j} + +\delta_{d(i)} + \eta_{h(i)} + \tau_{t(i)} + \epsilon_{ij} \end{aligned} \tag{9}$$

$\beta$ is the joint effect of a patient being high-power as well as 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, but these networks are likely to weaken the further away the encounter is post-retirement. 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 Retirement sample does not capture the entire population of military retirees in the same way that it does for active duty military members.

#### *5.3.2 Results*

Table A.6 presents the demographics and the break-down of the various ranks that comprise the Retirement 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.7): 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. Thus suggests that status is more likely to play a role than authority in the effort bonus provided by physicians to high-power patients.

# 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 higher-ranked than 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 rather than authority drives changes in physician behavior. Our results and conceptualization of the power differential between the doctor 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 measured "hard" benefits of being a high-power patient, such as reduced 30-day ED bounceback and hospital admission, and ignored "soft" benefits such as being treated with dignity and increased 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. In contexts with valued resources and clear power differentials (e.g., classrooms, courtrooms, and firms), how individuals are treated within the context can depend on the allocation of resources outside that context. For instance, private firms may show preferential treatment in hiring or promotions towards politicians' family members (Gagliarducci and Manacorda, 2020). Educators may be more likely to suspend students of color and from low socioeconomic backgrounds, even with all else constant (Barrett et al., 2021). Landlords may be 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 C. Gershenson, 2017). These examples can be explained, to some extent, by the effect of power on behavior. Even if one person has more control of resources in the primary context (such as a landlord in a rental context), varying the other person's control of resources outside that context (such as the tenant's access to legal resources) can affect behavior in the primary context. Our results emphasize the significance of policies and protective social norms as safeguards against the distortionary and often invisible effects of power.[10]

The policy implications for the healthcare setting are even more relevant. 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 (A. 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). 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 typically wielded in a careful and ethical manner. Rather, we are concerned with the inequitable variation in how that power is exercised, with the most vulnerable patients being the least likely to have their preferences integrated into care. To tackle this disparity, 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 emphasize the role of power in medical care, particularly in critical clinical decisions.

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

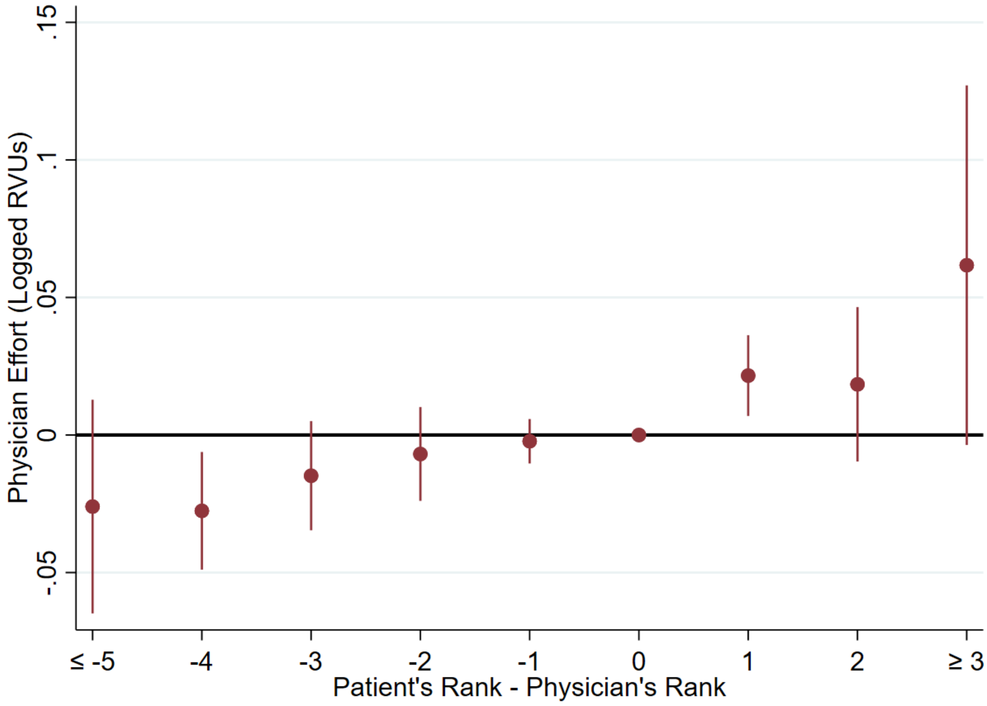


**FIGURE I**

Doctor-Patient Power Differential and Physician Effort

This graph plots relative 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), relative to the comparison group (i.e., when the patient and physician share the same rank, X-axis = 0). Due to the inclusion of patient rank fixed effects, the coefficient on each value of the "power differential" compares outcomes between patients of the same rank who are assigned to physicians of different ranks. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

