Innovations and Inequities in Access to Medical Services*

Alex Hoagland†

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Abstract

While ensuring equitable access to novel medical treatments is a major concern in improving their value, medical innovations may exacerbate inequitable access even to older services. I study this tradeoff in a model of physician decision-making with technological spillovers. I examine how improvements in the quality of a high-intensity treatment lead to both an expansion of its use as well as crowding-out of lower-intensity treatments. Crowd-out occurs not only because patients sort into the new treatment, but also because lower rates of utilization reduce the return to low-intensity treatments, inducing some patients to select out of treatment altogether. I further show that this crowding-out leads to inequities in access to low-intensity treatments, which may be further exacerbated when treatment appropriateness is not correctly observed. I study the model's implications in the setting of aortic valve replacement surgeries in Medicare patients. The rise of minimally-invasive procedures to treat this condition led providers to adjust practice styles along two margins: medium-risk patients became more likely to receive surgery, and high-risk patients received fewer treatments overall. Medicare patients in low-income counties are most likely to be crowded-out of surgeries; 80% of this crowd-out appears to be attributable to imperfect risk measurement.
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†Boston University, Department of Economics, 270 Bay State Road, Boston, MA, 02215. Email: alcobe@bu.edu. Website: alex-hoagland.github.io.

1 Introduction

Improving the quality of medical treatments has immense economic and social value, through both the economic returns from improved health states and the insurance value associated with reduced population risk.[1] Funding, developing, and disseminating novel medical technologies is one of the most promising ways to improve the return on the high levels of health spending in developed countries (Cutler et al., 2007). On the other hand, novel technologies may exacerbate health inequities, which have persisted for over two centuries across socioeconomic status, race, ethnicity, and other group identifiers (Adler and Rehkopf, 2008). Novel, typically high-cost medical interventions typically exacerbate these inequities, especially during the early years following their adoption (Arcaya and Figueroa, 2017).

Achieving the twin ideals of health innovation and health equity requires understanding the tradeoffs involved in pursuing these aims. Physicians may appropriately respond to improvements in one type of medical treatment by increasing their investments in that form of treatment; this results in well-documented inequities in which patients receive access to novel treatments. What is less apparent is how innovation adoption affects other patients who, rather than seeking out the innovative treatment, continue to vie for other, less-intensive interventions that physicians in their local market are now providing more infrequently. If physician specialization affects the returns to a procedure, medical innovations may lead physicians to reduce their volume of older techniques by more than the relative increase in volume of the new treatment, resulting in a second type of inequity: patients who are crowded-out of specialist interventions altogether. These inequities may be further exacerbated by incorrect perceptions of patient risk, either on the part of the physician, the patient, or the health system more generally.[2]

In this paper I present a model of physician decision-making that characterizes the tradeoff inherent in expanding access to medical innovations at the potential cost of these two dimensions of inequities. In the model, physicians select medical interventions for patients of differing risk levels from one of three treatments: two surgical interventions (a high-intensity and a low-intensity procedure), and standard maintenance care. The model incorporates technological spillovers in the style of Chandra and Staiger (2007), so that the returns to a treatment increase as the physician invests more in that technique (e.g., from learning-by-doing). I then consider the impact of an innovation that increases the average return of the high-intensity procedure. The model highlights that physicians may respond to such an innovation along two distinct margins. First, improvements in the high-intensity technique

[1] For a discussion of the value of medical innovations, see Murphy and Topel (2006) and Lakdawalla et al. (2017).

[2] For a broader discussion of the inequitable perceptions of patient risk, see Arkfeld (2021).

directly lead to an expansion in its use among intermediate-risk patients who previously selected less intensive interventions. Second, and more surprising, the novel technology generates a movement of high-risk patients out of low-intensity interventions and into maintenance care. This is due to a reduced return of the low-intensity intervention due to lower productivity spillovers, resulting in a set of patients who lose access to surgical interventions entirely as a result of the innovation.

The central insight from the model is that the crowding-out of treatment for high-risk patients may be inequitably borne by patients from certain groups within the population. The composition of patients crowded-out from surgical interventions in the model may differ systematically from the overall patient distribution, especially to the extent that patients of different groups are assigned different levels of surgical appropriateness or risk. Moreover, inequities may be exacerbated when risk is imperfectly observed, and certain groups are incorrectly assigned higher or lower levels of appropriateness for care. I quantify the extent to which measurement error in perceptions of patient risk may increase inequities in access not only to medical interventions, but to specialty care overall.

I then present an empirical test of the predictions of my model. My setting is the development and dissemination of transcather aortic valve replacement (TAVR) surgeries used to treat aortic stenosis in elderly patients in the United States. These minimally invasive procedures changed the scope of aortic stenosis treatments in two key ways: first, the procedure allowed surgeries to be performed on higher-risk patients who were previously deemed too risky for surgery; and second, the procedure could be performed by interventional cardiologists instead of cardiothoracic surgeons alone. The rise of this procedure therefore represented a novel disruption in the practice of interventional cardiologists by bringing in a new procedure that could be used on new patients, and therefore meaningfully changed their practice style.

I use this setting to test my model by estimating how TAVR adoption in local markets led interventional cardiologists to change their provision of other surgical interventions, including percutaneous coronary interventions (PCIs) such as angioplasties. I show that interventional cardiologists who began performing TAVR quickly specialized in the procedure, dedicating up to 20% of their time to the procedures in as little as three years. This specialization included an increased rate of screening patients for the appropriateness of valve replacements, and resulted in higher-risk patients receiving TAVR surgeries. However, this adoption caused a reduction in the volume of PCIs performed locally. Importantly, this shift was due to both the increased share of patients receiving TAVR *and* a shift of higher-risk patients out of interventional care altogether. Finally, I highlight that this exclusion of high-risk patients disproportionately affected patients living in low-income areas, with patients in the

bottom 40% of the income distribution being 10 percentage points more likely to lose access to surgical cardiac care than those in the top 60%. These findings are consistent with a systematic misperception of a patient's surgical risk across the income distribution.

The model presented in this paper is the first to provide a framework for considering the equity impacts of health innovations. Hence, this project contributes to both the literature on health innovations and health disparities. Recent work has suggested that changes in the allocation of high-value medical services may reduce racial disparities in care, particularly when those reallocations reduce geographic variation in the provision of services (Chandra et al., 2020). The theoretical framework presented in this paper highlights that while innovations may reduce disparities in the populations directly affected by the innovation, other disruptions in the supply of services also need to be taken into account.

Health disparities have been increasing in recent years, with some groups even experiencing disproportionate decreases in life expectancy as a result (Case and Deaton, 2015; Olshansky et al., 2012). This paper highlights that novel technologies may still exacerbate inequities in access even when the playing field of income is leveled, and particularly that these inequities may spillover into access for other specialty care (Arcaya and Figueroa, 2017). Finally, my results highlight that changes in the provision of one medical service may have unforseen consequences that affect the provision of others. In that regard, my work is related to the spillover effects of health services (Fadlon and Nielsen, 2019; Hoagland, 2022).

The paper proceeds as follows. Section 2 describes the adoption of TAVR in more detail, as well as providing an overview of the data used in this project. In Section 3, I lay out a model of physician decision-making in the presence of technological spillovers, and analyze how such a model implies a tradeoff between the adoption of novel medical technologies and inequities in who is crowded out from accessing specialty care. The model suggests several empirically testable implications, which I outline in Section 4; the results of these analyses are presented in Section 5. I then conclude with a discussion of the relevance of these results in Section 6.

2 Setting and Data

2.1 The Adoption of TAVR

Transcatheter aortic valve replacement surgery is a minimally-invasive alternative to surgical aortic valve replacement (SAVR); TAVR procedures involve the transfemoral placement of either a balloon-expandable valve or a self-expanding valve instead of an open surgical approach used in SAVR procedures. Numerous randomized trials of TAVR (for both valve

types) have indicated that the procedure is either superior or noninferior among patients at intermediate or high risk for mortality from typical surgery (Smith et al., 2011; Adams et al., 2014; Leon et al., 2016) and even among low-risk patients (Mack et al., 2019; Popma et al., 2019). These results led to the first TAVR device (from Edwards-SAPIEN) receiving approval from the United States' Food and Drug Administration's (FDA's) Center for Devices and Radiological Health for patients with severe surgical risk in November 2011 (Dvir et al., 2012). Over time, the procedure's use has been expanded to a wider pool of patients as it has continued to be shown to be noninferior to open surgical methods for patients with lower levels of surgical risk (Nishimura et al., 2014; Falk et al., 2017). As of 2017, more surgical interventions are performed percutaneously than using the traditional open methods (D'Agostino et al., 2018).

The adoption of TAVR is an ideal setting to study the tradeoffs between innovations and inequities for two reasons. First, the adoption of this novel technology was ultimately market-expanding: the median number of surgical interventions used to treat advanced aortic stenosis in the U.S. increased by roughly 1/3 following the adoption of TAVR, with the number of providers supplying these interventions nearly doubling (see Appendix). This increase in the total addressable market provided strong incentives for physicians to change the style of their practice in order to accommodate the opportunity to reach these patients, similar to the rapid expansion of percutaneous coronary intervention (PCI) as an alternative to coronary artery bypass graft (CABG) surgery (Cutler and Huckman, 2003). Second, TAVR—similar to the adoption of PCI as a substitute for CABG surgeries—disrupted the supply of these procedures. Whereas SAVR procedures are performed only by cardiothoracic surgeons, TAVR procedures are performed by a team of surgeons and interventional cardiologists (Adams et al., 2014).

Importantly, these two types of cardiac specialists receive differentiated training. Specifically, as noted by Huckman and Stern (2022), after completing a medical residency, interventional cardiologists complete three additional years of cardiology fellowship and an additional year of an interventional cardiologist-specific fellowship. On the other hand, cardiac surgeons typically complete a general surgery residency followed by multiple cardiothoracic surgery fellowships, a training program that lasts six to seven years. These unique training paths prepare each type of surgeon to hyper-specialize in different surgical approaches, typically open surgical approaches for cardiothoracic surgeons and percutaneous interventions for interventional cardiologists.

