Innovations and Inequities in Access to Medical Services*

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Abstract

Improving the return on health spending requires balancing tradeoffs between promoting novel treatments and ensuring equitable access to care. In addition to being costly, medical innovations may reduce availability of older services, an understudied source of inequity. I propose a framework to study this tradeoff, where innovations reduce other treatments' availability due to patient selection and reduced returns from specialization. Innovations lead some patients to lose access to care altogether, particularly those from high-risk groups. I apply the model to minimally-invasive valve replacement surgeries in the U.S., showing that innovation reduced local surgical volumes, particularly for patients of marginalized groups.

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JEL codes: I12, I14, O30, D63

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1 Introduction

Improving the quality of medical treatments has immense economic and social value, through both economic returns from improved health and insurance value from reduced population risk (Murphy and Topel, 2006; Lakdawalla et al., 2017). Funding, developing, and disseminating novel medical technologies is a promising way to improve the return on high levels of health spending in developed countries (Cutler et al., 2007). However, novel technologies may exacerbate health inequities, which have affected marginalized individuals across socioeconomic status, race, and ethnicity—among others—for over two centuries (Adler and Rehkopf, 2008).

Novel interventions, which are typically high-cost, may not be accessible to lower-income individuals during the early years following adoption, generating well-documented financial barriers to accessing care (Arcaya and Figueroa, 2017). In addition, medical innovation may place stricter limits on which patients can receive other interventions that physicians now provide less frequently. These scarcity-driven inequities are less well-understood and may be driven by a confluence of two mechanisms. First, physicians are capacity constrained in the services they can perform, so adopting innovative treatments mechanically reduces their availability for performing other procedures (Gandhi, 2023). Second, if physicians benefit from returns to specialization, this reduced availability may be compounded by a loss of skill, leading physicians to reduce their volume of older techniques by more than the take-up of the new treatment. The result is that patients may be crowded-out of access to specialist interventions altogether.[1] Achieving equitable expansion of health innovations requires a careful understanding of these tradeoffs.

I present a model of physician decision-making to characterize these effects. Physicians select one of three treatments for their patients: two surgical interventions of different intensity (in the empirical context, a high-intensity aortic valve replacement or a lower-intensity aortic valve support procedure), and standard maintenance ("watch and wait") care. The model incorporates technological spillovers so that returns to a treatment increase with how frequently it is performed, for example through physician learning-by-doing (Chandra and Staiger, 2007). I then show that an innovation which increases the return of the high-intensity procedure changes decision-making along two margins. First, the innovation directly induces some intermediate-risk patients to opt into receiving high-intensity interventions, leading to a mechanical decrease in the relative use of other procedures. Second, and more surprising, this expansion generates a flow of high-risk patients out of receiving interventions altogether,

[1] By "hyper-specializing" in a handful of procedures, some medical professionals can achieve higher-quality outcomes at lower-costs (Institute, 2023).

driven by the corresponding reduced returns from low-intensity interventions. These combined effects result in some patients losing access to surgical interventions entirely because of innovation.

The model's central insight is that this crowd-out for high-risk patients may be inequitably borne across patients. Inequitable crowd-out may arise directly—because patients of different groups are assigned different surgical appropriateness—or indirectly—because risk is imperfectly observed across groups, with some incorrectly assigned higher surgical risk. These inequities serve to inhibit even access to older, more cost-effective substitutes to novel technologies.

I empirically test the model predictions using the development and dissemination of transcatheter aortic valve replacement (TAVR) surgeries to treat aortic stenosis (AS) in the US. TAVR is a novel, minimally invasive alternative to open-heart surgeries used to replace a failing aortic valve. Importantly, TAVR expanded both the supply and demand for surgeries, as it both is appropriate even for patients previously deemed too high-risk for traditional surgery, and can be performed by interventional cardiologists (IVCs) instead of cardiothoracic surgeons alone. These disruptions meaningfully changed local markets for valve replacements.

I estimate how adopting TAVR changed the provision of other procedures by interventional cardiologists, focusing on valve support surgeries typically referred to as percutaneous coronary interventions (PCIs). These surgeries (e.g., angioplasties) are lower-intensity than traditional valve replacements; however, I observe that those adopting TAVR dramatically reduce their use of support procedures, resulting in a decline in total surgical volumes in a market. This crowd-out validates the predictions of my model: patients who lose access tend to be higher-risk, on the margin between selecting into surgical interventions at all. Additionally, patients losing access reside in markets with more health deprivation, including markets with a greater fraction of nonwhite patients.

The theoretical framework—as well as the empirical findings—fit into a larger discussion of the potentially inequitable gains from innovation. Although much of this discussion has focused on disruptions in the factor market including skilled-biased innovations (Violante, 2008; Acemoglu and Restrepo, 2020), a younger literature explores how innovations generate inequities for consumers purchasing products (Faber and Fally, 2022; Jaravel, 2019). This work argues the direction of innovation is endogenous, ultimately resulting in products aimed at higher-income households. Such income-driven innovation is found even in healthcare, where potential market size and patient incomes drive entry decisions for nongeneric drugs and funding for clinical trials (Acemoglu and Linn, 2004; Moradpour and Hollis, 2020). My work highlights a previously overlooked second dimension of inequity: endogenously

determined innovations may crowd-out even alternative products, further dividing access across groups.

The model presented in this paper is the first to provide a theoretical framework for considering both direct and spillover equity impacts of health innovations. Hence, this paper contributes to both literatures on health innovations and health disparities. Recent work has explored other policies that may reallocate access to high-value medical services in equity-improving ways, including general practitioner payments (Kaarboe and Siciliani, 2023) or reducing geographic variation in the provision of services (Chandra et al., 2022). I consider how innovations exacerbate these inequities, arguing that spillover consequences on populations not directly affected by a technology also need to be considered when evaluating an innovation's impact.

Health disparities have been increasing in recent years, with some groups even experiencing disproportionate decreases in life expectancy (Case and Deaton, 2015; Olshansky et al., 2012). This paper highlights that novel technologies may still exacerbate inequities even when cost-based inequities are eliminated, and underscores that inequities may spill over into access for other specialty services. In that regard, my work is also related to the spillover effects of health services (Fadlon and Nielsen, 2019; Hoagland, 2022).

I describe my setting and data in Section 2 before presenting my model in Section 3. The model suggests several empirically testable implications; I outline the empirical methods used for these tests in Section 4 and the results of these analyses in Section 5 before concluding in Section 6.

2 Setting and Data

2.1 The Adoption of TAVR

TAVR is a minimally-invasive alternative to surgical aortic valve replacement (SAVR), involving the transfemoral placement of either a balloon-expandable valve or a self-expanding valve instead of an open surgical approach. Numerous randomized trials of TAVR have indicated that the procedure is 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). Hence, the first TAVR device (Edwards-SAPIEN) received approval from the United States' Food and Drug Administration's Center for Devices and Radiological Health for patients with severe surgical risk in November 2011 (Dvir et al., 2012)); the procedure's use has been expanded over time to a wider pool of patient risk levels as comparison trials continued to show its noninferiority

(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). However, important gaps in access remain—as of 2017, fewer than half of patients indicated as candidates for valve replacement surgeries received a valve replacement (Li et al., 2022).

The adoption of TAVR is an ideal setting to study the tradeoffs between innovations and inequities for two reasons. First, this innovation was market-expanding: the median number of surgical interventions treating aortic stenosis in the U.S. increased by roughly 1/3 following the adoption of TAVR, with the number of providers supplying interventions nearly doubling (Appendix Table A.1). This increase in the total addressable market provided strong incentives for physicians to change practice styles, similar to the rapid expansion of PCIs as an alternative to coronary artery bypass graft surgery in the 1990s (Cutler and Huckman, 2003).

Second, TAVR disrupted the supply of surgeries: whereas SAVR could be 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 specialists receive differentiated training. Specifically, as noted by Huckman and Stern (2022), after completing residency, interventional cardiologists complete three additional years of cardiology fellowship and an additional year of an interventional cardiologist-specific fellowship; meanwhile, cardiac surgeons complete six to seven years of cardiothoracic surgery fellowships. These unique training paths allow surgeons to hyper-specialize in different approaches (e.g., open or percutaneous surgical methods) at the expense of losing other skills.

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 from 2010 to 2017.[2] I observe 100% of cardiology inpatient procedures performed, as well as patient risk and demographic information. I identify surgeon specialization using the Medicare Data on Provider Practice and Specialty (MD-PPAS) file. By 2017, when TAVR surpassed SAVR as the most popular intervention, interventional cardiologists were involved in over 1/5 of these procedures (Appendix Figure A.2). My main sample includes 9,858,536 Medicare patients with AS, including those who ultimately received intervention and those who did not.

Appendix Table A.2 presents relevant summary information for my sample. I observe demographic information, including patient race, area-level disadvantage scores, and zip-code level income. I use the Neighborhood Atlas' Area Deprivation Index scores, which

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

rank regions by socioeconomic disadvantage based on factors such as income, education, employment, and housing quality (Kind and Buckingham, 2018). I also construct relevant clinical information, including estimated surgical risk (see Section 4.1), surgical histories, and other patient risk factors using the methodology of Ellis et al. (2022).