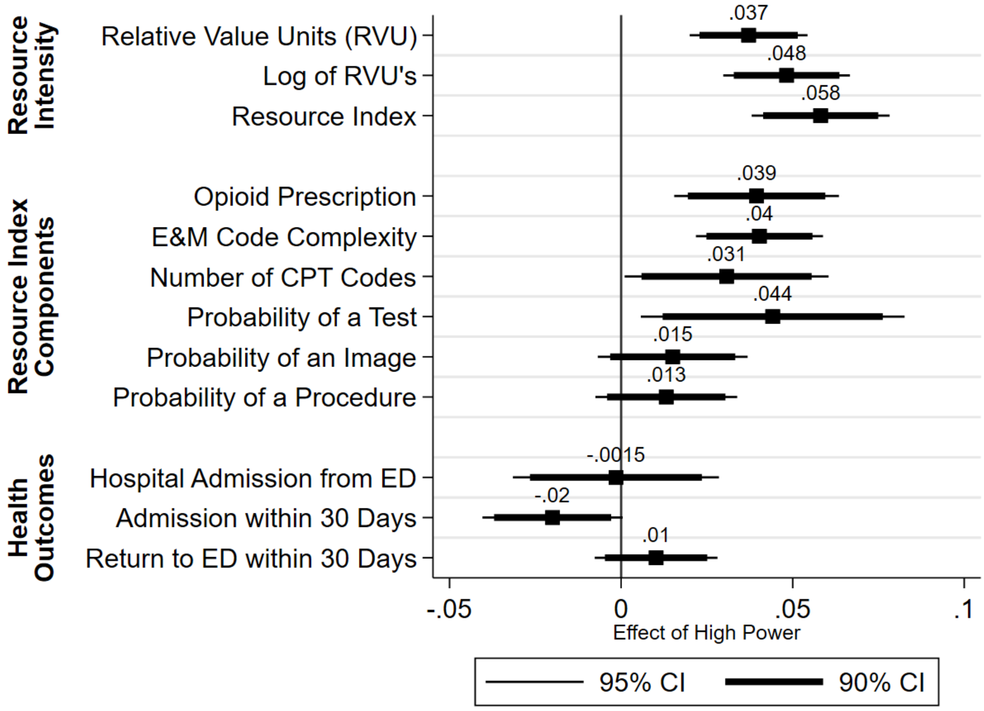


**FIGURE II**

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

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, and "low-power" otherwise. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. 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. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

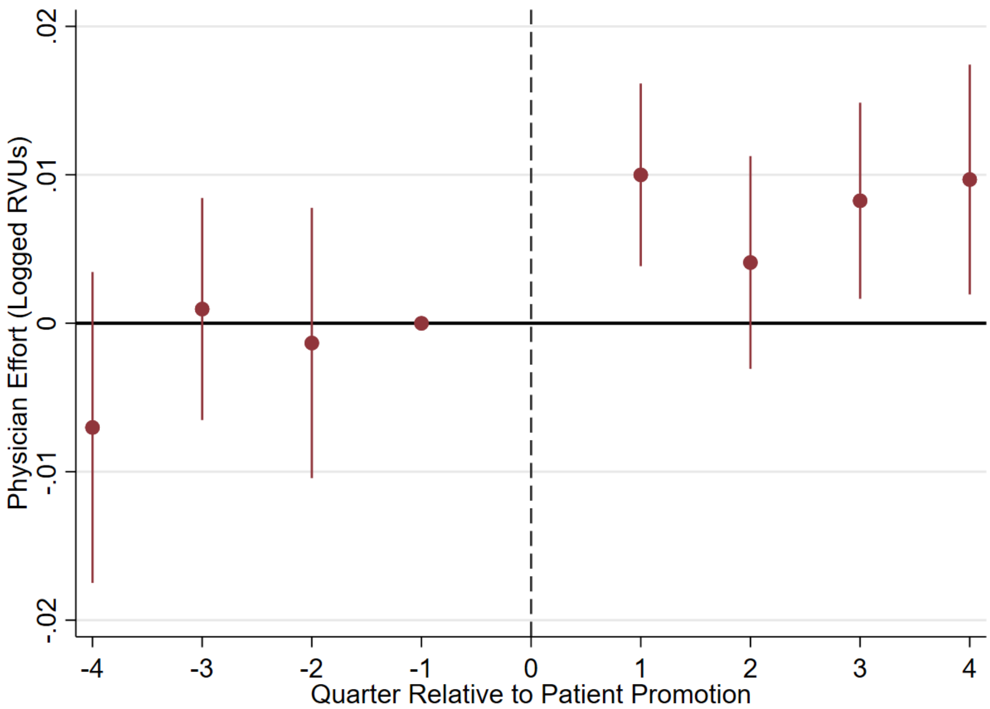


**FIGURE III**

Event Study: Patient Promotion and Within-Physician Effort

This graph plots relative within-physician effort on the Y-axis (i.e., logged RVUs) at each quarter pre- and post- the patient's promotion date on the X-axis, relative to the comparison group (i.e., physician effort 1 quarter prior to the promotion date). Encounters within 45 days of the promotion date are excluded. 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, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