2.2 Data

I assess the impact of TAVR adoption on treatment decisions for traditional Medicare patients seeking cardiology care using Medicare fee-for-service (FFS) claims data.[3] These data contain 100% of cardiology inpatient procedures performed by both cardiothoracic surgeons and interventional cardiologists on Medicare patients, and include important information about patient risk and demographics as well as demographic information for surgeons. I use data from 2010 to 2017, encompassing the years of TAVR's adoption and rapid diffusion. By 2017, surgeons were performing TAVR at higher volumes than SAVR; in addition, IV cardiologists were involved in over 1/5 of these procedures.[4] The adoption of TAVR, therefore, both expanded the pool of patients eligible for medical intervention and fundamentally changed the composition of the surgical team used to treat these patients.

My main sample includes all Medicare patients with aortic stenosis, including both patients who ultimately sought surgical intervention and those who did not. My final data set includes 9,858,536 unique traditional Medicare patients spanning 2010 to 2017.

Table 1 includes relevant summary information for the patients in my sample. I observe demographic information, including a proxy for income at the zip code level (both for the full zip code and specific to residents 65 and older, in order to better approximate Medicare incomes). I also construct relevant clinical information, including the number of chronic conditions and surgical history, as well as specific diagnostic items using the framework of Ellis et al. (2022). The final row summarizes the predicted surgical risk for patients; this is empirically estimated and discussed further in Section 4.1.

3 Model

This section presents a model of responses to medical innovations, adapted from Chandra and Staiger (2007). The model highlights both how innovations may have unintended consequences on other margins of treatment and how imperfect perception of patient risk may lead these consequences to exacerbate inequities in access to health services.

3.1 A Model of Treatment Choice

Suppose there is a continuum of patients suffering from a single disease. Patients and physicians can select from three possible treatments, indexed by $t \in \{0, 1, 2\}$: preventive

[3] Note that this data excludes individuals enrolled in Medicare Advantage plans.

[4] See Appendix Table 2 and Figure 7 for details on TAVR's expansion.

	Mean	SD	Min	Max
Patient Demographics				
Age	72.58	11.44	0	115
Female	0.52	0.50	0	1
White	0.86	0.35	0	1
Black	0.10	0.30	0	1
Hispanic	0.02	0.14	0	1
Other Race	0.04	0.20	0	1
Median County Income (all)	$55,621.54	$14,677.75	$13,037	$125,003
Median County Income (age 65 plus)	$39,931.21	$8,814.85	$12,709	$91,242
Clinical Characteristics				
# of Chronic Conditions	4.08	2.96	0	20
CC: Congestive Heart Failure	0.21	0.41	0	1
CC: Diabetes	0.32	0.47	0	1
CC: Hypertension	0.62	0.49	0	1
CC: Stroke	0.05	0.22	0	1
CC: Acute Myocardial Infarction	0.02	0.13	0	1
CC: Lung Disease	0.15	0.35	0	1
Surgical History & Risk				
Any Previous Cardiac Surgery	0.00	0.02	0	1
Any Previous Bypass Surgery	0.00	0.02	0	1
Any Previous Valve Surgery	0.00	0.02	0	1
Any Previous Revascularization	0.00	0.01	0	1
Predicted STS-PROM	0.03	0.02	0	0.63

Table 1. Summary Statistics of Aortic Stenosis Patients, 2010–2017

Table Notes: Table shows summary statistics for patients seeking interventional cardiologist care to treat aortic stenosis. $N = 43,414,162$ unique patient years spanning 2010-2017. Income is averaged at the zip code level and reported in 2021 USD. Chronic conditions are identified using the 100% Master Beneficiary Summary File (MBSF) Chronic Conditions segment. Surgical history is identified using the 100% Inpatient FFS Claims file. Predicted patient risk (STS-PROM) is predicted as described in Section 4.1.

maintenance ($t = 0$), low-intensity surgical interventions (e.g., PCIs, $t = 1$), and high-intensity surgical interventions (e.g., surgical valve replacement, $t = 2$).

The patient-specific appropriateness of each procedure depends on a patient risk index θ_{it} for patient i. When observed perfectly, θ_{it} captures both the diagnostic severity of each individual as well as their relative risk associated with an intervention—hence, individuals with lower θ_{it} will be more likely to receive intensive surgical treatments. In practice, θ_{it} is not observable; instead, physicians and patients proxy this risk based on a set of observable characteristics Z_{it}; I discuss this more in Section 4.3.

The expected utility of each procedure for a specific patient with characteristics $\{Z_{it}\}_t$ is given by

$$U_{it} = \beta_{it} Z_{it} + \alpha_t P_t + \varepsilon_{it}, t \in \{0, 1, 2\}, \tag{1}$$

where P_t represents the fraction of the population receiving treatment t. This expected utility incorporates the potential for productivity spillovers in the style of Chandra and Staiger (2007), captured in the second term of Equation 1; this allows for specialization to improve the expected utility of that treatment for the marginal patient (if $\alpha_t > 0$).

Since utilities are assumed to be linear, patients' treatment decisions can be characterized as two-way comparisons at any value of θ_{it}. To simplify these comparisons further, I make the natural assumption that treatment intensity levels are perfectly distributed across θ_{it}; mathematically, this is equivalent to the statement that the (absolute value) of the marginal utility of treatment with respect to patient risk is increasing in treatment intensity.[5] Practically, this means that patients make choices only along one of two margins: a choice between valve replacement and valve support techniques, or a choice between valve support techniques and preventive maintenance. Given this assumption, the surgical risk of patient i can be harmonized into a single univariate measure θ_i.

A patient with characteristics Z_i thus chooses the most intensive treatment ($t = 2$) only if $U_{i2} > U_{i1}$. Over the distribution of characteristics Z_i, the probability that a patient receives valve replacement is given by:

$$\begin{aligned}
\Pr\{t = 2\} &= \Pr\{U_{i2} - U_{i1} > 0\} \\
&= \Pr\{(\beta_{i2} - \beta_{i1}) Z_i + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{i1} - \varepsilon_{i2}\} \\
&= \Pr\{\beta_{21} Z_i + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{12}\},
\end{aligned} \tag{2}$$

[5] Or $|\partial U_{i2}/\partial \theta_2| > |\partial U_{i1}/\partial \theta_1| > |\partial U_{i0}/\partial \theta_0|$. Note that in the case where θ_{it} perfectly captures patient appropriateness for treatment, this assumption is not a special case. In practice, when θ_{it} is unobserved, these delineations will be less clear.

and the probability that a patient will choose the intermediate treatment ($t = 1$) is:

$$\begin{aligned}\Pr\{t = 1\} &= \Pr\{U_{i1} - U_{i0} > 0\} \\ &= \Pr\{(\beta_{i1} - \beta_{i0})Z_i + \alpha_1 P_1 - \alpha_0 P_0 > \varepsilon_{i0} - \varepsilon_{i1}\} \\ &= \Pr\{\beta_{10} Z_i + \alpha_{10} P_1 + \alpha_0 P_2 - \alpha_0 > \varepsilon_{10}\}. \end{aligned} \tag{3}$$

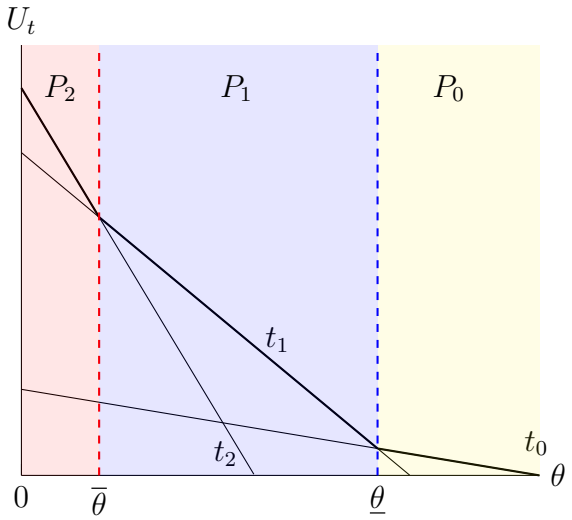
The equilibrium is therefore defined as a fixed point that solves the system of equations:

$$P_1 = \int_Z \Pr\{\beta_{10} Z + \alpha_{10} P_1 + \alpha_0 P_2 - \alpha_0 > \varepsilon_{10}\} f(Z) dZ \tag{4}$$

$$P_2 = \int_Z \Pr\{\beta_{21} Z + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{12}\} f(Z) dZ. \tag{5}$$

The equilibrium can be conceptualized in a simple single-crossing framework. If an initial allocation is such that all patients are sorted into high-intensity treatments, this will generate utility benefits such that some patients prefer either the lower-intensity intervention or maintenance care. As more patients select out of the highest-intensity intervention, decreases in the survival return to productivity spillovers move more patients out of surgery, until only the most appropriate patients receive high-intensity interventions. A similar market mechanism determines the allocation of low-intensity interventions to patients for whom high-intensity treatments are not justified, but who still receive benefit from medical intervention.

Figure 1. Treatment Decisions Based on Patient Risk



Notes: Graphical illustration of the selection of patients into treatment based on risk. The production possibilities frontier for all levels of θ defines the maximum utility for each patient and identifies distinct regions of treatment. Different colored regions indicate the fraction of patients receiving high-intensity treatments (red, defined as P_2); low-intensity treatments (blue, defined as P_1); and maintenance care (yellow, defined as P_0).

Figure 1 illustrates the allocation of patients to treatments, based on a perfectly observed patient risk (this assumption will be relaxed in Section 3.3. The figure plots patient utility $U_t(\theta)$ for each of the three possible choices of treatment as a function of patient risk θ. As patient risk increases, the utility of each treatment declines; however, by assumption, these decreases occur at faster rates for more intensive treatments. This creates three well-defined regions of treatment, where patients with the lowest risk select the high-intensity intervention t_2, patients with moderate risk select the low-intensity intervention t_1, and the highest risk patients choose to simply receive maintenance care t_0. These regions are defined by the threshold risk levels $\overline{\theta}$ and $\underline{\theta}$; these, combined with the underlying distribution of θ, define the market share of each treatment.