3 Model

Suppose there is a continuum of patients suffering from a single disease. Patients and physicians can select from three possible treatments, indexed by $s \in \{0, 1, 2\}$: preventive maintenance ($s = 0$), low-intensity surgical interventions ($s = 1$), and high-intensity surgical interventions ($s = 2$). Empirically, low-intensity interventions will correspond to valve support surgeries (PCIs), while high-intensity interventions represent full aortic valve replacements.

A procedure's patient-specific appropriateness depends on a risk index θ_{is} for patient i. When observed perfectly, θ_{is} captures both diagnostic severity and surgical risk; hence, individuals with lower θ_{is} are more likely to receive intensive treatments. In practice, θ_{is} is not observable; instead, physicians and patients proxy this risk based on a set of observable characteristics Z_{is}; I discuss this in Section 4.3.

The expected utility of each procedure for a patient with characteristics Z_{is} is given by

$$U_{is} = \beta_{is} Z_{is} + \alpha_t P_s + \varepsilon_{is}, s \in \{0, 1, 2\}, \tag{1}$$

where P_s represents the fraction of the population receiving treatment s. Equation 1 incorporates productivity spillovers in the style of Chandra and Staiger (2007), captured in the second term; that is, if $\alpha_s > 0$, increased investment in a procedure improves its average outcome regardless of Z_{is}.

Given linear utility, patients' treatment decisions can be characterized as two-way comparisons for any θ_{is}. To simplify these comparisons, I make the natural assumption that optimal treatment intensity is perfectly distributed across θ_{is}; this is equivalent to assuming the marginal utility of treatment with respect to risk is greater (in absolute value) for more intensive interventions.[3] Patients then choose treatment only along two margins: a choice between valve replacement and valve support surgeries, or a choice between supports and no surgery. This allows me to represent risk as a single measure across treatments, θ_i.

A patient thus chooses the intensive treatment, $s = 2$, only if $U_{i2} > U_{i1}$. Over the

[3] Or $|\partial U_{i2}/\partial \theta_2| > |\partial U_{i1}/\partial \theta_1| > |\partial U_{i0}/\partial \theta_0|$. Note that when θ_{is} perfectly captures patient appropriateness, this is not a special case.

distribution of Z_i, this probability is given by:

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

and the probability that a patient chooses the intermediate treatment ($s = 1$) is:

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

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

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

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

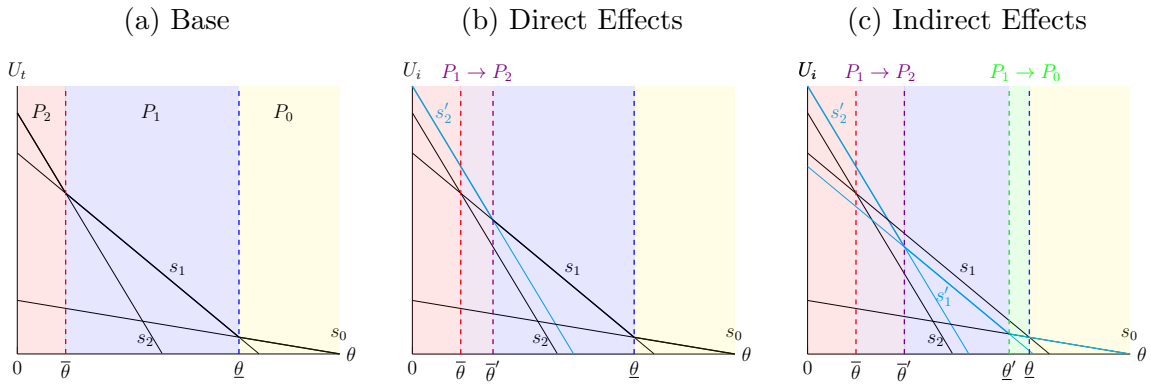
The equilibrium can be conceptualized in a simple single-crossing framework: any initial allocation generates utility benefits that induce marginal patients to switch between the three treatment options. These flows, in turn, affect the returns to each procedure; this further shifts patients across thresholds, altering the returns to each procedure once again. This cycle continues until a stable equilibrium is reached, as discussed in Chandra and Staiger (2007).

Figure 1, panel (a) illustrates the allocation of patients to treatments given perfectly observed risk. The figure plots patient utility $U_s(\theta)$ for each treatment. For each, utility is declining in risk; however, by assumption, these declines are steeper for more intensive treatments. This creates three well-defined treatment regions, where patients with the lowest risk select s_2, patients with moderate risk select s_1, and the highest risk patients choose no intervention s_0. Denote the cutoff risk levels $\overline{\theta}$ and $\underline{\theta}$; combined with the distribution of θ, these define each treatment's market share.

3.1 The Effect of Innovations

The model allows a direct comparison of how innovations affecting one treatment may modify others' availability. Consider an innovation in valve replacements (e.g., the adoption of TAVR). This innovation can be characterized as a uniform cost reduction across θ without

Figure 1. Treatment Decisions Based on Patient Risk



Notes: Graphical illustration of the selection of patients into treatment based on risk, and how innovations disrupt this. Panel (a) presents the production possibilities frontier for all levels of θ in the non-innovation case, which defines distinct treatment regions: high-intensity treatments (red, defined as P_2); low-intensity treatments (blue, defined as P_1); and maintenance care (yellow, defined as P_0). Panel (b) presents direct effects of innovations, which change the tradeoff between high- and low-intensity interventions (captured in purple and the change in $\overline{\theta}$ to $\overline{\theta}'$). Panel (c) highlights the indirect effects, where spillover externalities result in a larger share of patients in P_2 and movement from s_1 to s_0 (captured in green and the change in $\underline{\theta}$ to $\underline{\theta}$').

affecting survival utility, as TAVR is a noninferior risk-reducing procedure. Hence, this innovation shifts U_1 out by a fixed τ.[4]

The second and third panels of Figure 1 present the direct and indirect effects of this shift. In panel (b), the utility increase from s_2 directly attracts a greater share of patients, who switch from the low-intensity intervention (shown in purple). However, this flow also generates spillover externalities as physician skills change; this results in further utility increases for s_2 and corresponding decreases in utility of other interventions (s_1 in particular). Panel (c) shows these indirect effects as two separate flows out of s_1: some into s_2 and others into s_0 (shown in green). The new equilibrium has updated risk thresholds $(\overline{\theta}', \underline{\theta}')$.

Of particular interest is the shift in $\underline{\theta}$, which defines a share of patients who are crowded-out of treatment. To quantify this crowd-out, note that the risk thresholds $\overline{\theta}$ and $\underline{\theta}$ are defined, in expectation over ε, by

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

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

Based on this system, the comparative statics measuring how risk thresholds change in

[4]In general, τ need not be constant; the results in this section do not depend on this simplifying assumption.

response to changes in τ are

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

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

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

When the innovation is market-expanding for s_2, the shift in the extensive margin (Equation 9) is nonpositive—so 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 reductions in productivity spillovers for both s_0 and s_1 associated with changing risk thresholds, while the right side captures the differences in the marginal utility of each treatment. Hence, crowd out occurs when the relative change in the productivity spillovers between s_1 and s_0 is less than the difference in the magnitude of the marginal utilities between treatments. Given that the marginal returns of a surgical innovation tend to be much larger than marginal changes in returns from provider specialization, this condition is likely to be met in many cases. However, for innovations requiring extensive physician re-training for little benefit, these results need not hold.

3.2 Exacerbating Inequities

Any loss in efficient access to specialty care may be considered a market distortion. However, this loss in access to care may differ substantially across different patient groups, particularly when risk is heterogeneous across groups. These inequities may be further compounded when patient risk is imperfectly observed.

Assume that the condition for crowd-out is satisfied (Equation 11), so that there is a region C of patients who received s_1 prior to an innovation and s_0 after its adoption (defined by $[\underline{\theta}, \underline{\theta}']$). However, suppose that clinicians do not observe θ directly but a proxy $\hat{\theta}$.[5] I assume that $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} which correctly

[5]Note that $\hat{\theta}$ is a combination of physician assessment, patient beliefs, and clinical histories.

predicts θ except for an idiosyncratic, mean-zero error term ε:

$$\theta_{is} = \underbrace{Z_{is}\gamma}_{\hat{\theta}} + \varepsilon_{is}. \tag{12}$$

Suppose that among the variables contained in Z_{is}, there is a binary variable d_{ig} equal to 1 if patient i is a member of a group g, and 0 otherwise. Hence, d_{ig} encompasses membership to demographic groups (e.g., a low-income indicator) or clinical indicators (e.g., patients with diabetes or smokers).[6] The coefficient γ_d captures a discrete shift in predicted risk based on membership in d. For ease of exposition, I assume throughout this section that d_{ig} is independent to all other, non-group covariates $Z_{is,-g} = Z_{is} \setminus d_{ig}$.