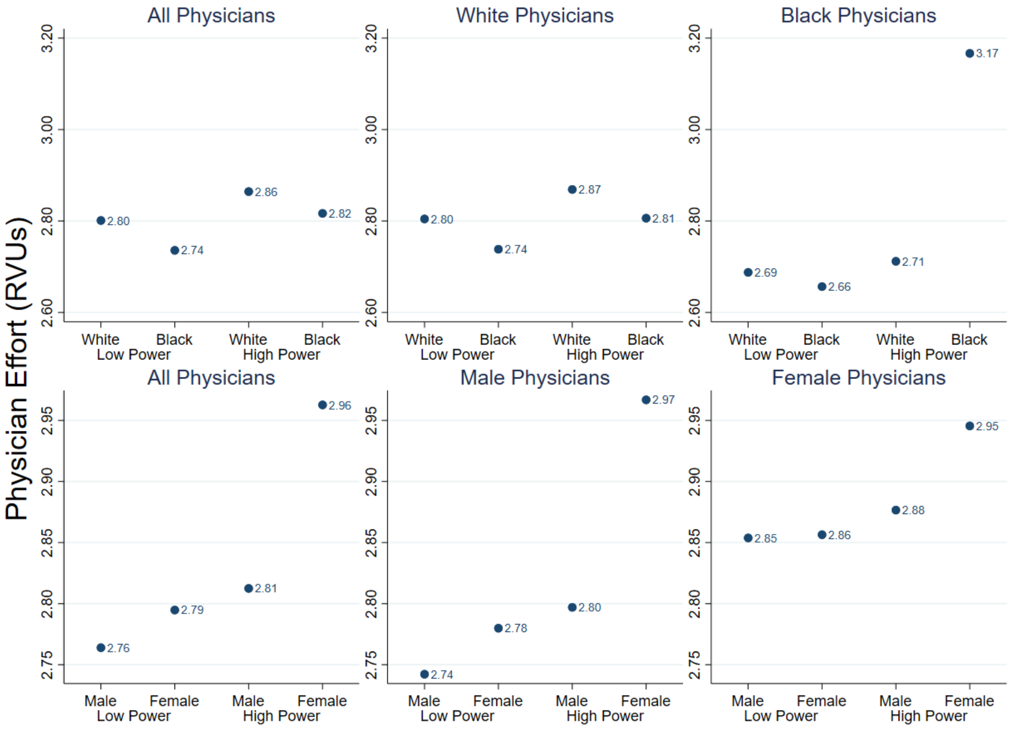


**FIGURE IV**

Heterogeneity in Power Effects by Patient and Physician Race and Sex

This graph plots predicted physician effort (RVUs) on the Y-axis by two variables on the X-axis: (i) patient high-/low-power, and (ii) patient White/Black (top row) and patient male/female (bottom row). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. The leftmost column includes encounters with all physicians, the middle column limits encounters to White physicians (top row) or male physicians (bottom row), and the rightmost column limits encounters to Black physicians (top row) or female physicians (bottom row). All estimates in this graph are obtained by regressing RVUs on a saturated triple interaction between an indicator for whether the patient is high-power, patient race/sex, and physician race/sex. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. All Y-hats (Predicted RVUs) are estimated at the means of all control variables including patient rank, meaning that patient rank is held constant for all estimates within a row.

**TABLE 1**

Frequency Tables: Patient and Physician Ranks

| **Rank** | **Patient** | **Physician** |
|---|---|---|
| Enlisted - Junior | 27.60% | |
| Enlisted - Middle | 29.44% | |
| Enlisted - Senior | 6.09% | |
| 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 Physicians | | 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

| | (1) Sample Mean | (2) Coefficient on High-Power | (3) Coefficient on High-Power | (4) Coefficient on High-Power | (5) Coefficient On High-Power |
|---|---|---|---|---|---|
| Age | 27.816 | 17.180*** | -0.231 | -0.141 | -0.153 |
| | | (0.322) | (0.143) | (0.137) | (0.132) |
| Race - Black | 0.232 | -0.110*** | -0.003 | 0.006 | 0.004 |
| | | (0.012) | (0.010) | (0.006) | (0.006) |
| Gender - Female | 0.303 | -0.086*** | 0.006 | 0.015* | 0.012 |
| | | (0.018) | (0.010) | (0.009) | (0.009) |
| Charlson Score | 0.018 | 0.0134*** | -0.005* | -0.002 | -0.002 |
| | | (0.002) | (0.003) | (0.002) | (0.002) |
| **Fixed Effects** | | | | | |
| Patient Rank | | No | Yes | Yes | Yes |
| Hospital | | No | No | Yes | Yes |
| Month-Year | | No | No | No | Yes |
| *N - Observations* | | | | | |
| Low-power patients | 1,526,525 | 1,526,525 | 1,526,525 | 1,526,525 | 1,526,525 |
| High-power patients | 21,326 | 21,326 | 21,326 | 21,326 | 21,326 |
| Total Observations | 1,547,851 | 1,547,851 | 1,547,851 | 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. Due to the inclusion of patient rank fixed effects, the coefficient on “High power” compares outcomes between high-power and low-power patients of the same rank. 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.$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$t