3.2 The Effect of Innovations

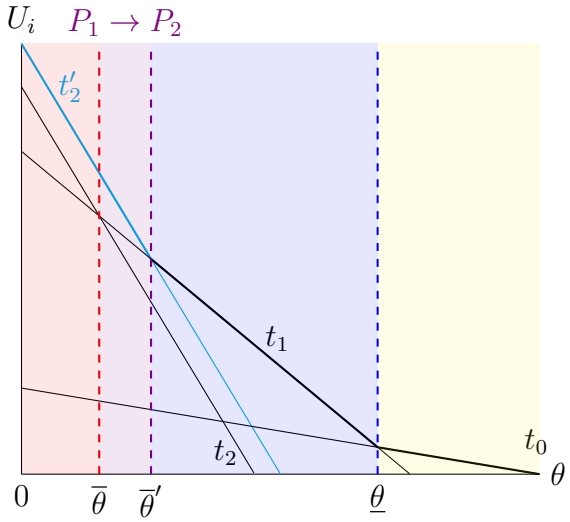
The model allows a direct comparison of how innovations affecting one style of treatment may modify the provision of other treatments. To that end, consider the innovation in valve replacement technology ($t = 2$) reflected in the transition from SAVR to TAVR. This innovation can be characterized as one that reduces the cost of treatment for the patient across all risk levels θ, without affecting the survival utility (based on the noninferiority of TAVR as discussed in Section 2). Hence, I model this innovation as a linear increase in the expected utility U_1 by some amount τ.[6]

Figure 2 illustrates two separate effects of this shift in U_1. First, panel (a) highlights direct effects of the intervention—as the high-intensity intervention increases patient utility for all levels of risk, a greater share of patients will select the high-intensity intervention over the low-intensity one. This is reflected in a change in the risk threshold between the two interventions, captured by the change in $\overline{\theta}$ to $\overline{\theta}'$ (with the patients switching treatments identified in purple). This increase in the market share of high-intensity interventions results in further increased utility from the intervention and a corresponding decrease in the utility of the low-intensity intervention due to the presence of productivity spillovers in the model. Therefore, second, panel (b) introduces the indirect effects of the innovation's disruption in productivity spillovers. These include both shifts into t_2 as the utility from high-intensity interventions increases further and shifts out of t_1 into t_0 as the return to the low-intensity intervention decreases. This treatment crowd-out is shown in the change in $\underline{\theta}$ to $\underline{\theta}$' (highlighted in green in the figure). Changes along both margins continue in response to changes in the productivity spillovers affecting the utility from all three treatments until a new equilibrium is reached.

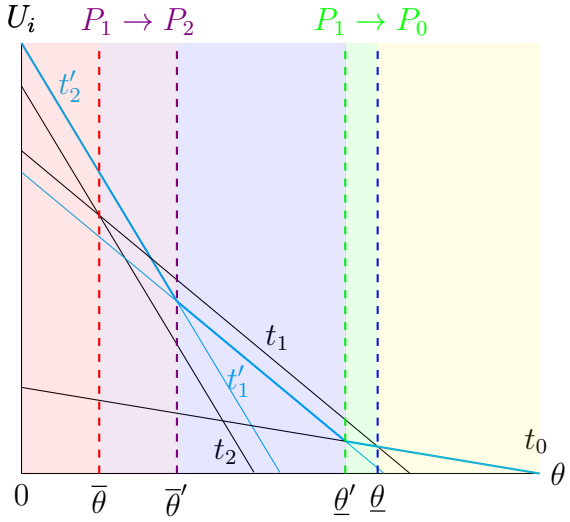
[6]Note that this increase need not be constant across θ, but the resulting implications presented here do not depend on this simplifying assumption.

Figure 2. Treatment Decisions Based on Patient Risk

(a) Direct Effects



(b) Indirect Effects



Notes: Graphical illustration of the effect of an innovation changing the return to high-intensity interventions $U_2(\theta)$. Panel (a) highlights the direct effects of the intervention, which changes the tradeoff between high- and low-intensity interventions and results in a greater share of patients selecting high-intensity interventions (captured in the purple area and the change in $\overline{\theta}$ to $\overline{\theta}'$). Panel (b) highlights the indirect effects of the innovation, which generate changes in the productivity spillovers to both t_2 and t_1, resulting in both a larger share of patients selecting into t_2 and movement from t_1 to t_0 (captured in the green area and the change in $\underline{\theta}$ to $\underline{\theta}$').

Of particular interest is the magnitude of the shift in $\underline{\theta}$, which defines a share of patients who are crowded-out of (or, depending on the direction of the shift, crowded-*in to*) treatment. To quantify this shift, note that the risk thresholds $\overline{\theta}$ and $\underline{\theta}$ are defined, in expectation over ε, by the equations

$$\beta_2\overline{\theta} + \alpha_2 F(\overline{\theta}) + \tau = \beta_1\overline{\theta} + \alpha_1\left(F(\underline{\theta}) - F(\overline{\theta})\right) \tag{6}$$

$$\beta_1\underline{\theta} + \alpha_1\left(F(\underline{\theta}) - F(\overline{\theta})\right) = \beta_0\underline{\theta} + \alpha_0\left(1 - F(\underline{\theta})\right). \tag{7}$$

Given the assumptions outlined in Section 3.1, the shares P_1 and P_2 can be directly calculated given a distribution for θ, yielding the above result.

Based on this system, I compute the comparative statics of interest measuring how risk thresholds change in response to changes in τ as

$$\frac{\partial\overline{\theta}}{\partial\tau} = \frac{\beta_{10} + (\alpha_0 + \alpha_1)f(\underline{\theta})}{\alpha_1^2 f(\overline{\theta})f(\underline{\theta}) - [\beta_{21} + f(\overline{\theta})(\alpha_1 + \alpha_2)][\beta_{10} + f(\underline{\theta})(\alpha_0 + \alpha_1)]} \tag{8}$$

$$\frac{\partial\underline{\theta}}{\partial\tau} = \frac{\alpha_1 f(\overline{\theta})}{\alpha_1^2 f(\overline{\theta})f(\underline{\theta}) - [\beta_{21} + f(\overline{\theta})(\alpha_1 + \alpha_2)][\beta_{10} + f(\underline{\theta})(\alpha_0 + \alpha_1)]}, \tag{9}$$

where $\beta_{ij} = \beta_i - \beta_j$ for $i, j \in \{0, 1, 2\}$.

When the innovation is market-expanding, the shift in the extensive margin threshold (Equation 9) is nonpositive—meaning that patients are crowded-out from treatment—if and only if

$$\frac{\alpha_1 f(\overline{\theta})}{\beta_{10} + (\alpha_0 + \alpha_1)f(\underline{\theta})} \leq 0 \tag{10}$$

$$\Leftrightarrow \underbrace{-\alpha_0 f(\underline{\theta})}_{\partial P_0/\partial\theta} - \underbrace{\alpha_1[f(\underline{\theta}) - f(\overline{\theta})]}_{\partial P_1/\partial\theta} \geq \beta_1 - \beta_0. \tag{11}$$

The terms on the left side of the inequality in Equation 11 represent the reduction in productivity spillovers for both t_0 and t_1 associated with changing the risk thresholds θ, while the right side of the inequality captures the differences in the marginal utility of each treatment. Note that both sides are necessarily negative numbers. Hence, a market-expanding innovation in the high-intensity treatment will result in a crowding-out of patients receiving any surgical intervention when the relative change in the productivity spillovers between t_1 and t_0 is less than the difference in the marginal utilities between treatments (in absolute value).

Given that changes in the effectiveness of a treatment due solely to provider specialization are estimated to be much smaller than the marginal returns of an effective treatment itself,

this condition is likely to be met in many cases (Chandra and Staiger, 2007). A similar condition allows us to conclude that the innovation itself is market-expanding:[7]

$$\frac{\partial \overline{\theta}}{\partial \tau} \geq 0 \tag{12}$$

$$\Leftrightarrow -(\alpha_1 + \alpha_2) f(\overline{\theta}) \geq \beta_2 - \beta_1 \tag{13}$$

That is, innovations can easily be seen to be market expanding when the spillovers arising from specialization do not swamp differences in the marginal returns across treatments.[8]

3.3 Exacerbating Inequities

The crowding-out of lower-value medical interventions due to provider specialization may directly contribute to inequities in who has access to care. In this section, I relax the assumption that patient risk is perfectly observed, and instead assume that risk is proxied based on observable demographic and clinical information. This highlights two features of the crowd-out induced by innovations: first, when risk is *correctly* proxied based on observable demographic information (e.g., income, socioeconomic status, race-ethnicity, sex and gender identity, or sexuality), certain groups may be more likely to be crowded out of care. Second, and pivotally, this inequity may be further exacerbated by *incorrect* rules for assigning patient risk, leaving some groups without access to even low-intensity medical interventions despite true underlying medical appropriateness.

Throughout what follows, assume that the condition for crowd-out is satisfied (Equation 11), so that there is a region C of patients who received low-intensity interventions prior to the innovation and no medical intervention after its adoption. C is therefore defined by the region of the (true) patient risk distribution on the interval $[\underline{\theta}, \underline{\theta}']$. I suppose that medical care professionals do not observe θ directly but are presented with a proxy for risk $\hat{\theta}$.[9] I assume that $\hat{\theta}$ is a linear combination of observable characteristics Z_{it}, and that it correctly predicts θ except for an idiosyncratic, mean-zero error ε:

$$\theta_{it} = \underbrace{Z_{it}\beta}_{\hat{\theta}} + \varepsilon_{it}. \tag{14}$$

[7] Note that Equation 13 is simplified by assuming that the extensive margin change is also negative; the full condition—which has the same intuition, albeit less clearly visible—is presented in the Appendix.

[8] Note that it is possible for an innovation to be market-contracting in the model; however, this requires that the productivity spillovers from the low-intensity treatment be so high that any perturbation in $\overline{\theta}$ leads to patients sorting back into t_1 from both t_0 and t_2. This is an unrealistic scenario in practice.

[9] Note that this proxy may be the result of physician assessment, patient beliefs, clinical risk information, or some combination of all of these.