If group membership is informative (e.g., γ_d is nonzero), patients in different groups have different likelihoods of treatment crowd-out. Given the underlying distribution of θ and $Z_{is}\gamma$, the fraction of patients in C who belong to g is determined by Bayes' rule:

$$\begin{aligned}
s_{C,g} = Pr(i \in g | i \in C) &= Pr(i \in C | i \in g) \frac{Pr(i \in g)}{Pr(i \in C)} && (13)\\
&= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\gamma_{-g} + \gamma_g \in [\underline{\theta}, \underline{\theta}']] \right. && (14)\\
&= \frac{s_g}{s_C} \left[\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g}) \right] && (15)\\
&= s_g \frac{\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g})}{\int_{\underline{\theta}}^{\underline{\theta}'} f(\theta) d\theta}. && (16)
\end{aligned}$$

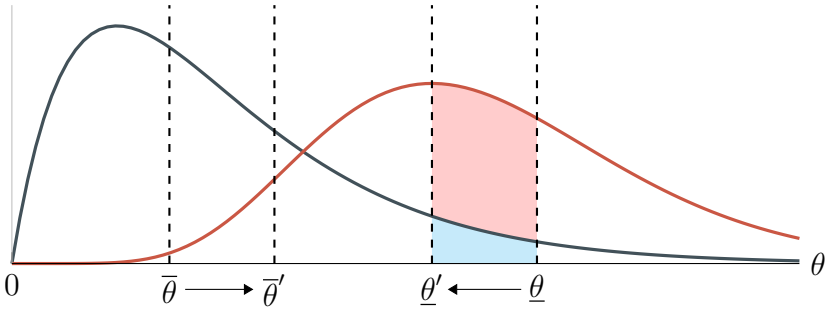
Here, s_g indicates the relative size of group g in the population, and $s_C = F(\underline{\theta}) - F(\underline{\theta}')$ is the relative size of C. In general, these two are not equal, meaning that C may over- or under-include members of g relative to the population. Although this difference arises from true (average) differences in patient risk, systematic differences in who accesses care may still have important differential long-term effects.

Figure 2 presents the intuition of this result. The graph highlights the crowd-out region associated with an innovation, as well as the risk distributions for patients of two different groups. Even when risk is correctly measured, these groups have different likelihoods of losing access to specialty treatment.

Further inequities arise, however, when γ_d is not correctly measured. Imperfect proxying may be the result of provider error, but may also result from other factors such as patient

[6] Such indicators routinely inform patient risk calculations (van Ryn and Burke, 2000).

Figure 2. Inequities in Crowdout



Notes: Graph shows potential inequities associated with patients crowded out of specialty care following an innovation. Patient pool is divided into two groups with heterogeneous risks; patient risk θ determines treatment status, denoted by $\{\overline{\theta}, \underline{\theta}\}$. Innovations shift these cutoff values, creating a crowd-out region (shaded) for each distribution.

beliefs or biased health system measurements.[7] However it arises, measurement error distorts the likelihood that members of g are represented in C. To quantify this relationship, suppose that instead of using γ_g in risk calculations, $\hat{\theta}$ relies on the use of a "noisy signal" $\hat{\gamma}_g$, defined as

$$\hat{\gamma}_g = \gamma_g + \nu, \tag{17}$$

where ν is an idiosyncratic error in group risk measurement.[8] 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 $s_{C,g}$ (Equation 16). That is, the increased likelihood for a member of g being represented in C is

$$I(\nu) = \frac{s'_{C,g}(\nu)}{s_{C,g}} \tag{18}$$

$$= \frac{1}{s_{C,g}} \int_{\underline{\theta}-\gamma_d-\nu}^{\underline{\theta}'-\gamma_d-\nu} f(X_{i,-g}\gamma_{i,-g}) d(X_{i,-g}\gamma_{i,-g}). \tag{19}$$

Importantly, notice that

$$\frac{\partial I}{\partial \nu} = \frac{1}{s_{C,g}} \left[f_{X_{-g}\gamma_{-g}}(\underline{\theta} - \gamma_d - \nu) - f_{X_{-g}\gamma_{-g}}(\underline{\theta}' - \gamma_d - \nu) \right]. \tag{20}$$

That is, ν affects the relative crowd-out of members of group g in proportion to the initial composition of g in C and the relative comparison points used in assessing the risk of non-members. Appendix Figure A.1 presents the intuition behind these inequities. Intuitively,

[7] E.g., risk scores; see Obermeyer et al. (2019).

[8] Note ν does not represent classical measurement error, nor is it necessarily centered around 0. In the simplest model, ν is common across provider-patient assessments; however, the model could easily generalize ν to either vary across providers or patients, as appropriate.

measurement error results in patients of a specific group being misplaced along a risk distribution. For example, if surgical risk is systematically over-estimated for members of g, then members of g may be more likely to be in the crowd-out region of an innovation. This ultimately results in an over-representation of group members among those who lose access to specialty interventions after an innovation.

3.3 Empirical Implications

The model predicts that innovations may exacerbate health inequities through two steps. First, technological spillovers from interventions may create "crowd-out regions" that shift high-risk patients out of care altogether. Second, these affected patients may be systematically different from the overall population, an inequity which is exacerbated if risk is incorrectly proxied.

Three empirical implications arise from this model. First, I test for the direct and indirect effects of innovation by assessing how adopting physicians substitute patients along treatment margins. I then identify which patients are affected along each margin, paying particular interest to the existence and magnitude of crowd-out regions generated by TAVR. Finally, I examine whether crowded-out patients are inequitably distributed across members of different groups, including patient race, income, and ADI. This differential access to specialized medical interventions may be informed both by true and perceived differences in risk across groups; however, given the long-term effects of inequities in accessing care, even identifying aggregate differences sheds important light on potential equity tradeoffs associated with innovation.

4 Methods

To test these implications, I assess the effects of TAVR's adoption on access to heart valve surgeries within a local market.[9] The model abstracts away from many features complicating physician decision-making; however, I can test its basic insights on physician substitution of techniques across patients based on their observed risk.

I consider two types of surgical interventions, in keeping with the model: valve replacements (TAVR or SAVR) and valve supports (PCIs). Appendix Table A.3 defines the procedure and diagnosis codes used to identify these services. Due to the high comorbidity of aortic stenosis and coronary artery disease, valve support surgeries were frequently per-

[9]Throughout, I use U.S. commuting zones to define local markets; results are robust to other measures, such as health service areas.

formed when a patient's risk was too high for them to qualify for a full replacement through SAVR. Hence, TAVR's adoption may affect both margins of treatment for patients seeking PCIs from interventional cardiologists.[10]

4.1 Estimating Patient Risk

A patient's risk for cardiac surgery is typically based on risk models constructed by The Society of Thoracic Surgeons (STS), which account for pre-operative factors that may influence surgical outcomes (O'Brien et al., 2009). I model patient risk θ using the STS Predicted Risk of Mortality model (STS-PROM), which predicts the likelihood of surgical mortality using logistic regression based on patient demographics, health conditions, and time trends (see Appendix Table A.4 for the full specification). The STS-PROM model is generally used to classify patients into one of three risk categories: low risk (score $\leq 3\%$), moderate risk (score between 3% and 8%), and high risk (score $\geq 8\%$). Traditional valve replacements are generally limited to low-risk patients, while valve supports can be done on higher-risk patients.[11]

The empirical distribution of predicted risk in my sample closely matches the population STS-PROM model (Appendix Figure A.3). I estimate an average (median) risk of 3.6% (4.8%), with 40% of patients identified as low-risk, 44% as intermediate-risk, and 15% as high-risk.[12]

4.2 Effect of Innovations

To estimate the causal impact of TAVR's adoption on interventional cardiologist treatment decisions, I use a "stacked" regression design to avoid bias from naive staggered adoption designs with heterogeneous treatment effects (Goodman-Bacon et al., 2019; de Chaisemartin and D'Haultfoeuille, 2019).[13] I identify adoption cohorts (at the quarter-year level) $r \in \{1, ..., N^1\}$ and stack them into a single estimation with cohort-specific time and group fixed

[10]There is new evidence that PCIs can be performed with TAVR (Bajaj et al., 2017; Søndergaard et al., 2019); although this began after my sample, it should be considered in future applications.

[11]Some work questions the STS-PROM in physician decision-making (Catalano et al., 2020; Khan et al., 2019); however, given that this is still the model most commonly used by practitioners to approximate θ, I incorporate it here.

[12]The current STS-PROM model used on a similar population classifies 33% as low-risk, 42% as intermediate-risk, and 25% as high-risk (Kumar et al., 2018).

[13]My results are robust across other novel specifications, as illustrated in the Appendix (Callaway and Sant'Anna, 2018; Sant'Anna and Zhao, 2020).

effects (Cengiz et al., 2019):

$$\Pr(\text{Treatment}_{im,r}) = \alpha_{m,r} + \tau_{t,r} + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\{t - E_{imt,r} = k\} + \epsilon_{imt,r}. \tag{21}$$

The outcomes of interest are treatment decisions for patients (i) seen at time t, residing in a market m whose first TAVR adoption placed them in cohort r. Throughout, I cluster standard errors at the commuting zone level.

Throughout, the identifying assumption is that the timing of TAVR's adoption is exogenous at the market level, in the sense that interventional cardiologists did not adopt TAVR as a result of underlying changes in the expected volume of patients seeking valve support (not valve replacement) surgeries. This can be examined directly by assessing the differential pre-trends between adopting and non-adopting markets for indications that surgical volumes were already changing prior to adoption.