**TABLE 3**

Spillover Effects

| | $DepVar_{jt}^{LowPower}$: **Average DV per physician** $j$**'s low-power patient on date** $t$ | | | |
|---|---|---|---|---|
| . | (1) Logged RVU's | (2) Negative Outcome | (3) 30-day hosp adm | (4) 30-Day ED return |
| 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 |

Unit of analysis is physician-date. The dependent variable 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. Independent variable of interest, $HighPower_{jt}$, 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. 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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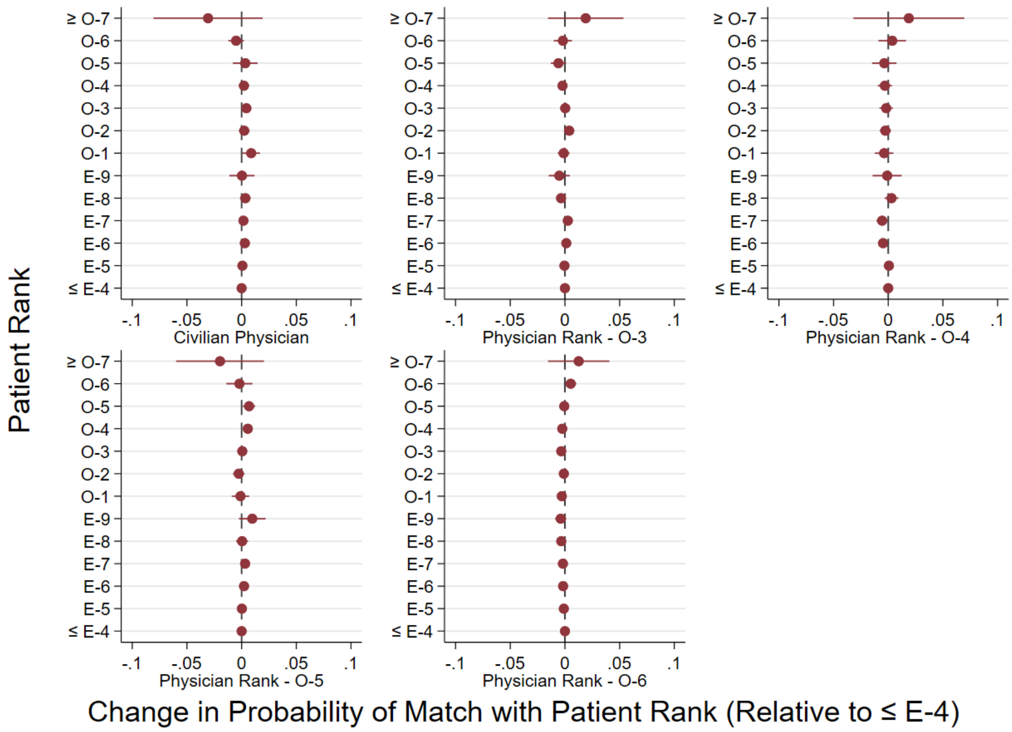


**FIGURE A.1**

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).

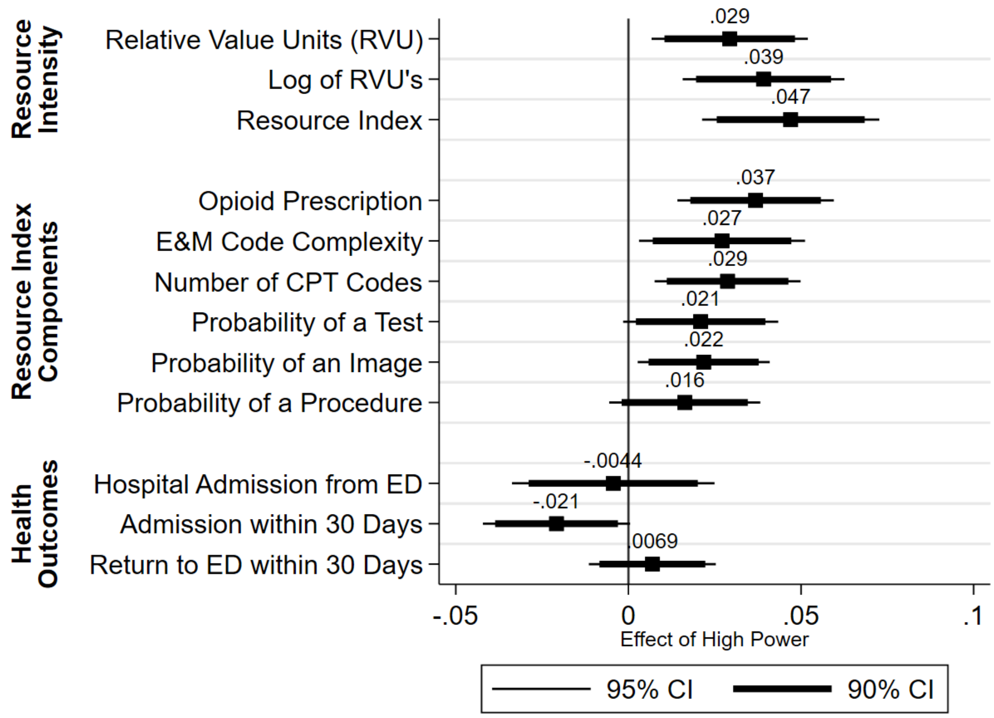


**FIGURE A.2**

High Power Patients and (standardized) Physician Effort, Resource Use, and Health Outcomes – with Physician 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 – *with the inclusion of physician fixed effects.* Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. Additionally, physician fixed effects allows comparisons to be made within-physician. 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. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