Suppose that among the variables contained in Z_{it}, there is a binary variable d_{ig} which is equal to 1 if patient i is a member of a group g, and 0 otherwise. Note that this general form encompasses many different scenarios, including both demographic groups (e.g., patient race or socioeconomic status) and clinical indicators (e.g., patients with diabetes, high BMI, or smokers).[10] The coefficient β_d used in translating d_{ig} to risk captures a discrete shift in predicted risk based on group membership. For ease of exposition, I assume throughout this section that d_{ig} is independent to all other, non-group covariates $Z_{-g} = Z_{it} \setminus d_{ig}$.[11]

It is immediately apparent that if group membership is informative in predicting patient risk (meaning that β_d is nonzero), patients will have different likelihoods of having lower-intensity treatment crowded-out based solely on their group membership. Given information about the underlying distributions of θ and its proxy $Z_{it}\beta$, we can identify the fraction of patients in C who belong to g using Bayes' rule:

$$s_{C,g} = Pr(i \in g | i \in C) = Pr(i \in C | i \in g) \frac{Pr(i \in g)}{Pr(i \in C)} \tag{15}$$

$$= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\beta_{-g} + \beta_g \in [\underline{\theta}, \underline{\theta}']] \right] \tag{16}$$

$$= \frac{s_g}{s_C} \left[\int_{\underline{\theta} - \beta_d}^{\underline{\theta}' - \beta_d} f(Z_{it,-g}\beta_{i,-g}) d(Z_{it,-g}\beta_{i,-g}) \right] \tag{17}$$

$$= s_g \frac{\int_{\underline{\theta} - \beta_d}^{\underline{\theta}' - \beta_d} f(Z_{it,-g}\beta_{i,-g}) d(Z_{it,-g}\beta_{i,-g})}{\int_{\underline{\theta}}^{\underline{\theta}'} f(\theta) d\theta}. \tag{18}$$

Here, s_g indicates the relative size of group g in the population, and $s_C = F(\underline{\theta}) - F(\underline{\theta}')$ is the relative size of the crowd-out region. In general, Equation 18 does not equal either 0.5 or s_g, meaning that the crowd-out region may be non-representative of membership to g in the overall population. Although this difference arises from true (average) differences in underlying patient risk, such systematic differences in who receives access to care may still have important long-term effects that differ across groups.

Further inequities arise, however, when β_d is not correctly measured. Such imperfect risk proxying may be the direct result of providers who incorrectly gauge the size of risk differences across groups, but may also be the result of other factors, such as patient beliefs or health system measurements such as risk scores, which have been shown to suffer from bias (Obermeyer et al., 2019). However it arises, this measurement error will distort the likelihood that members of group g are represented in the crowd-out region C. To quantify

[10] Indeed, such indicators, such as patient race, sex/gender, and BMI routinely inform patient risk calculations (van Ryn and Burke, 2000).

[11] Note that this assumption is not critical to the results presented here, but merely simplifies their presentation.

the relationship between measurement error and this inequity, suppose that instead of using β_g in risk calculations, $\hat{\theta}$ relies on the use of a "noisy signal" $\hat{\beta}_g$, defined as

$$\hat{\beta}_g = \beta_g + \nu, \tag{19}$$

where ν is an idiosyncratic error in group risk measurement.[12] I define the inequity resulting from the presence of ν as the change in the representation of members of group g in C, relative to the initial representation $s_{C,g}$. Hence, I define the multiplier increase in members of g represented in C as

$$I(\nu) = \frac{s'_{C,g}(\nu)}{s_{C,g}} \tag{20}$$

$$= \frac{1}{s_{C,g}} \int_{\underline{\theta}-\beta_d-\nu}^{\underline{\theta}'-\beta_d-\nu} f(X_{i,-g}\beta_{i,-g}) d(X_{i,-g}\beta_{i,-g}), \tag{21}$$

where $s_{C,g}$ is defined as in Equation 18. The result in Equation 21 follows directly from the calculation in Equations 15 to 18.

Given information about the parameters governing the initial risk thresholds $\underline{\theta}$ and $\underline{\theta}'$, as well as the distribution of other covariates $X_{i,-g}\beta_{-g}$, the multiplier $I(\nu)$ can be easily calculated. In particular, notice that

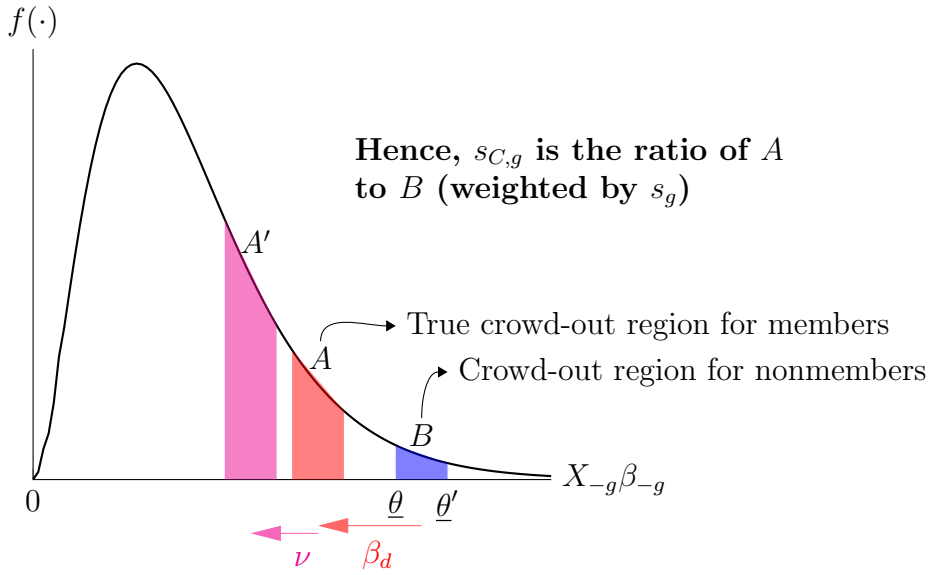
$$\frac{\partial I}{\partial \nu} = \frac{1}{s_{C,g}} \left[f_{X_{-g}\beta_{-g}}(\underline{\theta} - \beta_d - \nu) - f_{X_{-g}\beta_{-g}}(\underline{\theta}' - \beta_d - \nu) \right]. \tag{22}$$

That is, the magnitude of the measurement error ν in $\hat{\beta}_d$ affects the relative crowd-out of members of group g in proportion to (i) the initial composition of g in C and (ii) the relative comparison points used in assessing the risk of nonmembers.

Figure 3 captures the intuition behind these inequities. The figure shows, for a given distribution of observable *non-group* characteristics $X_{-g}\beta_{-g}$ and risk cutoffs $\underline{\theta}$ and $\underline{\theta}'$, the regions for which different types of patients will be crowded out of low-intensity interventions by the medical innovation. When the patient is a member of group g, the discrete risk shift β_d results in them being crowded out of treatment when their proxied non-group risk lies in the red region A. Similarly, for patients that are not members of g, the crowd-out region is defined simply by having a proxied risk level $\hat{\theta}_{-g} \in [\underline{\theta}, \underline{\theta}']$ (the blue region B). Hence, the fraction of crowded-out patients in g is given by the ratio of A to B (weighted by s_g).

[12] Note that unlike the classical measurement error readers may immediately associate ν with, this parameter is not random noise (in particular, it is not necessarily centered around 0). In the simplest version of the model, ν is common across provider-patient assessments; however, the model could easily be generalized to allow ν to either vary across providers or patients, as appropriate for the context.

Figure 3. Inequities in Crowdout Associated with Imperfect Risk Assessment



Notes: Figure illustrates the relative "crowd-out regions" for members and nonmembers of a group g when used in a proxy for patient risk, as well as the effect of measurement error in β_d on the relative crowd-out rates of members and nonmembers. The figure plots an inverse gamma distribution with parameters $(3, 1)$ for observable non-group covariates used in predicting patient risk, $f(X_{-g}\beta_{-g})$. The figure assumes that the membership variable d_{ig} is independent of all other covariates X_{-g}. The region A (in red) represents the crowd-out region for members of a group g given β_d, and region B (in blue) the corresponding region for nonmembers. Hence, the relative sizes of A and B (weighted by the overall size of the group g in the population) indicate the representation of members of g in the crowd-out region. Changes in ν affecting $\hat{\beta}_d$ shift the region A', ultimately affecting the relative representation of members of group g in the crowd-out region.

Intuitively, measurement error in the binary coefficient β_d results in differences in the location of the crowd-out region for the group members. The figure plots the case when $\nu > 0$, or when patient risk for members of the group is overestimated; this shifts the crowd-out region to a pool of lower-risk patients (represented in the figure as the magenta region A'). To the extent that this shift captures a larger share of patients in the population, this will lead to an *over-representation* of group members in the pool of patients who lose access to specialty interventions following the innovation's adoption.

3.4 Empirical Implications

The central mechanism by which innovation adoptions are linked to health inequities, therefore, consists of two steps. First, when technological spillovers in medical interventions affects physician treatment decisions, innovation adoptions may create "crowd-out regions" that shift patients out of specialty care altogether. Second, the patients in crowd-out regions may be systematically different from the overall population, an inequity that is exacerbated when patient risk is imperfectly observed and incorrectly proxied.

Three empirical implications of interest arise from this model. First, I can directly test for the presence of technological spillovers by assessing the extent to which a medical innovation crowds out the use of other interventions. In particular, given sufficient data on patient risk, I can test whether the development of TAVR affected both the extensive margin risk threshold (e.g., between low-intensity interventions and no intervention) and the intensive margin risk threshold (e.g., between high- and low-intensity interventions). Quantifying the extent to which TAVR's adoption led to decreases in utilization of lower-intensity procedures among the highest-risk patients identifies the existence and magnitude of these crowd-out regions.

Second, in addition to examining heterogeneity in crowd-out across patient risk, I can empirically test the prediction that patients in the crowd-out region will be (potentially inequitably) distributed across members of different groups. The extent to which an innovation leads to differential access to specialized medical interventions may be informed both by true and perceived differences in risk across groups. Nevertheless, given that inequities in access to care may have long-term and/or spillover affects in future health outcomes, even identifying aggregate differences sheds important light on the potential equity problems arising from an innovation's adoption.