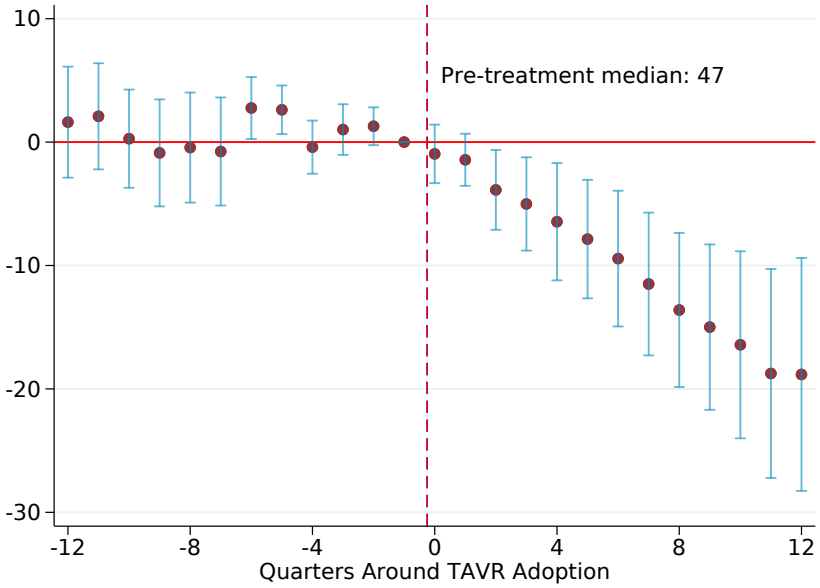
4.3 Heterogeneity & Inequities in Post-Innovation Access

I also examine heterogeneity in these results across two key dimensions: patient risk and market-level indicators for access to health services. I assess inequities across three dimensions: the racial makeup of a commuting zone, a commuting zone's Area Deprivation Index (ADI) score (averaged over the 9-digit zip codes making up the commuting zone), and a region's socioeconomic status (proxied by the fraction of cardiac patients who are dually-eligible for Medicaid). For each measure, I assess heterogeneous treatment effects by binning the analytic sample and estimating traditional difference-in-differences regressions within each bin. Where applicable, I adjust these results for multiple inferences using sharpened false discovery rate control methods (Anderson, 2008). This approach allows for a direct comparison of the effects of TAVR's adoption across patients of differing surgical risk, and markets with greater levels of disadvantage than others.

5 Results

TAVR's adoption expanded surgeries to older, higher-risk patients. I observe the average likelihood of valve replacements double within the first three years following adoption from a baseline of 0.03% (Appendix Figure A.4). Following adoption, surgical patients are estimated to be 4 years older and roughly 0.2% riskier (Appendix Figure A.5). I then turn to examining the overall market impacts of TAVR's adoption.

Figure 3. 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. Markets with fewer than 10 inpatient surgeries per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

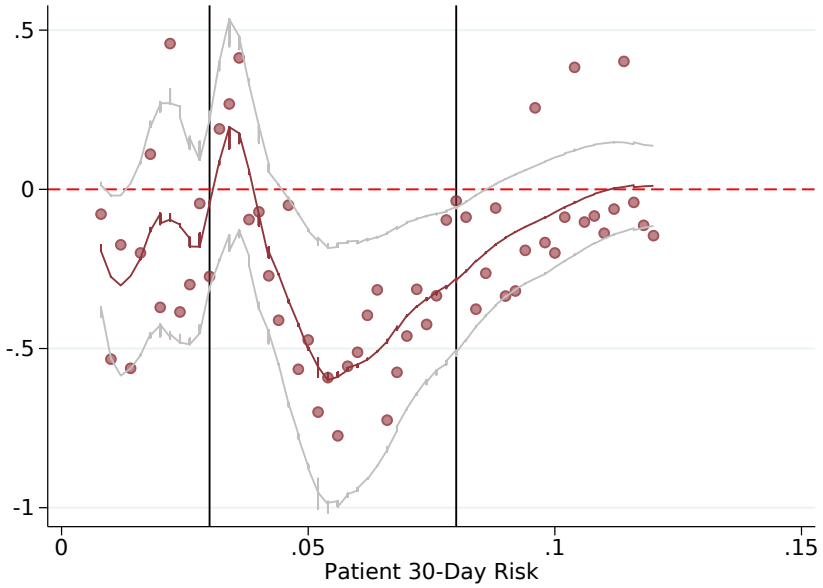
Figure 3 presents the dynamic effects of TAVR adoption on interventional cardiology procedures at the commuting zone level, estimated according to Equation 21. The figure shows a marked decline in total surgical volume: the median commuting zone performs almost 200 procedures annually pre-adoption, but within three years following adoption, volume drops by an average of 40%. This decline is driven by a drop in valve support surgeries that swamps the takeup of valve replacements (Appendix Figure A.6).[14]

These findings corroborate the model's predictions that patients will be crowded out from access to any surgical care. Next, I isolate which patients are losing access to valve treatments, beginning with heterogeneity across patient risk. To address this, I first examine the effect of TAVR adoption on the average predicted risk of patients in each treatment group. I find that TAVR caused the conditional risk of valve replacement patients to increase, but do not observe a corresponding change in the risk composition of valve support patients (Appendix Figure A.7). This suggests that the composition of valve support patients changed along both risk margins. I investigate this further by separately estimating the treatment

[14] Appendix Figure A.11 shows that in markets adopting TAVR, the fraction of interventional cardiologists screening patients for aortic stenosis (and subsequently, appropriateness for valve replacement surgery) increases by roughly 1/3 (one percentage point). This is in line with recent findings suggesting that physicians adapt their diagnostic screening strategies in response to available technologies (Mullainathan and Obermeyer, 2021).

effects associated with TAVR's adoption on bins of patient risk, in order to identify the crowd-out region of interest.

Figure 4. Heterogeneous Effects of TAVR Adoption on Surgical Volumes by Patient Risk



Notes: Figure shows estimated heterogeneous treatment effects of TAVR's adoption on total surgical volume for patients in different risk bins. STS-PROM risk is binned (width=0.2 percentage points); each point represents a difference-in-differences coefficient of TAVR's adoption on surgical volume within the bin. Effects are smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008) and Benjamini et al. (2006). See Appendix Figure A.8 for individual point estimates and standard errors. Markets performing fewer than 10 surgeries per quarter are dropped. Vertical lines indicate STS-PROM delineation between low-risk patients (3%) and high-risk patients (8%).

Figure 4 shows the results across the distribution of 30-day risk.[15] I bin patients based on their estimated surgical risk, and estimate simple difference-in-differences coefficients of the effect of TAVR's adoption on surgical volumes within each bin. Each point in the figure represents an estimated coefficient; these effects are then smoothed using a local linear regression weighted by the number of patients in each bin (see Appendix Figure A.8 for a version without smoothing). Throughout, standard errors are adjusted for multiple hypothesis testing (Benjamini et al., 2006).

Such an exercise is informative in identifying which groups of patients experienced the largest declines in access to valve surgeries as a result of TAVR's adoption in their market. In the model, patients whose risk placed them on the margin between low-intensity surgery (valve supports) and maintenance care were likely to be induced out of surgical care as a result of an innovation. As predicted, Figure 4 shows a clear region of patients crowded out

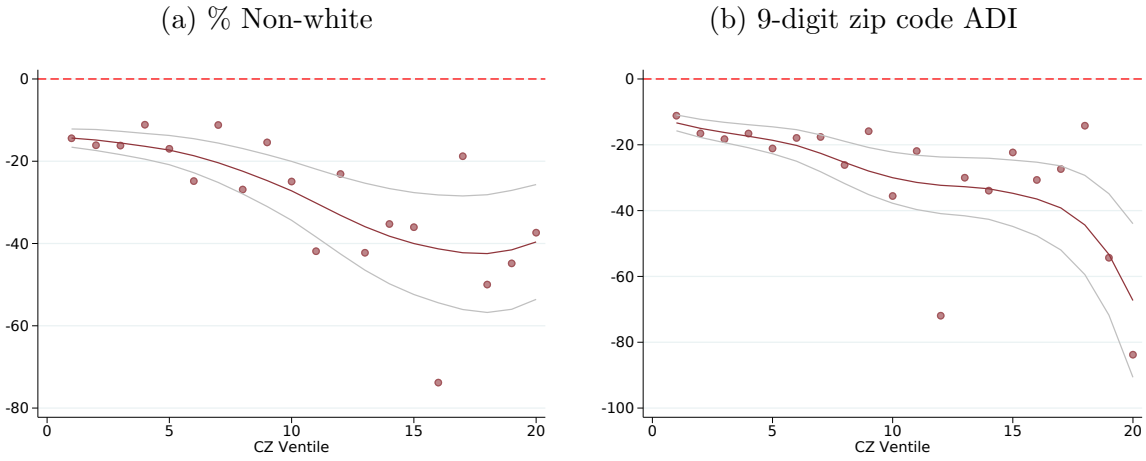
[15]Results are similar across 60- and 90-day risk.

from treatment, specifically for patients whose risk is between 4.5% and 9%. Patients in this group lost access to surgeries at a rate of roughly 0.5 surgeries per quarter per bin; this corresponds to about 15 surgeries at the commuting zone-quarter level, in line with Figure 3. These results suggest that TAVR induced some relatively low-risk patients to switch into valve replacements, but also drove higher-risk patients out of valve surgeries altogether.

5.1 Inequities in Access to Surgical Care

My results indicate that TAVR's adoption resulted in lower access to valve surgeries for higher-risk patients. As predicted by the model, this lost access may differentially affect the most vulnerable populations, especially to the extent that groups exhibit heterogeneity in surgical risk assignment. I estimate how the effects of adopting TAVR differ across markets in inequitable ways.