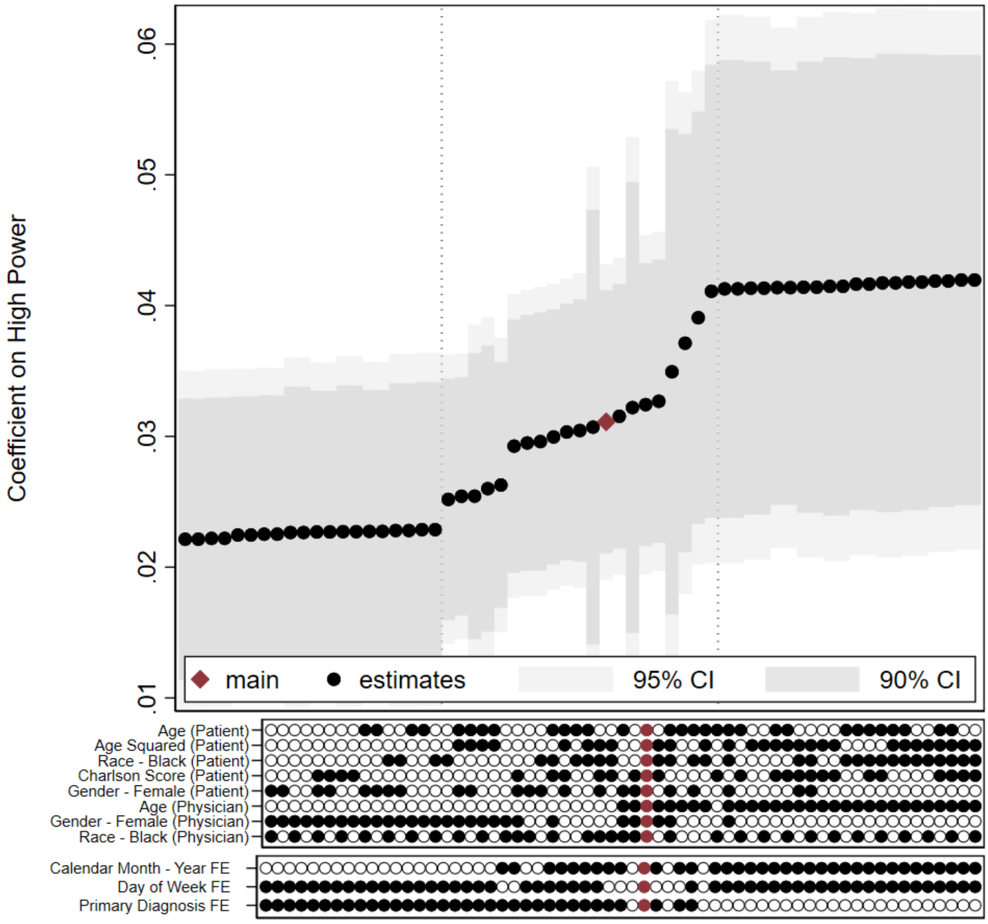


**FIGURE A.3** Specification Curve

This figure plots the distribution of the (20 smallest, 20 largest, and 20 random) $\beta$ coefficients from Equation 5 from approximately 1200 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. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. 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.