The model suggests that I can go one step further to empirically quantify how much of an observed inequity in crowd-out is attributable to true group differences in risk instead of errors in risk proxying. Finally, therefore, I can use the identified model parameters—including

both treatment risk thresholds and the distribution of observed patient demographics—to present suggestive evidence on imperfect risk proxying in selecting cardiac interventions for patients of different groups. These calculations are suggestive as they require strong assumptions about true patient risk, which is unobserved to the econometrician as well as the provider; a further discussion of this is presented in Section 4.3.

4 Methods

To test the empirical implications of the model, I examine the effects of TAVR's adoption on crowd-out and inequities in access to specialized services at the local level. Although the model is highly stylized and abstracts away from many features complicating physician decision-making, I can test the basic insights of the model by examining how disruptions to the value of surgical intervention (e.g., the adoption of a minimally-invasive technique) altered physician use of closely-related procedures among patients seeking care from interventional cardiologists.

In my empirical exercise, I assess the role of TAVR's adoption in utilization of percutaenous coronary interventions (PCIs) used to treat coronary artery disease (CAD), such as angioplasties and valvuloplasties. Due to the relatively high rate of comorbidity of CAD with aortic stenosis, revascularization surgeries such as PCI were frequently performed on patients whose risk levels made them unfit to receive open surgery for a valve replacement through SAVR. Hence, the adoption of TAVR will have a direct impact on the margin of treatment between a full valve replacement surgery and percutaneous revascularization, particularly when the decision of care is made by an interventional cardiologist.[13]

4.1 Estimating Patient Risk

A patient's risk for cardiac surgery is typically based off of several risk models constructed and maintained by The Society of Thoracic Surgeons (STS). These models account for preoperative factors that may influence a patient's surgical outcomes, and predict patient risks for adverse outcomes such as surgical mortality, permanent stroke, infection, and length of stay, among others (O'Brien et al., 2009).

In my empirical application, I model patient risk θ using the STS Predicted Risk of Mortality model (STS-PROM). This model predicts the likelihood of 30-day surgical mortality following a cardiac surgery using a logistic regression including patient demographics, health

[13]Note that there is new evidence that PCI can be performed in addition to TAVR in order to treat both CAD and AS (Bajaj et al., 2017; Søndergaard et al., 2019). This evidence comes after the timeframe of my sample, but should be considered in future assessments of this tradeoff.

conditions, and time trends. Patient demographics include important social determinants of health, including race/ethnicity, gender, and income level (Ash et al., 2017). Health conditions include general counts of chronic conditions as well as finer indicators for specific conditions and symptoms, utilizing the Diagnostic Items framework of Ellis et al. (2022). The full set of covariates used can be found in Appendix Table 3.

The STS-PROM model is generally used to classify patients into one of three risk categories: low surgical risk (with a risk score $\leq 3\%$), moderate surgical risk (with a risk score between 3% and 8%), and high surgical risk (with a risk score $\geq 8\%$). Patients deemed low risk are those most likely to receive open surgical interventions (e.g., SAVR), while PCI interventions can be performed on intermediate-risk patients as well. There is recent evidence calling into question the effectiveness of using the STS-PROM model as the basis for physician decision-making (Catalano et al., 2020; Khan et al., 2019); however, I continue to use this model as it remains the model most commonly used by practitioners to approximate θ.

4.2 Effect of Innovation on Crowdout

I estimate the causal impact of TAVR adoption on individual interventional cardiologist treatment decisions using two-way fixed effects (TWFE) "event study" regressions of the following form:

$$\Pr(\text{Treatment}_{is}) = \alpha_s + \tau_t + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\left\{t - E_{st} = k\right\} + \epsilon_{st}. \tag{23}$$

Here, the outcome variables of interest are treatment decisions for a patient i being seen by interventional cardiologist s.[14] The regression specification controls for both surgeon and time fixed-effects, using quarters as the time unit of interest. Using this specification allows me to estimate a dynamic treatment effect which captures how physician practices evolve in the quarters relative to E_{st}, the surgeon's time of TAVR adoption. I also adjust for potentially correlated responses within a market by clustering standard errors at the local health market level.[15]

Recent work has highlighted that TWFE estimators can be difficult to interpret without strong modeling assumptions (Callaway and Sant'Anna, 2018). In particular, coefficients estimated by TWFE models represent the weighted average of many two-by-two comparisons. When treatment effects are heterogeneous across groups—and hence, these

[14] E.g., s for surgeon.

[15] The local market is defined as the commuting zone using relevant U.S. Census data.

comparisons—some comparisons may be assigned negative weights (de Chaisemartin and D'Haultfoeuille, 2019; Goodman-Bacon, 2018). This makes the interpretation of estimated treatment effects—static or dynamic—difficult to interpret. In the Appendix, I include robustness checks showing that the results I obtain by estimating Equation 23 are robust when using alternative estimators such as those proposed by de Chaisemartin and D'Haultfoeuille (2019) and Sant'Anna and Zhao (2020).

A principal implication of the model is that the adoption of TAVR should have heterogeneous impacts across different values of patient risk; in particular, the model suggests that TAVR's adoption should meaningfully change treatment decisions for patients at both margins of receiving low-intensity care. I therefore estimate potentially hetergeneous treatment effects across the empirically observed distribution of patient risk. I implement two estimators using the methodology of Xie et al. (2012): a parametric estimator that assesses the impact of TAVR adoption across different bins of patient risk; and a nonparametric estimator which this heterogeneity more flexibly.

4.3 Inequities in Post-Innovation Access

Finally, I identify how crowd-out inequitably affects groups of differing populations. Throughout, I focus on income-based inequities in access to non-TAVR cardiology services, in keeping with the predictions of the model.[16] These inequities are identified in two stages.

In the first step, I identify the differential probability with which minority individuals are likely to be crowded out of non-TAVR medical interventions. This is done by estimating a version of Equation 23 which interacts the dynamic treatment effect coefficients of interest with a dummy variable identifying if a patient resides in a county with average income for Medicare patients in the bottom two quintiles of the distribution. I limit attention to patients with estimated risk greater than 5% and use the rate of PCI interventions as my outcome variable. This specification therefore identifies income-based heterogeneity in the likelihood that a patient will be in the crowd-out region between receiving low-intensity medical interventions and maintenance care, as in Equation 18.

Under perfect risk perception, the share of low-income patients in this crowd-out region will be proportional to the estimated effect of being low-income on predicted patient risk. Hence, in the second step, I compare the empirically estimated share of patients in the crowd-out region to the share that would be predicted based on the estimated differential risk of being low-income. That is, I reconstruct the estimated share $s'_{C,g}$ using the empirically estimated STS-PROM regression coefficients for income (as shown in Appendix table 3). I

[16] Race-based inequities are presented as well in the Appendix.

then compare the magnitude of these two shares in order to estimate the extent to which patient risk may be imperfectly proxied by income (the parameter ν in Equation 21).

5 Empirical Results

The empirical distribution of predicted patient risk closely resembles the population risk distribution predicted by the STS-PROM model (Appendix Figure 8). The average (median) predicted risk is 3.6% (4.8%). 40% of patients are identified as low-risk, 44% as intermediate-risk, and 15% as high-risk (predicted risk $\geq$ 8%). Patient income is a significant predictor of surgical risk—patients living in the lowest-income counties (measured as the bottom two quintiles of the income distribution) have an expected increase in their risk of surgical mortality of approximately 0.4% ($p < 0.001$).

The adoption of TAVR, as expected, increased both the unconditional likelihood that an individual patient would receive a surgical intervention and the conditional average risk of surgical patients (Appendix Figure 9). The adoption of this minimally-invasive technique meaningfully expanded the pool of patients eligible for surgery—the adoption was associated with an increase in both the average likelihood an individual would receive surgery (from 1.2% to 1.8%) and the conditional risk of the average surgical patient (from about 4% to 6%).[17] Overall, TAVR allowed surgeries to be performed on older, higher-risk patients.

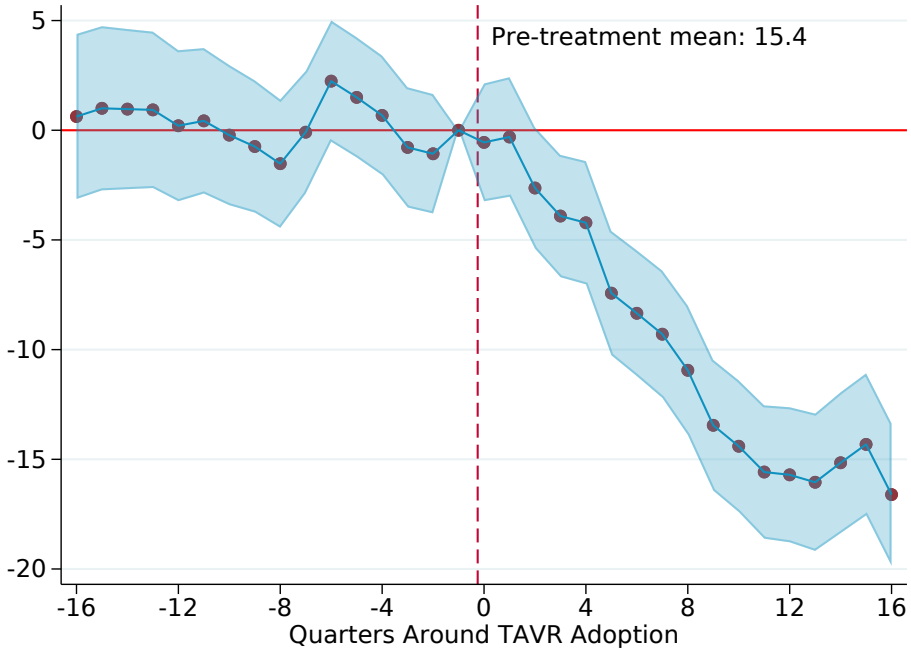
Figure 4 shows the estimated impact of this shift on surgical volume. The figure shows event study regression coefficients estimating the impact of TAVR adoption on the total volume of procedures performed by interventional cardiologists—including both high-intensity valve replacement surgeries and percutaneous procedures— at the local market (commuting zone) level. Here, the effect of market-level adoption of TAVR (measured as the first TAVR procedure performed in the commuting zone) is estimated to dramatically reduce the overall surgical volume of IVCs. The average commuting zone performs about 15 such procedures every 3 months prior to adoption; however, within the first 2-3 years following adoption, the total volume is reduced by about 20% for the average CZ. This is driven by a larger reduction in the provision of PCI procedures than the corresponding takeup of TAVR, leaving fewer patients receiving surgical treatments in total (see Appendix Figure 10).[18]

These findings indicate that although TAVR ultimately reached higher-risk patients seeking valve replacement surgeries, fewer patients were treated overall. To examine how adop-

[17] The Appendix Table further highlights changes in the types of patients receiving surgery following TAVR's adoption in a local market.