Figure 5. Inequities in TAVR's Effects on Local Access to Valve Surgeries



Notes: Figure show heterogeneous effects of TAVR adoption on total volumes of valve replacements in a commuting zone. CZs are binned by ventiles according to disadvantage, measured in panel (a) as the fraction of nonwhite patients, and in panel (b) as the average ADI at the patient 9-digit zip code level. Each point represents a difference-in-differences coefficient; effects are smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008) and Benjamini et al. (2006). Markets performing fewer than 10 surgeries per quarter are dropped. See Figure A.9 for results for dually-eligible Medicaid patients.

Figure 5 presents the results. In each panel, I sort commuting zones into ventiles based on a commonly used measure for health equity: in panel (a), the share of nonwhite patients, and in panel (b), the average ADI, measuring an area's overall economic disadvantage. In both panels, a clear gradient emerges; local markets with the most racial diversity experience a decline in total surgical access twice as large as that experienced by the least diverse areas.

These differences are estimated to be even larger when examining local markets with limited employment, education, and housing (measured by the ADI).[16] These results provide strong evidence that the local adoption of a highly innovative technique may generate inequitable loss in access to other services by the most vulnerable patient groups.[17]

Finally, I explore the hypothesis that surgical crowd-out is exacerbated by limited productivity spillovers, reducing the returns to low-intensity valve support surgeries. I assess the effect of TAVR's adoption on risk-adjusted surgical outcomes—including readmission and mortality—for valve support procedures in a market. I find little evidence that TAVR's adoption affected either of these in the long term (Appendix Figure A.10); there is some evidence that the likelihood of readmission increased by about 10% immediately following TAVR's adoption, but this is neither estimated precisely nor persistent over time. However, productivity returns to a procedure may encompass much more than extreme outcomes such as surgical mortality; instead, these returns may capture features of a local healthcare market such as the ease of obtaining a surgical referral and waiting times for a surgery. Future work may further explore the exact mechanisms underlying the shift of patients out of valve support procedures following innovations in valve replacements.

6 Conclusion

Inequities in access to high-return health services have persisted for decades, leaving patients of lower-incomes or marginalized groups with poorer treatments and, subsequently, health outcomes. Innovations in health treatments—which may generate significant health benefits, but are also particularly costly—may further entrench these differences.

I present a theoretical framework to consider the equity implications of expanding access to novel medical technologies. The model highlights a tension between increased access to an innovation and overall access to specialized health services, arising from both surgical capacity constraints and externalities from physician specialization. Increased provider investment in an innovative treatment area may generate a flow of patients out of surgical interventions altogether due to the diminished returns of low-intensity procedures. I test these predictions

[16] I also perform this exercise stratifying markets on dual eligibility, and find little evidence of inequities borne by dually-eligible Medicare patients (Appendix Figure A.9).

[17] The estimates shown in Figure 5 aggregate differences in true underlying risk and compounding inequities from incorrect risk assignment. As a simple, back-of-the-envelope calculation, consider that the change in the risk threshold for valve support interventions went from a baseline of 8% to about 4.5% (Figure 4). Nonwhite patients would have to be twice as likely to be in this risk band to generate Figure 5; however, in the data, nonwhite and white patients are equally likely to be in this crowd-out region. This suggests that roughly half of the observed inequities arise from "true" risk differences (nonwhite individuals have an increased risk of surgical mortality of 1.1%; see Appendix A.4) and half from misperceptions of patient risk based on race.

empirically in the setting of minimally-invasive valve replacement surgeries, and show that TAVR generated novel inequities in access to valve surgeries generally.

Importantly, the patients affected by this crowd-out may differ systematically from the patient population. What's more, when true patient risk is unobservable, information such as a patient's race, ethnicity, gender identity or sexual orientation may color these risk estimates, amplifying inequities for vulnerable groups.

Taken together, the model and empirical results suggest room for considering equity implications and potential downstream effects of an innovation at the time of adoption, particularly by large fee-setting regulators such as CMS. In particular, low-cost innovations benefitting a wider pool of patients may distort access less, especially among marginalized groups (Chandra et al., 2022). Perhaps more interestingly, however, the model also suggests that any policies which aim to reduce inequities in risk assignment may have *spillover benefits*: any reduction in the relative risk differences across groups will not only directly reduce population-level differences in access to treatments, but will also dampen the value of demographic information used in forming risk estimates. These potentially snowballing positive effects may make policies which specifically target reductions in inequality across patient groups particularly appealing to regulators.

Future work can build on the tension highlighted in this paper in several directions. New research may generalize the model to include multiple dimensions of patient risk or consider longer-term consequences of losing access to specialty care. These generalizations may lend themselves well to empirical applications which identify health disparities (Mullainathan and Obermeyer, 2021). Additionally, future work may identify the extent to which selection affects market outcomes, either by providers selecting into innovation (Huckman and Stern, 2022) or those "cherry-picking" patients as a result of innovations (Gandhi, 2023; Cram et al., 2008; Desai et al., 2009). Finally, while this project highlighted racial and geographic disparities exacerbated by medical innovations, this framework can be extended to many other inequities and structural forces which worsen health outcomes for marginalized groups. These include more direct examinations of discrimination at the point of care, as well as systematic gaps in seeking out specialty services due to barriers or eroded trust in the healthcare system (Webb Hooper et al., 2019).

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A Appendix

A.1 Tables

	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 A.1. 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".

	All	PCI	SAVR	TAVR
Age	73.6	73.4	74.6	81.4
	(0.003)	(0.006)	(0.016)	(0.023)
Female	0.50	0.45	0.38	0.47
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Black	0.11	0.10	0.05	0.04
	(0.0001)	(0.0002)	(0.0004)	(0.0006)
Hispanic	0.02	0.02	0.01	0.01
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Other Minority Race	0.04	0.04	0.03	0.02
	(0.0001)	(0.0001)	(0.0003)	(0.0004)
Average 5-Zip Income	$65,456	$64,677	$67,389	$70,519
	(5.03)	(9.68)	(34.38)	(55.66)
ADI	51.7	53.2	48.2	46.1
	(0.008)	(0.015)	(0.051)	(0.076)
Dual Eligible	0.25	0.23	0.12	0.11
	(0.0001)	(0.0002)	(0.0006)	(0.0009)
# of Chronic Conditions	5.7	6.5	6.0	7.4
	(0.001)	(0.002)	(0.005)	(0.007)
Predicted STS-PROM Risk: 30-day	0.050	0.058	0.053	0.045
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Predicted STS-PROM Risk: 60-day	0.069	0.071	0.072	0.065
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Predicted STS-PROM Risk: 90-day	0.081	0.080	0.084	0.077
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
N	11,581,620	3,038,436	263,387	112,424

Notes: Table shows summary statistics for patients in analytical sample, 2010–2017. Patients are grouped based on if they ever had a PCI, SAVR, or TAVR surgery (groups may not be mutually exclusive). Income is averaged at the 5-digit zip code level (reported in 2021 USD). The Area Deprivation Index (ADI) ranks 9-digit zip codes by socioeconomic disadvantage nationally; higher ADI indicates greater disadvantage (Kind and Buckingham, 2018). Predicted patient risk (STS-PROM) is predicted as described in Table A.4.

Table A.2. Summary Statistics: Patients

Version	Codes	General Description
Panel A: SAVR		
ICD-9-PCS	3521, 3522	Open and other replacement of aortic valve
ICD-10-PCS	02RF0*	Open replacement of aortic valves
Panel B: TAVR		
ICD-9-PCS	3505, 3506	Endovascular replacement of aortic valve
ICD-10-PCS	02RF3*, 02RF4*	Percutanenous and/or endoscopic replacement of aortic valves
Panel C: PCIs		
ICD-9-PCS	0061–0066	Percutaneous transluminal coronary angioplasty (PTCA)
	3510–3514	Open heart valvuloplasty without replacement
	3721–3723	Cardiac catheterization
ICD-10-PCS	0270*—0273*	Dilation of coronary arteries, percutaneous approach
	027F*—027J*	Dilation of heart valves, percutaneous approach
	02NF0ZZ, 02NG0ZZ,	Release heart valves, open approach
	02NH0ZZ, 02NJ0ZZ	Release heart valves, open approach
	02QF0ZZ, 02QG0ZZ,	Repair heart valves, open approach
	02QH0ZZ, 02QJ0ZZ	Repair heart valves, open approach
	037G*–037Q*	Dilation of arteries with intraluminal device, percutaneous
	057L*–057S*	Dilation of veins with intraluminal device, percutaneous

Table A.3. Definitions of Interventional Cardiology Procedures

Notes: Table shows inpatient hospital procedure codes (ICD-9-PCS and ICD-10-PCS) used to identify valve replacement surgeries (TAVR and SAVR) and interventional cardiology procedures (PCIs). Interventional cardiologists are identified using the Medicare Data on Provider Practice and Specialty (MD-PPAS) files, 2010–2017. * indicates all relevant ICD codes with the listed prefix.