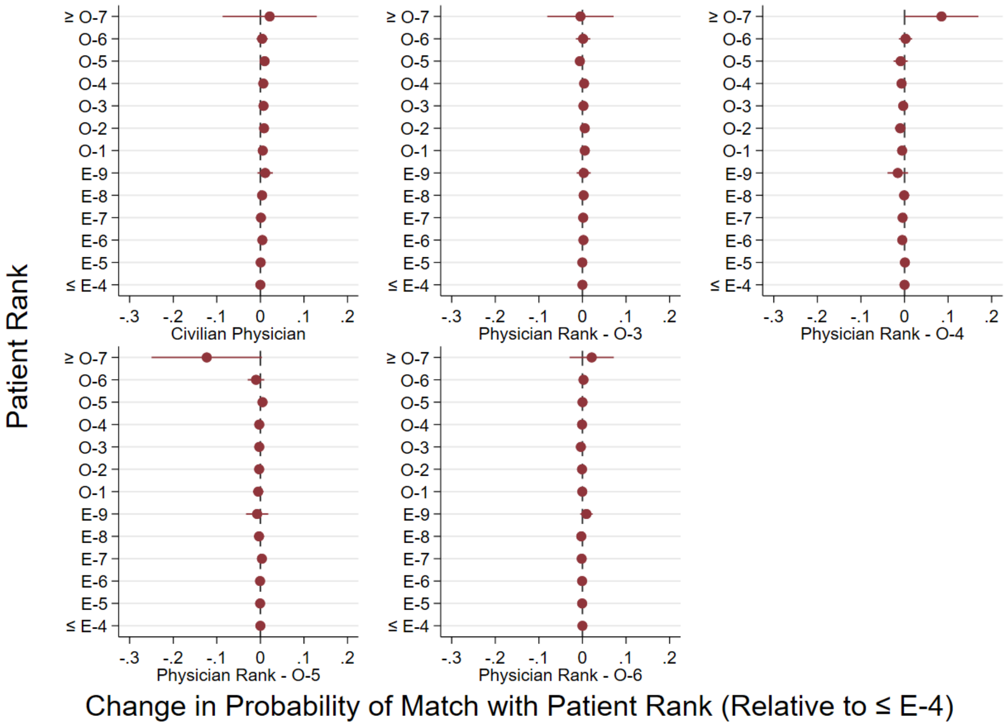


**FIGURE A.4**

Evidence for Identification Assumption in the Constrained Sample: 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).

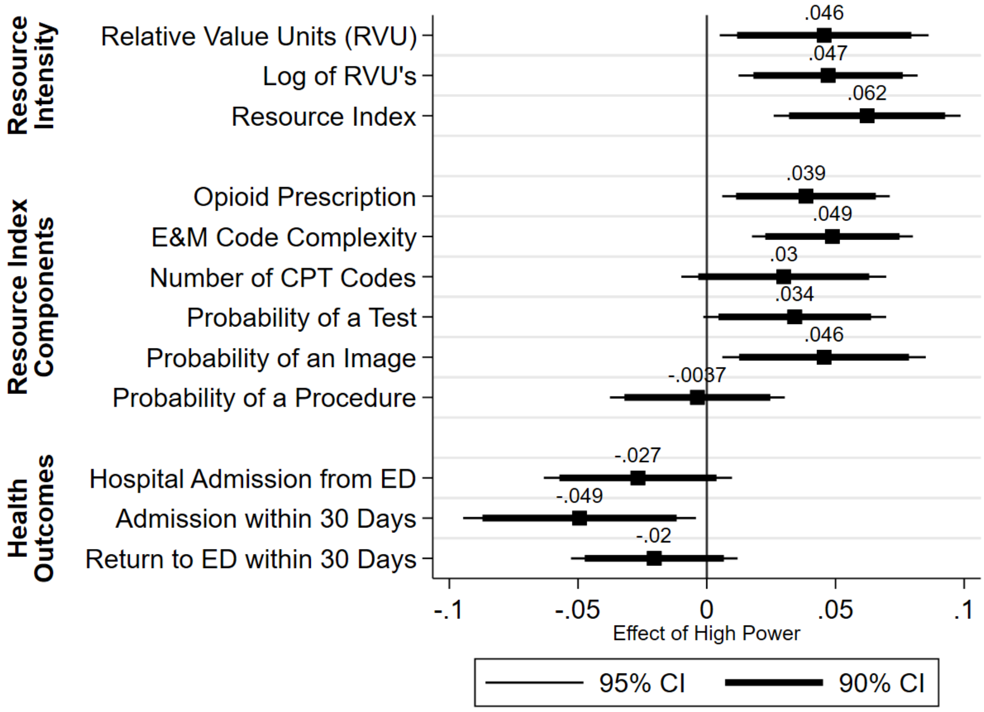


**FIGURE A.5**

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

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 – *limited to only those encounters that occur at the highest quartile of ED capacity.* High-power patients are those assigned to physicians they strictly outrank. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. 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. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