[18] In the Appendix, I include evidence that shows surgeons also raise their rate of testing for patient appropriateness for valve replacement surgeries. This is in keeping with the recent findings of Mullainathan and Obermeyer (2021). See Figure 11 for additional results at the individual physician level.

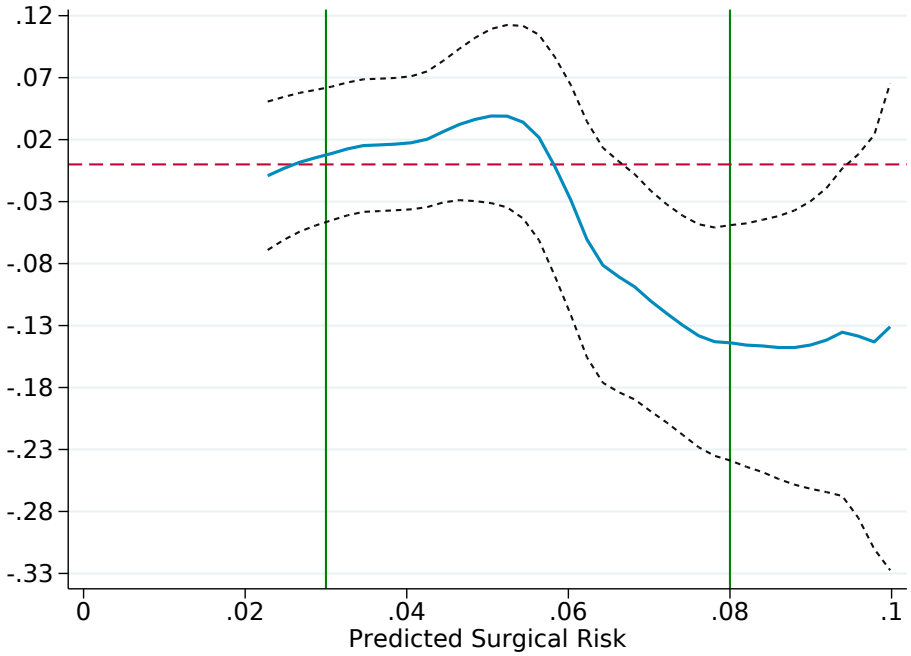
Figure 4. Effect of TAVR Adoption on Total IVC Surgical Volumes, Commuting Zone Level



Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs, including all SAVR, TAVR, and PCI procedures. Interventional cardiologists who perform fewer than 10 inpatient surgeries per year are dropped from estimation, and standard errors are clustered at the commuting zone level. *Abbreviations:* IVC = Interventional Cardiologist

tion creates a crowd-out region of patients who receive neither intervention, I assess how the treatment effect of TAVR adoption on PCI use varies across observable patient risk. Two findings are striking: while the average surgical risk of patients receiving TAVR goes up following adoption (in line with TAVR being a lower-risk procedure than SAVR), there is not a corresponding increase in the average conditional risk of a patient receiving PCI (Appendix Figure 12). This suggests that there is considerable change in the composition of which patients receive PCI not only at the lower risk threshold, but also at the threshold between PCI and no surgical intervention. Second, the overall likelihood that patients receive any surgical intervention (including TAVR, SAVR, or PCI interventions) declines after TAVR is adopted in the local market (Appendix Figure 13).

Figure 5. Likelihood of Surgical Crowd-out Across Predicted Patient Risk



Notes: Figure shows the heterogeneous relationship between the impact of TAVR adoption on the likelihood of receiving cardiac surgery and patient risk. Nonparametric estimator is constructed using the methodology of Xie et al. (2012), and estimated on all patients who have not been diagnosed with aortic stenosis.

I therefore perform a decomposition analysis in order to assess how TAVR adoption may affect patients in ways that systematically vary with patient risk. Figure 5 shows the results, using the method of Xie et al. (2012) in order to estimate a nonparametric relationship between a patient's risk and their likelihood of receiving any surgical intervention. For each level of patient risk, the figure shows an estimated impact of TAVR's adoption on the likelihood that a patient with that risk level will receive any surgical intervention (including

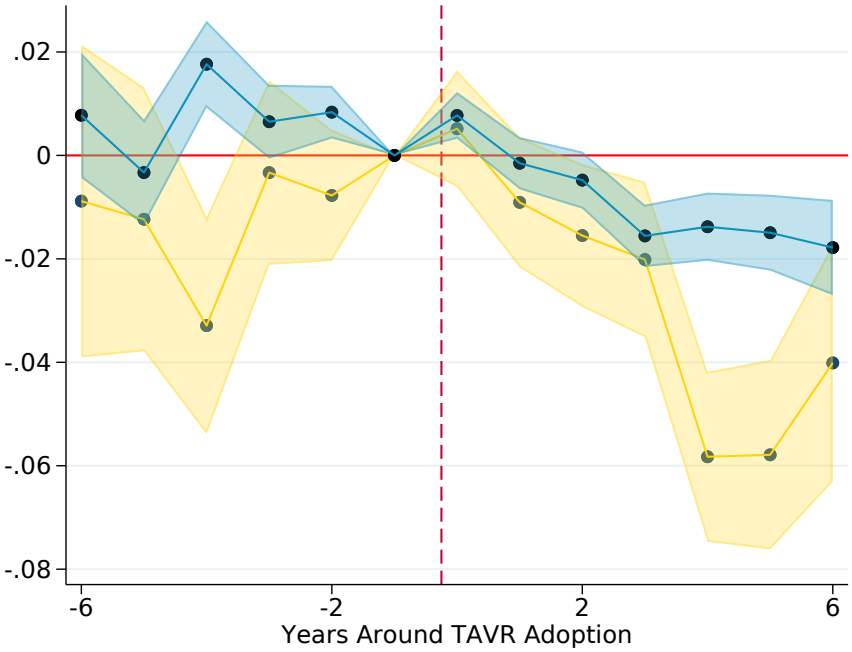
both valve replacements and PCIs). Notice that the crowd-out occurs for patients at the boundary between medium- and high-risk, as predicted in the model. In this setting, the region of patient risk where patients lose access to surgical interventions is estimated to be between about 6.5% and 10.0%.

5.1 Inequities in Access to Surgical Care

My results indicate that TAVR's adoption led to fewer total surgical interventions for patients in the "crowd-out" region, with patient risks on the boundary between intermediate- and high-risk. In this section, I assess the extent to which this crowd-out may exacerbate income-based inequities in accessing cardiac surgeries.

Figure 6. Heterogeneous Effect of TAVR Adoption on Cardiac Surgery Use Across Income Distribution

(a) Total Procedure Volume (SAVR/TAVR + PCI)



Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions, including SAVR, TAVR, and PCIs. Estimated regressions are shown for two groups—the group of individuals qualifying for either low-income premium subsidies or dually enrolled in Medicaid is shown in gold, while those on traditional Medicare without any such subsidies are shown in gold. In each group, I limit attention to patients in the "crowd-out region," or patients with estimated STS-PROM risk scores in the interval (6.5%, 10.0%). Standard errors are clustered at the commuting zone level.

Figure 6 assesses the extent to which TAVR's adoption led to a increased rate of crowd-out for traditional Medicare patients with different levels of income. The figure shows two event

study figures assessing the rate at which patients in the crowd-out region (with estimated STS-PROM risk scores between 6.5% and 10.0%) lose access to cardiac surgeries following TAVR adoption for two groups: all Medicare patients receiving premium or copayment subsidies or dually enrolled in Medicaid (shown in gold), and all non-subsidized traditional Medicare patients (shown in blue).[19] Patients with lower incomes are three times as likely to lose access to cardiac surgeries following TAVR's adoption (a difference in total likelihood of receiving surgery of 6 percentage points instead of 2).

This income gap in access to services is an aggregate of two effects: the inequities associated with changes to surgeon risk thresholds for different interventions, and the compounding inequities that arise from incorrect perceptions of patient surgical risk. In the absence of any imperfect risk proxying, I can use the empirically observed distribution of patient risk and the estimated changes in risk threshold to identify the share of low-income patients in the crowd-out region.[20] Based on the empirical distribution of patient risk, the change in the threshold for revascularization from 8% to about 6.5% should have affected low-income individuals only twice as much as high-income individuals. This suggests that approximately 2/3 of the new inequities in access to services arise not from adjustments to physician practice styles alone, but specifically from misperceptions of patient risk.

6 Conclusion

In this paper, I present a theoretical framework to consider the potential equity implications of expanding access to novel medical technologies. The model highlights a tension between increased access to a novel technology and overall access to specialized health services when there are returns to physician specialization. Increased provider investment in a high-intensity intervention may result in a "crowd-out region" of patients who lose access to surgical interventions altogether due to the diminished returns of low-intensity procedures. Importantly, the composition of the patients in this crowd-out region may differ systematically from the overall distribution of patients. These inequities in who loses access to medical services are further exacerbated when patient risk is not directly observed and imperfectly proxied.

The predictions of this model can be seen empirically in the diffusion of TAVR among interventional cardiologists. This technology quickly led to an expansion of valve replacements for medium-risk patients, but also reduced the extent to which high-risk patients received less intensive procedures such as PCIs. This loss of access to services among high-risk pa-

[19] Note that about 23% of Medicare patients in my sample are in this "low-income" group.