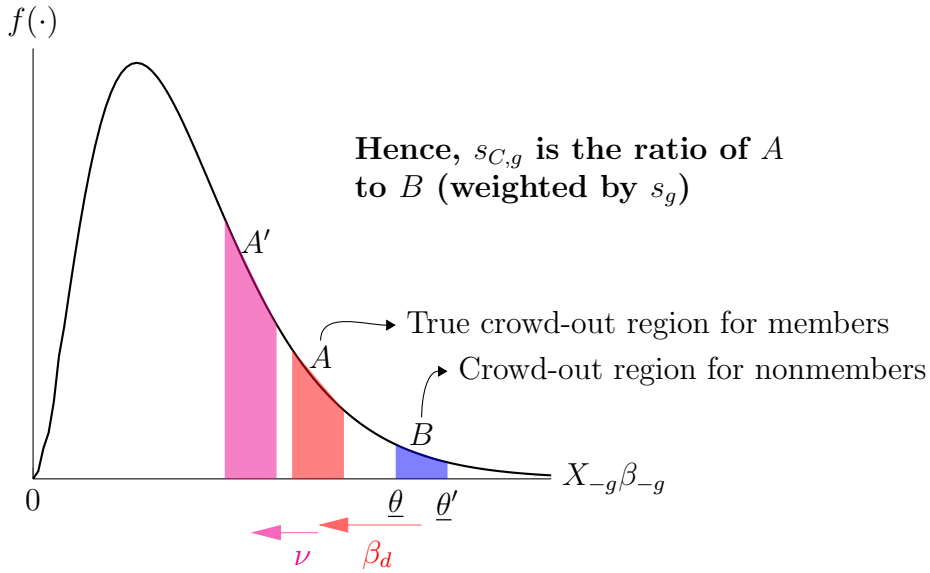
	30-Day Mortality		60-Day Mortality		90-Day Mortality	
	ME	95% CI	ME	95% CI	ME	95% CI
Panel A: Patient Demographics						
Patient age	-0.000	[-0.001,-0.000]	-0.000	[-0.000,-0.000]	0.000	[-0.000,0.000]
Female	0.007	[0.006,0.008]	0.006	[0.004,0.007]	0.004	[0.002,0.006]
Black	0.011	[0.008,0.014]	0.009	[0.006,0.013]	0.009	[0.005,0.012]
Hispanic	0.006	[-0.000,0.013]	0.010	[0.002,0.017]	0.010	[0.002,0.018]
Other Minority Race	0.011	[0.007,0.015]	0.015	[0.010,0.019]	0.014	[0.009,0.019]
ADI (5-digit ZIP)	0.000	[-0.000,0.000]	0.000	[-0.000,0.000]	0.000	[-0.000,0.000]
ADI (9-digit ZIP)	0.000	[0.000,0.000]	0.000	[0.000,0.000]	0.000	[0.000,0.000]
Log(Median Zip Income)	-0.006	[-0.010,-0.003]	-0.010	[-0.014,-0.006]	-0.013	[-0.017,-0.009]
Dual Eligible	0.049	[0.047,0.051]	0.061	[0.059,0.064]	0.069	[0.066,0.072]
Panel B: Chronic Conditions						
# of Chronic Conditions	0.004	[0.004,0.004]	0.006	[0.005,0.006]	0.007	[0.007,0.008]
CC: AMI	0.005	[0.003,0.007]	0.006	[0.003,0.008]	0.005	[0.002,0.007]
CC: COPD	0.008	[0.006,0.009]	0.011	[0.009,0.012]	0.011	[0.009,0.013]
CC: CHF	0.018	[0.016,0.019]	0.024	[0.022,0.025]	0.026	[0.024,0.028]
CC: Diabetes	-0.003	[-0.005,-0.002]	-0.004	[-0.005,-0.002]	-0.004	[-0.005,-0.002]
CC: Hypertension	0.006	[0.004,0.009]	0.006	[0.003,0.009]	0.006	[0.002,0.009]
CC: Stroke	-0.000	[-0.002,0.001]	-0.001	[-0.003,0.001]	-0.002	[-0.004,0.000]
Panel C: Previous Healthcare Utilization						
Any Previous Surgery	0.011	[0.002,0.021]	0.007	[-0.005,0.018]	0.001	[-0.013,0.014]
# of Previous Surgeries	0.006	[0.004,0.008]	0.006	[0.003,0.009]	0.005	[0.002,0.008]
Previous PCI	-0.009	[-0.018,0.001]	-0.004	[-0.016,0.009]	0.003	[-0.011,0.017]
Previous SAVR	0.021	[0.014,0.028]	0.023	[0.014,0.031]	0.022	[0.013,0.031]
Previous TAVR	0.006	[-0.008,0.020]	0.012	[-0.004,0.028]	0.013	[-0.004,0.030]
Any ED Visit	0.016	[0.014,0.018]	0.025	[0.023,0.027]	0.030	[0.028,0.032]
# of ED Visits	-0.001	[-0.002,0.000]	-0.005	[-0.005,-0.004]	-0.006	[-0.007,-0.005]
Any Hospital Stay	0.032	[0.023,0.041]	0.017	[0.008,0.026]	0.004	[-0.006,0.013]
# Hospital Stays	-0.023	[-0.024,-0.022]	-0.034	[-0.035,-0.033]	-0.037	[-0.038,-0.035]
# of Readmissions	0.016	[0.015,0.018]	0.029	[0.028,0.031]	0.034	[0.032,0.035]
# of Days Admitted	-0.000	[-0.000,-0.000]	0.001	[0.001,0.001]	0.002	[0.002,0.002]
Observations	377,532		377,532		377,532	

Table A.4. STS-PROM Logistic Regression Coefficients

Notes: Table shows estimated marginal effects (ME) and 95% confidence intervals (CI) according to the STS-PROM model. Regressions include year-quarter fixed effects, and are estimated for the $N = 377,532$ patients who received TAVR or SAVR procedures during the analytic period.

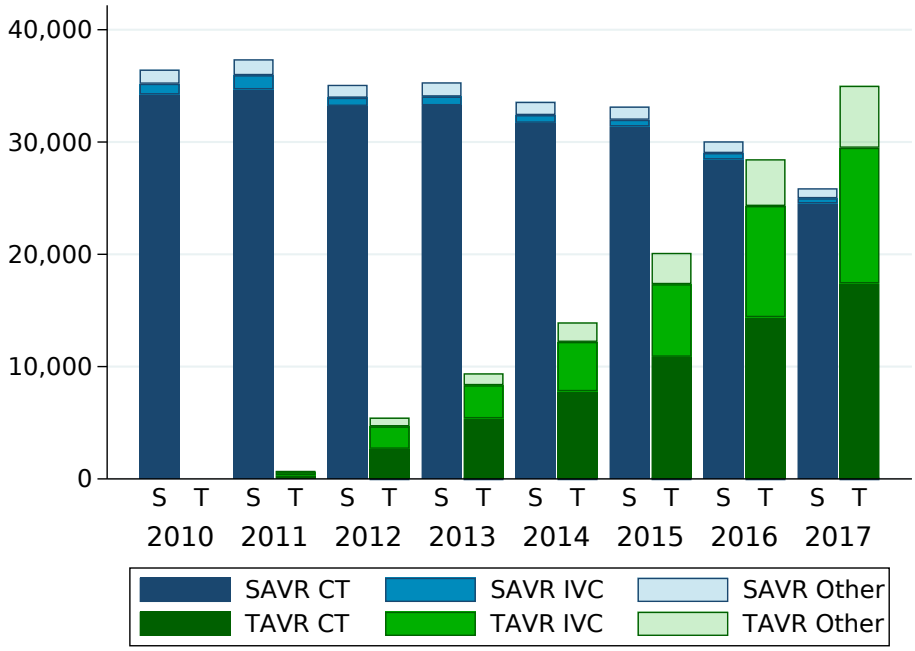
A.2 Figures

Figure A.1. 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.

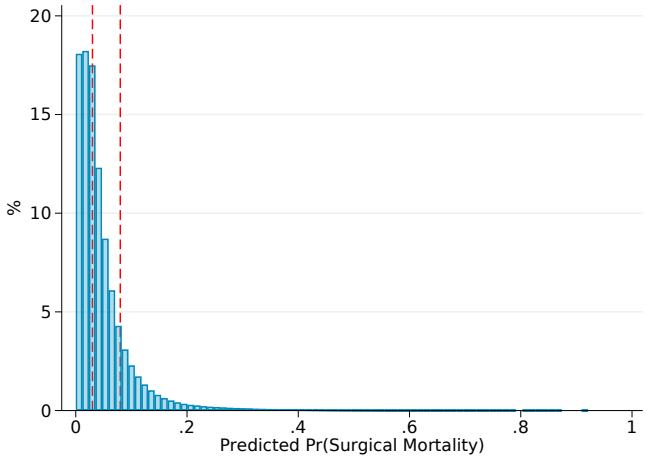
Figure A.2. Timeline of TAVR Adoption



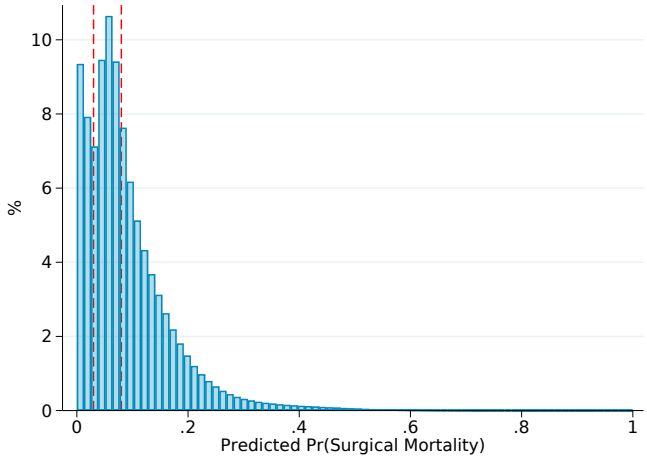
Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic 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 A.3. Predicted Patient Risk of Surgical Mortality (STS-PROM)