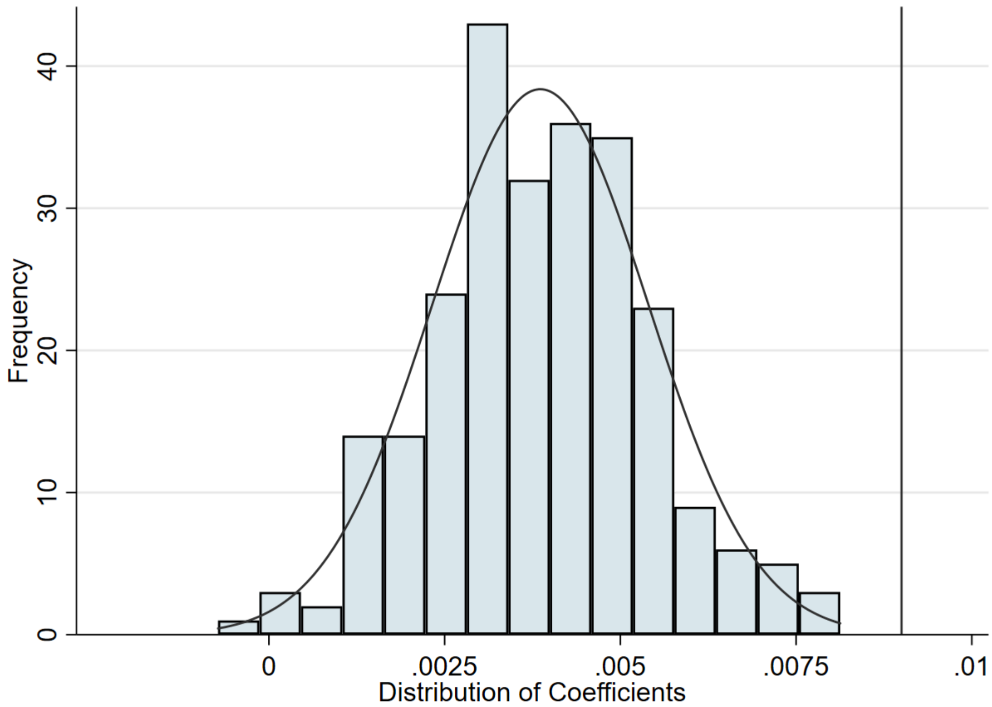


**FIGURE A.6**

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, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

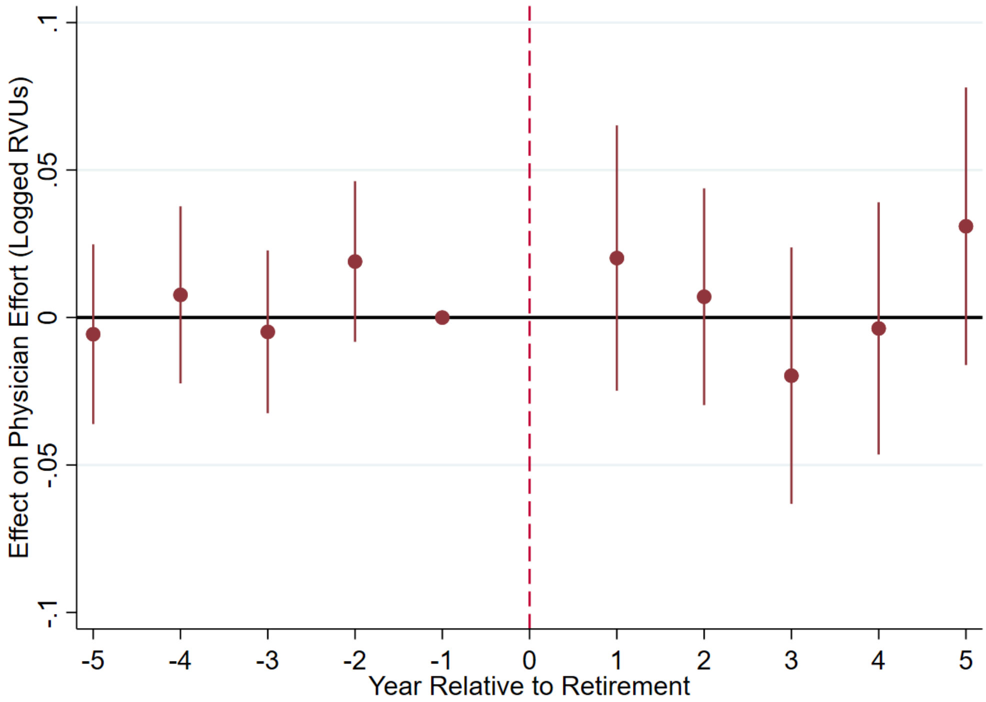


**FIGURE A.7**

Event Study: Effect of Patient Retirement on Physician Effort (Logged RVUs)

This graph plots the relative interaction coefficient from regressing physician effort (i.e., logged RVUs) on an interaction between an indicator for patient being high-power and each year pre- and post- the patient's retirement date, relative to the comparison group (i.e., 1 year prior to the retirement date). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Due to the inclusion of patient rank (at time of retirement) fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

**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: Effort and Resource Use*** | | | | | |
| RVUs | 0.072*** (0.017) | 2.77 | 1.94 | 1 | 82 |
| Log of RVUs | 0.031*** (0.006) | 0.81 | 0.64 | 0 | 4.41 |
| Resource Index | 0.152*** (0.026) | 0 | 2.62 | -3.91 | 12.70 |
| ***Panel B: Resource Index Components*** | | | | | |
| Opioid Prescription | 0.016*** (0.005) | 0.21 | 0.41 | 0 | 1 |
| E&M Complexity | 0.038*** (0.009) | 2.78 | 0.94 | 1 | 6 |
| Number of CPT Codes | 0.062** (0.030) | 1.53 | 2.00 | 0 | 10 |
| Probability of a Test | 0.019** (0.008) | 0.23 | 0.42 | 0 | 1 |
| Probability of an Image | 0.004 (0.003) | 0.06 | 0.23 | 0 | 1 |
| Probability of a Procedure | 0.006 (0.005) | 0.34 | 0.47 | 0 | 1 |
| ***Panel C: Health Outcomes*** | | | | | |
| Admission from ED | -0.000 (0.003) | 0.05 | 0.21 | 0 | 1 |
| 30-Day Admission | -0.003* (0.002) | 0.02 | 0.14 | 0 | 1 |
| 30-Day Return to ED | 0.003 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. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. 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