[20] Note that this back-of-the-envelope calculation abstracts away from any errors in the STS-PROM model.

tients disproportionately fell on patients living in low-income areas, potentially exacerbating geographic and socioeconomic disparities in access to health care. Back-of-the-envelope calculations suggest that these inequities are magnified due to incorrect measures for patient risk across income groups.

This empirical application highlights the value of using the theoretical framework in considering the general equilibrium effects of innovation diffusion on equitable access to health services. In addition, the findings suggest that corrections to risk prediction models may be far more effective at reducing the inequities associated with TAVR's adoption than adjustments to provider reimbursement for TAVR and other novel procedures. Taken together, the theoretical framework and the empirical exercise suggest that there is room for considering equity implications and potential downstream effects at the time of an innovation's deployment, particularly by large regulators such as CMS.

Future work can build on the central tension highlighted in this paper in several directions. New research may generalize the model to include multiple dimensions of patient risk, or consider further, more long-term consequences of losing access to specialty care. These generalizations may lend themselves well to novel empirical applications using machine learning techniques in novel assessments of patient characteristics and identifying systematic disparities in those assessments across groups (Mullainathan and Obermeyer, 2021). Additionally, future work may identify the extent to which physician selection into innovation adoption affects long-run market outcomes, including equitable access to health services (Huckman and Stern, 2022). Finally, while this project highlighted socioeconomic and geographic disparities exacerbated by medical innovations, this framework can be extended to many other inequities and structural forces that worsen health outcomes for minority patients of many groups. These include a more direct examination of biases and discrimination at the point of care or systematic gaps in seeking out specialty services, either due to coverage or mistrust.

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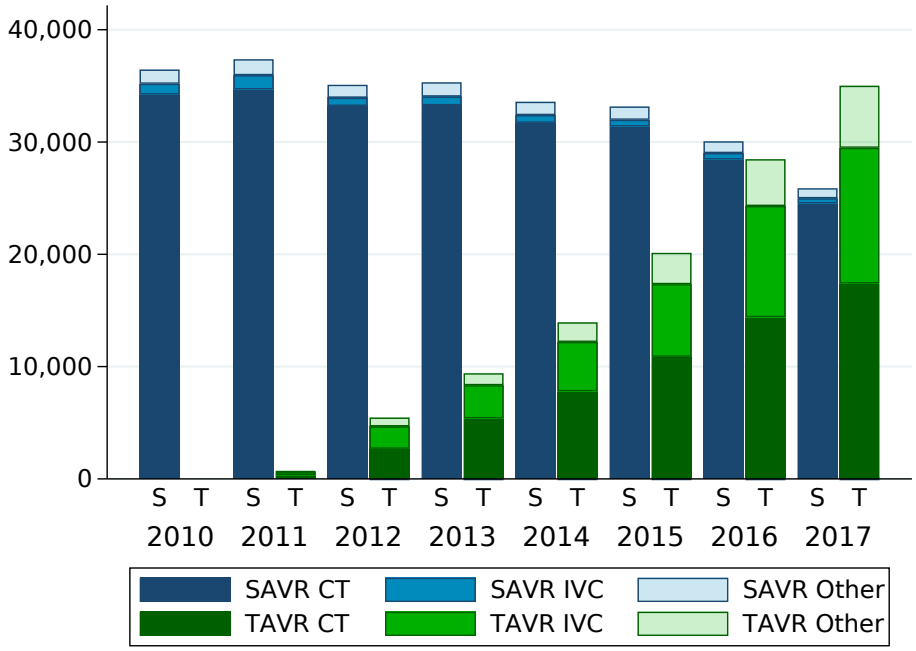
A Appendix

	All Surgeries (N)			Cardiothoracic Surgeons			Interventional Cardiologists		
	All	SAVR	TAVR	All	SAVR	TAVR	All	SAVR	TAVR
2010	36,458	36,453	0	95.97%	95.97%	0.00%	2.62%	2.62%	0.00%
2011	38,084	37,376	705	94.37%	93.29%	1.08%	4.034%	3.32%	0.72%
2012	40,564	35,124	5,463	92.02%	83.52%	8.54%	6.69%	1.81%	4.90%
2013	44,736	35,369	9,409	91.10%	75.99%	15.21%	8.34%	1.76%	6.59%
2014	47,530	33,638	13,944	88.54%	68.02%	20.62%	10.67%	1.46%	9.23%
2015	53,301	33,225	20,134	85.55%	59.88%	25.77%	13.23%	1.13%	12.12%
2016	58,539	30,104	28,469	80.91%	49.37%	31.60%	17.88%	0.99%	16.90%
2017	60,896	25,933	35,010	77.15%	40.92%	36.31%	20.57%	0.76%	19.83%

Table 2. Role of Cardiologists in Aortic Stenosis Procedures, 2010–2017

Table Notes: Each cell represents the fraction of the surgical type performed by the type of medical professional in a given year. Sample is limited to all aortic valve replacement surgeries (TAVR/SAVR) procedures. Totals do not add up to 100% because some procedures are performed by a team comprised of both CT surgeons and IV cardiologists, and others are performed by physicians with other listed specialties (e.g., internal medicine). Cardiothoracic surgeons are those whose primary specialty is listed as "cardiac surgery", "thoracic surgery", or "general surgery"; interventional cardiologists are those whose primary specialty is listed as "interventional cardiology", "cardiology", or "cardiovascular disease".

Figure 7. Timeline of TAVR Adoption



Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic surgeons ("CT") are those whose primary specialty is listed as "cardiac surgery", "thoracic surgery", or "general surgery"; interventional cardiologists ("IVC") are those whose primary specialty is listed as "interventional cardiology", "cardiology", or "cardiovascular disease". Other surgeons include those with specialties outside of these fields (e.g., internal medicine) who also performed the procedures over time.

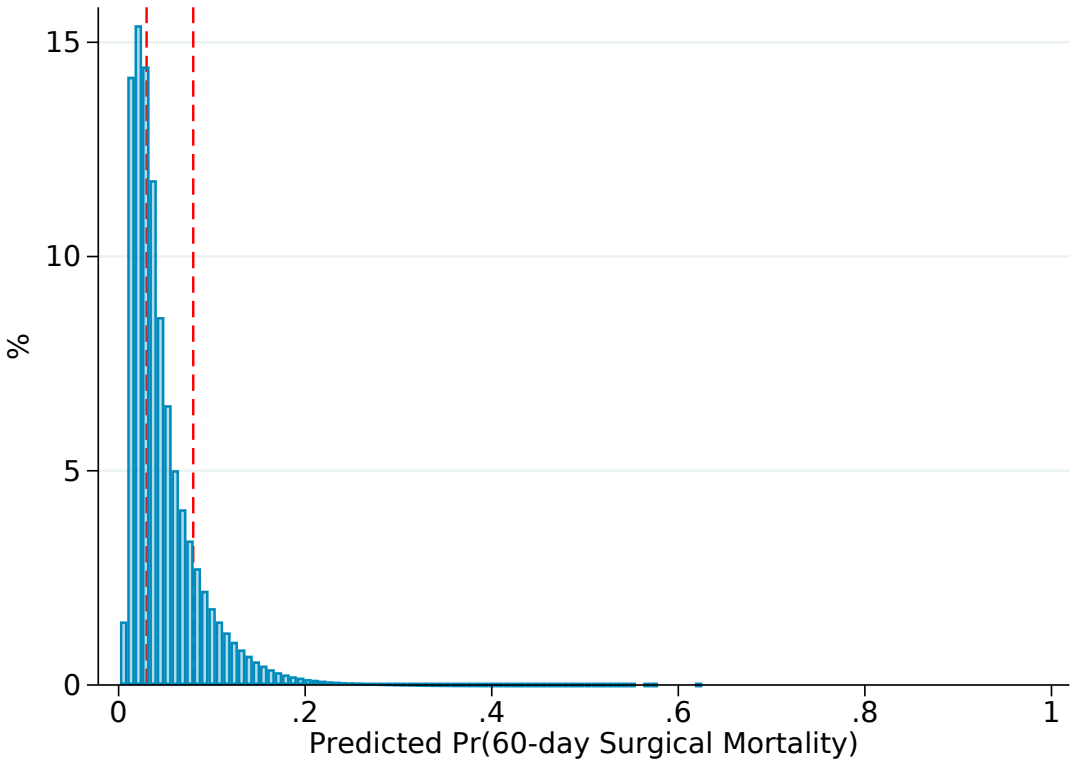


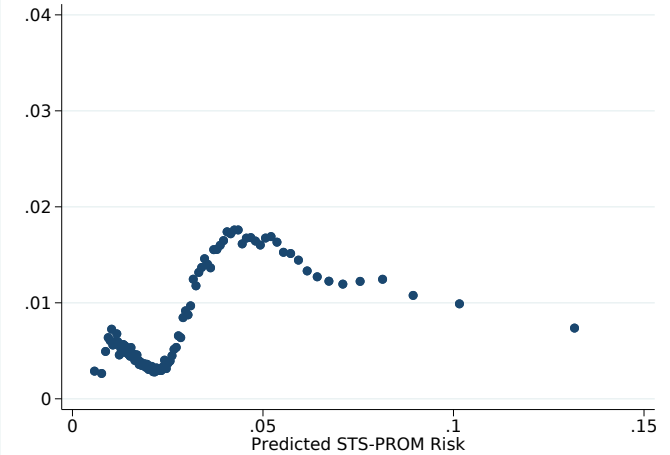
Figure 8. Predicted Patient Risk of Surgical Mortality (STS-PROM)