(a) Pr(30-Day Mortality)

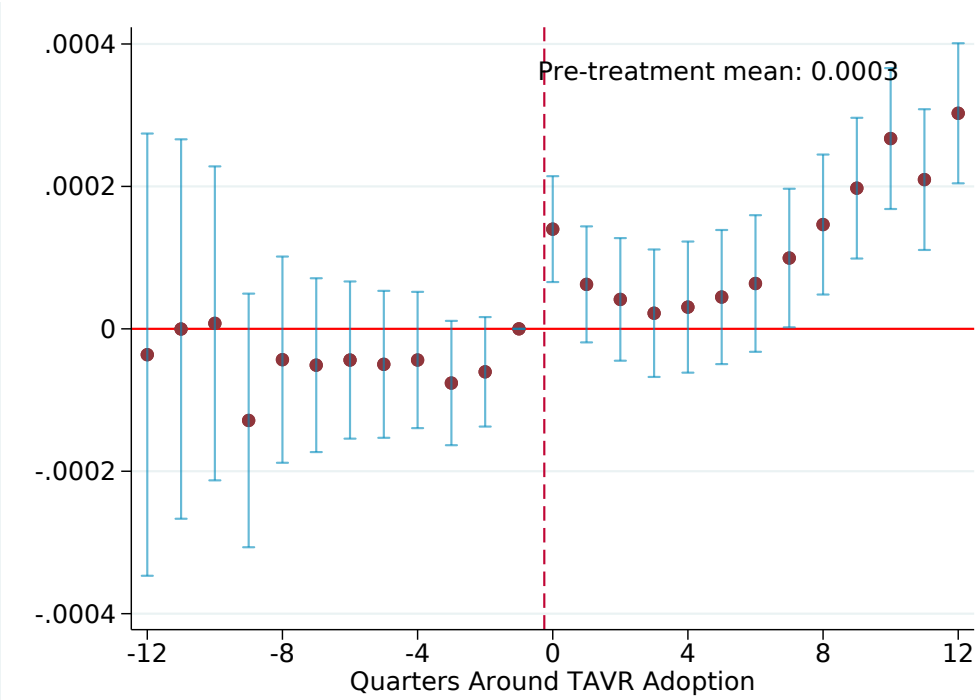


(b) Pr(90-Day Mortality)



Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table A.4.

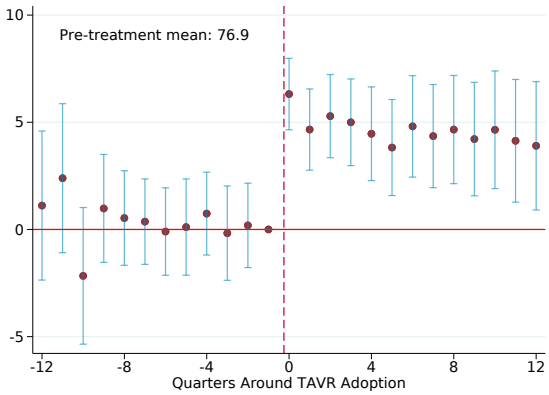
Figure A.4. TAVR Adoption Increases Individual Probability of SAVR/TAVR Surgery



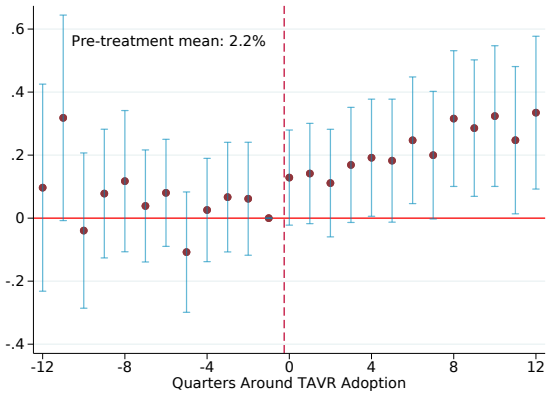
Notes: Figure shows estimated likelihood of an individual patient receiving valve replacement surgery (TAVR or SAVR) following TAVR adoption in their market. Surgical candidates are identified using the diagnostic codes associated with TAVR, SAVR, or PCI procedures in the Medicare data. Standard errors are clustered at the commuting zone level.

Figure A.5. Effect of TAVR Adoption on Average Age/Risk of TAVR/SAVR Patients

(a) Patient Age



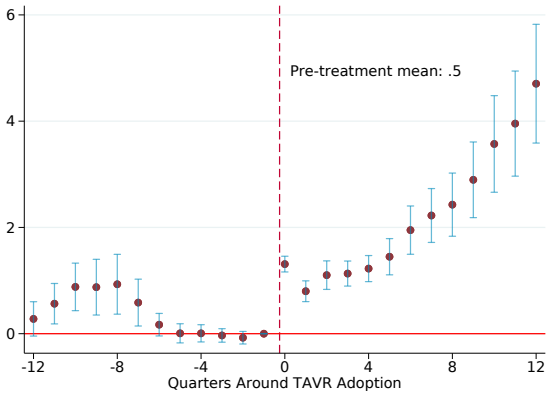
(b) $\sinh^{-1}$(30-Day Patient Risk)



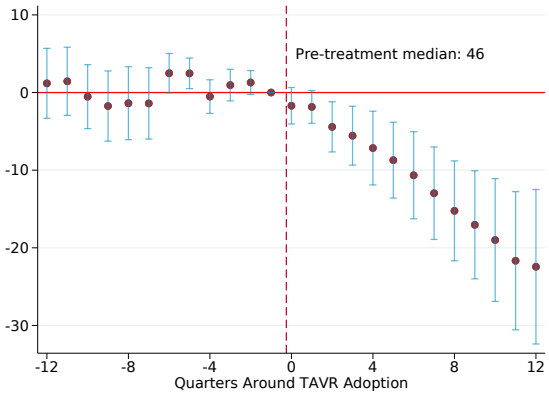
Note: Figures show effect of TAVR adoption at the CZ level on estimated age and risk for patients receiving high-intensity heart surgeries (TAVR and SAVR). Panel (a) shows the effects on patient age, while panel (b) shows effects on the inverse hyperbolic sine of 30-day STS-PROM risk score (hence, coefficients are roughly interpretable as percentage changes; see (Bellemare and Wichman, 2020)). Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