| | Black vs White Patients | | | Female vs Male Patients | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All Physicians | White Physicians | Black Physicians | All Physicians | Male Physicians | Female Physicians |
| High Power | 0.072*** | 0.066** | 0.137 | 0.047** | 0.045 | 0.074 |
| | (0.020) | (0.027) | (0.144) | (0.022) | (0.028) | (0.051) |
| Patient Race - Black | -0.068*** | -0.066*** | -0.025 | | | |
| | (0.005) | (0.005) | (0.021) | | | |
| High Power * Black | 0.030 | 0.002 | 0.477 | | | |
| | (0.032) | (0.030) | (0.284) | | | |
| Patient Sex - Female | | | | 0.031*** | 0.034*** | 0.018 |
| | | | | (0.009) | (0.009) | (0.013) |
| High Power * Female | | | | 0.108** | 0.134*** | 0.061 |
| | | | | (0.044) | (0.045) | (0.058) |
| Observations | 1,360,726 | 1,115,563 | 33,200 | 1,547,851 | 1,246,651 | 301,200 |
| Mean RVUs | 2.77 | 2.79 | 2.71 | 2.77 | 2.77 | 2.81 |
| Unique Physicians | 1,339 | 1,059 | 40 | 1,340 | 1,034 | 306 |

This table presents regression coefficients from regressing physician effort (RVUs) on an interaction between (i) patient being high- vs low-power, and (ii) patient race (Cols 1-3) OR patient sex (Col 4-6), as described in Equation (8). Patients are considered "high-power" if they strictly outrank their assigned physicians, and "low-power" otherwise. Due to the inclusion of patient rank fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. Cols 1-3 are limited to both Black and White patient encounters; Cols 2 limits encounters to White physicians; Col 3 limits encounters to Black physicians. Cols 4-6 include all patient encounters; Col 5 limits encounters to male physicians; Col 6 limits encounters to female physicians. Other covariates include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex, fixed effects for hospital ED, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. Standard errors are clustered at the hospital-level.

**TABLE A.4**
Characteristics of Encounters Pre- and Post- Patient Promotion

| | (1) Sample Mean Mean | (2) Coefficient on Promoted | (3) Coefficient on Promoted | (4) Coefficient on Promoted | (5) Coefficient On Promoted |
|---|---|---|---|---|---|
| Age | 25.44 | -1.99*** | 0.958*** | 0.919*** | 0.922*** |
| | | (0.148) | (0.058) | (0.055) | (0.054) |
| Race - Black | 0.215 | 0.006** | 0.005** | -0.004* | -0.005** |
| | | (0.003) | (0.003) | (0.002) | (0.002) |
| Gender - Female | 0.310 | 0.006 | -0.017*** | -0.016*** | -0.018*** |
| | | (0.005) | (0.005) | (0.003) | (0.003) |
| Charlson Score | 0.014 | -0.001 | 0.001** | 0.001* | 0.001** |
| | | (0.001) | (0.001) | (0.001) | (0.001) |
| **Fixed Effects** | | | | | |
| Promotion Rank | | No | Yes | Yes | Yes |
| Physician | | No | No | Yes | Yes |
| Month-Year | | No | No | No | Yes |
| *N - Observations* | | | | | |
| Patient Before Promotion | 117,756 | 117,756 | 117,756 | 117,756 | 117,756 |
| Patient After Promotion | 302,122 | 302,122 | 302,122 | 302,122 | 302,122 |
| Total Observations | 419,878 | 419,878 | 419,878 | 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) Log RVUs | (2) Resource Index |
|---|---|---|
| ***Panel A: Promotions Sample*** | | |
| Post-Promotion | 0.009*** | 0.037*** |
| | (0.002) | (0.007) |
| Sample Mean | 2.67 | -0.23 |
| Observations | 419,610 | 419,610 |
| ***Panel B: Retiree Sample*** | | |
| High Power | 0.0019** | 0.084*** |
| | (0.008) | (0.030) |
| Post-Retirement | -0.041*** | -0.062 |
| | (0.012) | (0.046) |
| High Power x Post-Retirement | -0.006 | 0.052 |
| | (0.010) | (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, and physician rank. Panel B presents the regression coefficients from regressing physician effort (Logged RVUs, Col 1) and resource use (Resource Index, Col 2) on (i) an indicator for the encounter occurring post-patient retirement and (ii) an indicator for 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. Due to the inclusion of patient rank (at time of retirement) fixed effects, the coefficient on "High power" compares outcomes between high-power and low-power patients of the same rank. Other covariates in both analyses include: patient age, age-squared, race, sex, and Charleson score, physician age, race, and sex (when not using physician fixed effects), fixed effects for hospital, patient diagnosis (first 3 digits of ICD-9/10 code), year-month, and day-of-week. 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.