	30-day surgical mortality
Any previous surgery	-0.0211
	(-0.71)
# of previous surgeries	-0.0895
	(-4.63)
Previous bypass	-0.859
	(-37.41)
Previous valve replacement	-0.662
	(-34.02)
Previous PCI	-0.699
	(-35.98)
Patient age	0.0309
	(51.76)
Female	0.0446
	(4.03)
Black	0.186
	(9.92)
Hispanic	0.0582
	(1.16)
Other Minority Race	0.0500
	(1.71)
# of Chronic Conditions	-0.0557
	(-17.38)
CC: CHF	1.156
	(81.22)
CC: Diabetes	0.177
	(14.30)
CC: Hypertension	-0.450
	(-20.84)
CC: Stroke	0.377
	(23.95)
CC: AMI	0.844
	(60.13)
CC: COPD	0.305
	(24.64)
Income Quintile 1	0.0890
	(4.56)
Income Quintile 2	0.0474
	(2.61)
Income Quintile 3	0.0237
	(1.46)
Income Quintile 4	0.0235
	(1.59)
Observations	714,400

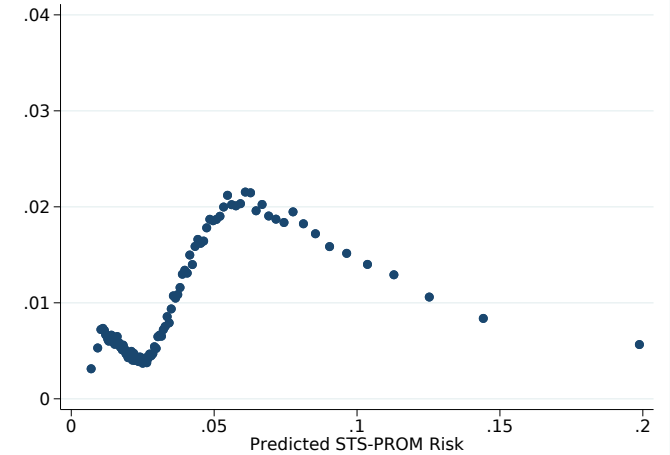
Table 3. STS-PROM Logistic Regression Coefficients

Figure 9. Likelihood of Surgical Intervention Before/After TAVR Adoption

(a) Prior to Adoption (2010)



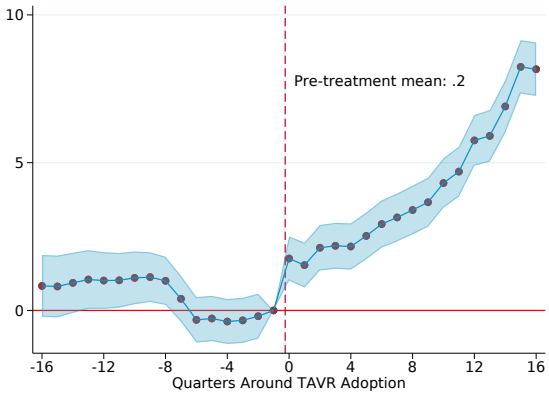
(b) Adoption Years 0–2 (relative time)



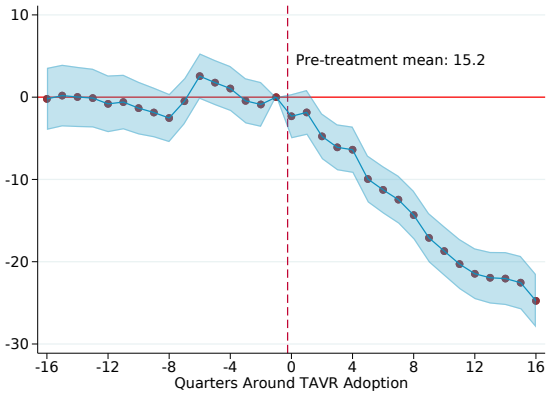
Notes: Figure shows estimated likelihood of an individual patient receiving valve replacement surgery (TAVR or SAVR) by estimated risk (based on STS-PROM score). Panel (a) shows relationship in year prior to TAVR approval (2010), while Panel (b) shows relationship in commuting zones during the first three years of TAVR adoption.

Figure 10. Effect of TAVR Adoption on Total IVC Surgical Volumes, Commuting Zone Level

(a) SAVR/TAVR Surgeries



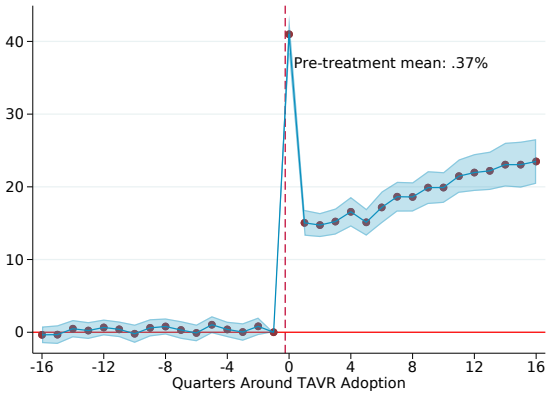
(b) PCIs



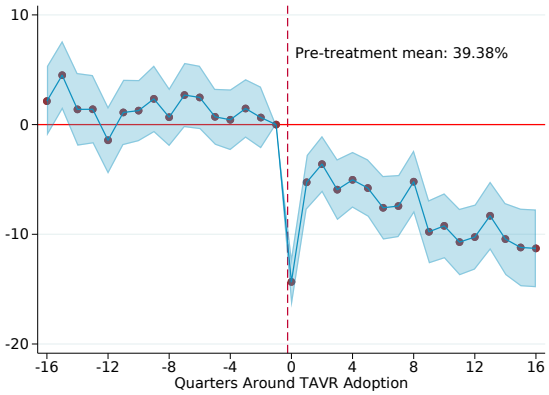
Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs. Panel (a) shows the effect on all SAVR/TAVR surgeries, and panel (b) shows the effect on PCI procedures. Interventional cardiologists who perform fewer than 10 inpatient surgeries per year are dropped from estimation, and standard errors are clustered at the commuting zone level. *Abbreviations:* IVC = Interventional Cardiologist

Figure 11. Effect of TAVR Adoption on Interventional Cardiologist Treatment Shares

(a) SAVR/TAVR Surgeries



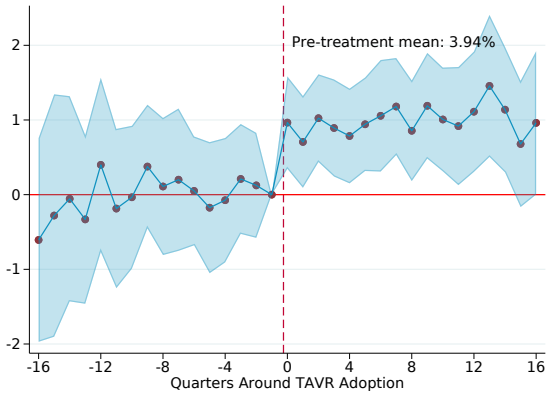
(b) PCIs



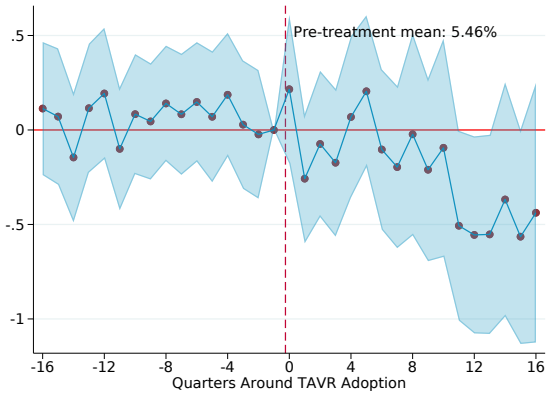
Notes: Figure shows estimated impact of TAVR adoption on treatment decisions made by interventional cardiologists. The outcome variable in each panel is the total volume of each procedure performed by an interventional cardiologist; panel (a) shows the effect of TAVR on the use of all valve replacement surgeries, while panel (b) shows its effect on the use of PCIs. Interventional cardiologists who perform fewer than 10 inpatient surgeries per year are dropped from estimation, and standard errors are clustered at the commuting zone level.

Figure 12. Effect of TAVR Adoption on IVC Treatment Decisions (Risk)

(a) SAVR/TAVR Surgeries

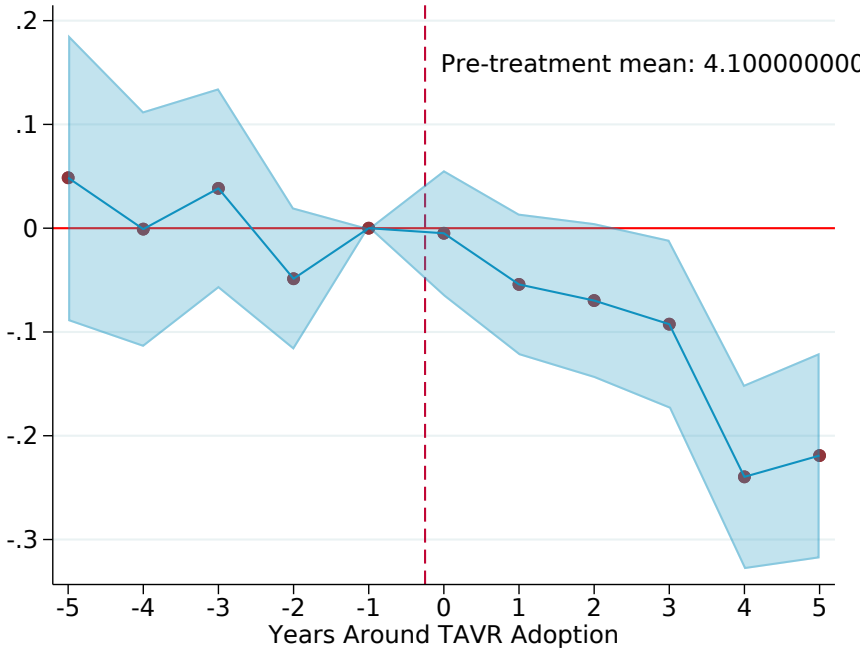


(b) PCI Interventions



Notes: Standard errors are clustered at the physician level.

Figure 13. Effect of TAVR Adoption on Total IVC Surgical Volumes, Commuting Zone Level



Notes: Figure shows estimated impact of TAVR adoption on the likelihood that a patient will receive any surgical intervention, including all SAVR, TAVR, and PCI procedures regardless of provider type. Patient pool is restricted to patients with appropriate cardiac symptoms who have not previously received surgery. Standard errors are clustered at the commuting zone level.