Figure A.6. IVC Surgical Volume Responses to TAVR Adoption, Commuting Zone Level

(a) SAVR/TAVR Surgeries

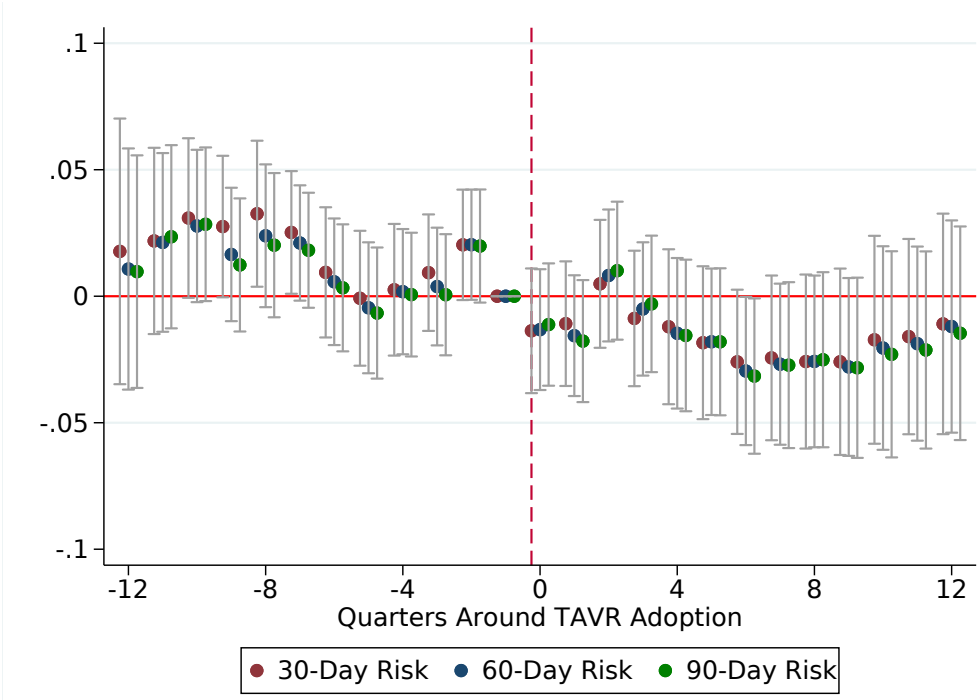


(b) PCIs



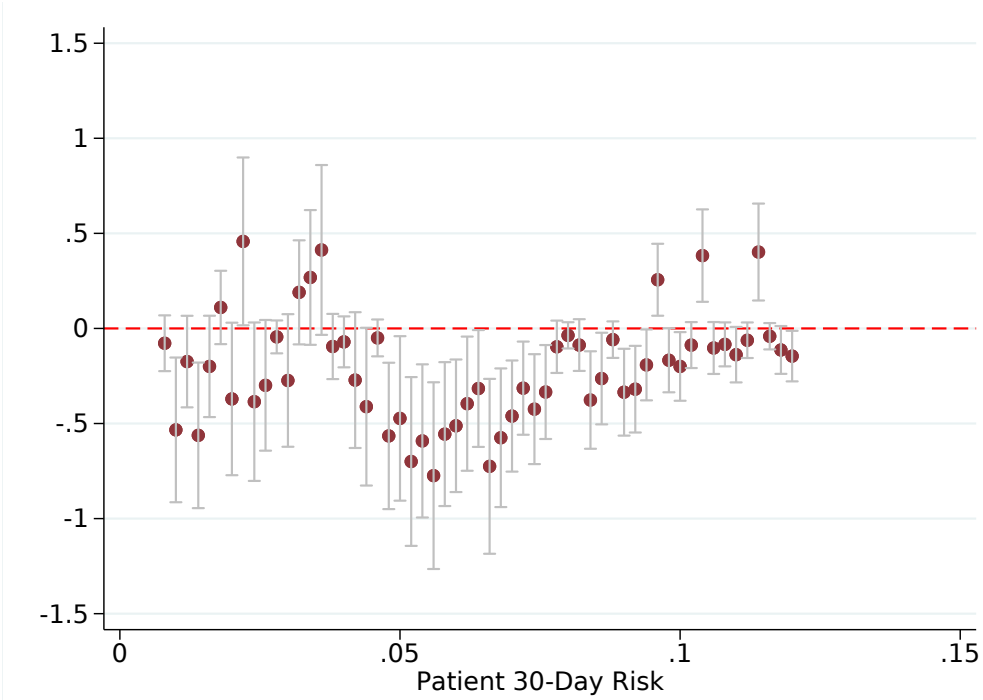
Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs. Panel (a) shows the effect on all SAVR/TAVR surgeries, and panel (b) shows the effect on PCI procedures. Markets with fewer than 10 inpatient surgeries per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

Figure A.7. Effect of TAVR Adoption on Average Risk of PCI Patients



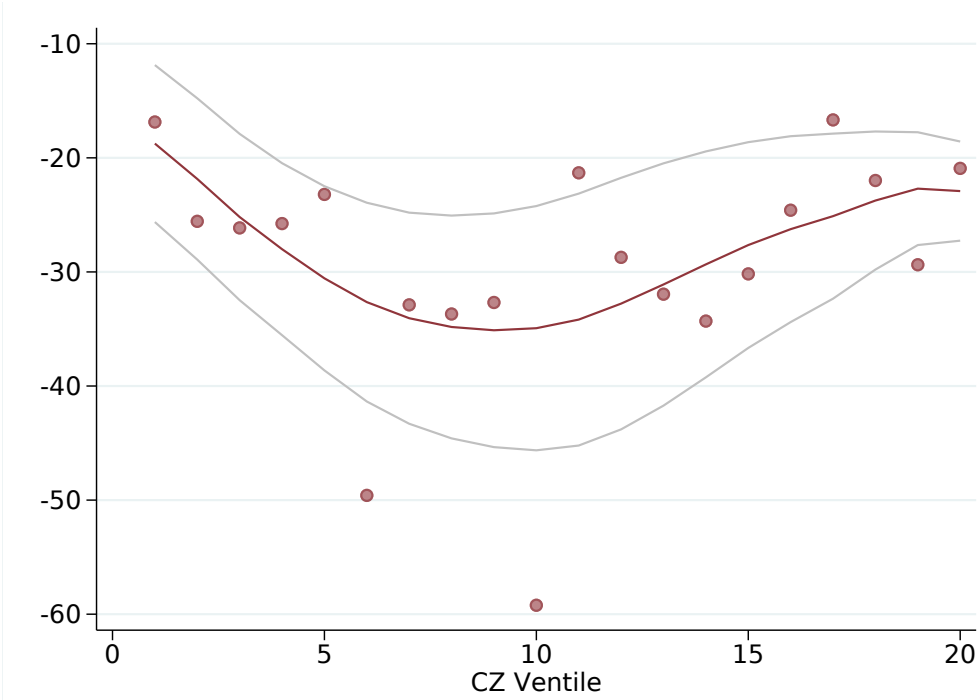
Note: Figure shows effect of TAVR adoption at the CZ level on estimated mortality risk (STS-PROM) for patients receiving low-intensity treatments (PCI). Figure shows results for 30-, 60-, and 90-day predicted risk. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

Figure A.8. Heterogeneous Effects of TAVR Adoption on Surgical Volumes by Patient Risk



Note: Figure shows estimated heterogeneous treatment effects of TAVR's adoption on total surgical volume for patients in different risk bins. STS-PROM risk is binned (width=0.2 percentage points); each point represents a difference-in-differences coefficient of TAVR's adoption on surgical volume within the bin. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008) and Benjamini et al. (2006). Markets performing fewer than 10 surgeries per quarter are dropped. Vertical lines indicate STS-PROM delineation between low-risk patients (3%) and high-risk patients (8%). Compare with Figure 4.

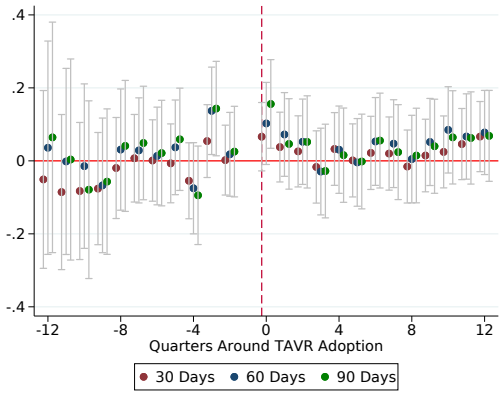
Figure A.9. Potential Inequitable Effects of TAVR Adoption on Surgical Volumes: Dual-Medicaid Eligibility



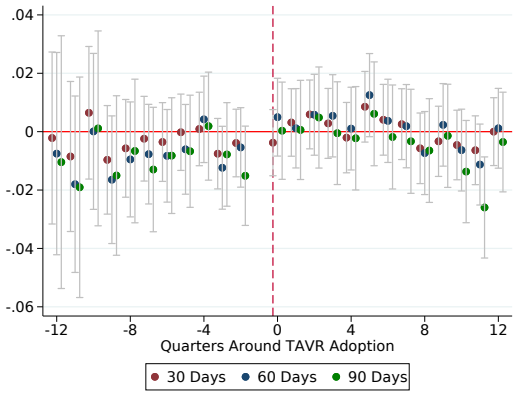
Note: Figure show heterogeneous effects of TAVR adoption on total volumes of valve replacements in a commuting zone. CZs are binned by ventiles according to the fraction of patients in a market who are dually-eligible for Medicaid. Each point represents a difference-in-differences coefficient; effects are smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008) and Benjamini et al. (2006). Markets performing fewer than 10 surgeries per quarter are dropped. Compare with Figure 5.

Figure A.10. Effect of TAVR Adoption on PCI Surgical Outcomes

(a) Readmission

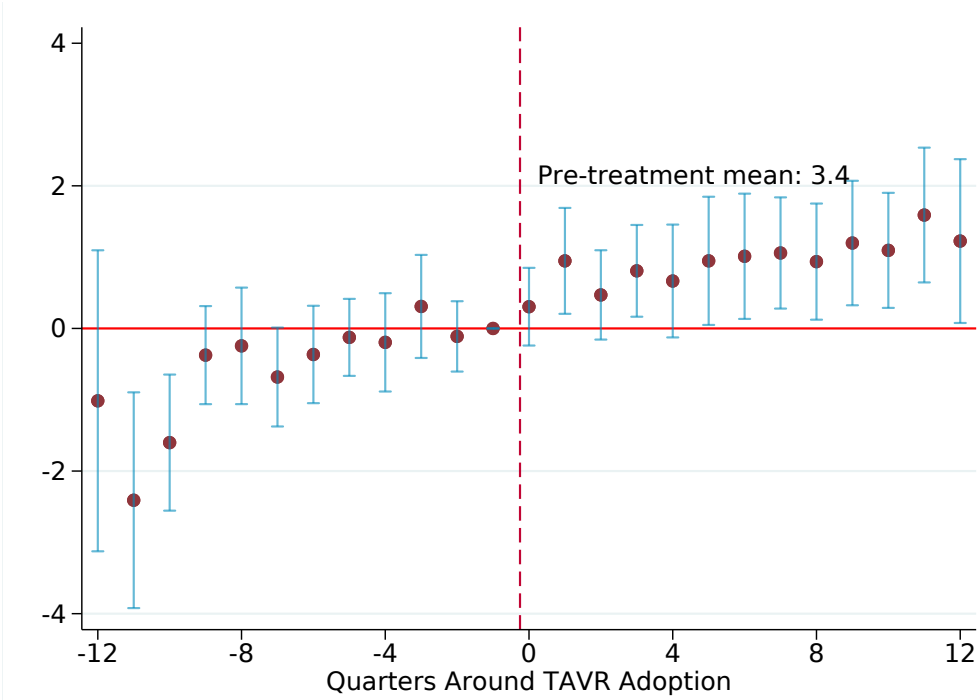


(b) Mortality



Note: Figures show effect of TAVR adoption at the CZ level on readmissions (panel A) and mortality (panel B) following PCI procedures. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

Figure A.11. Effect of TAVR Adoption on Screening for Surgical Viability



Note: Figure shows effect of TAVR adoption at the CZ level on the fraction of IVCs performing Computed Tomography Angiography (CTA) screening to diagnose aortic stenosis and discuss valve replacement surgeries (CPT code 71275). Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.