Innovations and Inequities in Access to Medical Services*

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Abstract

Improving returns on health spending requires balancing tradeoffs between promoting innovative treatments and equitable access to care. In addition to being cost-prohibitive, innovation adoption may reduce the availability of older, adjacent services through either specialist skill degradation or capacity constraints. These spillover effects may lead to overall reductions in access to care, possibly exacerbating allocative inefficiencies and health inequities. I propose a model of physician specialization to study these effects. When innovations compete for inputs to other procedures, total access to care drops, causing some patients to forego care altogether. This crowd-out may be inequitably borne across patient groups or markets. I apply the model to aortic valve replacement and support interventions, showing that innovation reduced intervention volumes and exacerbated allocative inefficiencies, particularly for patients of marginalized groups.

Keywords: Innovation Diffusion, Health Inequities, Capacity Constraints, Physician Skill, Allocative Efficiency

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 returns from improved health and insurance value from reduced population risk (Murphy and Topel, 2006; Lakdawalla et al., 2017). 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, can be inaccessible to lower-income individuals immediately following adoption, generating well-documented financial barriers to care (Hoagland and Kipping, 2024; Arcaya and Figueroa, 2017). In addition to financial considerations, the indirect effects of innovations may also alter access to other, existing technologies. These effects vary based on the characteristics of the innovating technology. On the one hand, technological advancements may expand access to earlier, now cheaper, generations of a technology; for example, innovation in durable goods markets such as MRI machines may reduce the price of older models and subsequently, improve access (Gowrisankaran and Rysman, 2012). On the other hand, some innovations may instead inhibit the availability of older technologies, thereby reducing overall access. This occurs insofar as an innovation competes with other health interventions for scarce inputs, such as capacity-constrained physician or operating room time (Gandhi, 2023; Kalouptsidi, 2014) or physician learning and skill development (Chandra and Staiger, 2007; Gong, 2018).

Importantly, if an innovative intervention limits the availability of an existing technology, the result may be reduced *overall* access to either technology, resulting from a confluence of two mechanisms. First, hyper-specialized physicians facing capacity constraints may respond to innovations by becoming more selective in performing older procedures. Second, if physicians benefit from specialization, reduced availability may be compounded by a loss of skill, leading to volume reductions for older techniques that outpace innovation take-up.[1] The result of this process may be that patients lose access to specialized treatment entirely, with unique impacts on equitable access to healthcare and allocative efficiency. To ensure procedural innovations maximize social welfare gains, it is important to understand under what conditions these inefficiencies or inequities arise and how severe their effects might be.

I present a model of physician decision-making characterizing these effects. Physicians select one of three treatments for patients: two interventions of different intensity (in the

[1] "Hyper-specializing" may allow hospitals and medical professionals to achieve higher-quality outcomes (Clarify Health Institute, 2023).

empirical setting, a high-intensity aortic valve *replacement* or a lower-intensity aortic valve *support* procedure), and standard maintenance care. The model incorporates technological spillovers—meaning treatment returns increase with volume (Chandra and Staiger, 2007, 2016)—and constraints on the total availability of interventions. Innovations that increase returns to high-intensity procedures change decision-making along two margins. First, some intermediate-risk patients are sorted into higher-intensity interventions, decreasing the use of lower-intensity procedures and corresponding returns for inframarginal patients continuing to receive them. Second—and more surprising—reduced returns result in some high-risk patients no longer receiving any intervention at all.

The model's central insight is that extensive margin changes may inequitably affect some patient groups and exacerbate allocative inefficiencies across markets. Inequitable crowd-out may arise directly—because different groups have different surgical appropriateness—or indirectly—because risk is imperfectly observed across groups. To the extent that this crowd-out is more common in markets that already have low thresholds for treating patients, these unequal or inequitable losses may drive a further wedge exacerbating allocative inefficiencies in which patient groups receive care both within and across local markets.

I empirically test these predictions using the dissemination of transcatheter aortic valve replacement (TAVR) procedures in the US. TAVR is a minimally invasive and cost-effective alternative to open-heart surgery treating aortic stenosis; importantly, TAVR expanded both supply and demand for valve replacements, as it is performed by interventional cardiologists (instead of only cardiothoracic surgeons) and is appropriate for patients deemed too high-risk for traditional open-heart surgery. Hence, I use TAVR's adoption in a local market as a shock to the high-intensity intervention in the model. TAVR's adoption has been used previously to study physician learning and centralized access to innovations (Yang, 2023) and hospital- and market-level adoption decisions (Huckman and Stern, 2022; League, 2023).

I estimate how TAVR's adoption affected the availability of lower-intensity procedures, focusing on the provision of valve support interventions (percutaneous coronary interventions, or PCIs). Although adjacent to—not replaced by—TAVR, I observe the provision of PCIs falls dramatically following adoption, causing *total* procedural volume to decline by roughly 8%. This validates the model predictions: patients foregoing care are higher risk—on the extensive margin of selecting any intervention—and inequitable differences are observed both within and across markets. TAVR's effects are most pronounced for markets with greater health deprivation or a greater share of nonwhite patients; even within a market, patients living in more disadvantaged zip codes or hailing from historically marginalized racial and ethnic groups are more likely to lose access to care. Importantly, patients most likely to lose access to PCIs post-adoption also resided in markets with lower risk-adjusted treatment

thresholds, meaning they were the least likely patients to receive interventions conditional on risk even *prior* to TAVR's adoption. This suggests these spillover effects may exacerbate allocative inefficiencies, rather than reallocate resources away from overuse of unnecessary or lower-return PCIs.

I find evidence that both physician skill degradation and capacity constraints are important potential mechanisms driving these effects (Kleiner, 2019; Harris et al., 2020). TAVR's adoption led interventional cardiologists to hyper-specialize either in providing PCIs or TAVRs, resulting in fewer operators providing a high volume of PCIs and potentially affecting quality. When examining PCI outcomes directly, I find TAVR's adoption by an individual operator leads to a 15% increase in 30-day post-operative mortality and a 5% increase in complication rates, driven primarily by increased transfusion rates. These effects are driven by operators who specialized in TAVR post-adoption; indeed, PCI operators in the bottom quintile of adoption intensity experienced improved PCI outcomes. Second, I show capacity constraints—primarily the use of the catheterization lab—also affected volume. After TAVR's adoption, fewer individual patients received care in catheterization labs each quarter, but total utilization—measured either in dollars or inpatient days—was unchanged.

The model and empirical findings fit into a discussion of the potentially unequal impact of technological change (Skinner and Staiger, 2015; Gans, 2024). Although much of this discussion studies skilled-biased innovations in the factor market (Violante, 2008; Acemoglu and Restrepo, 2020), recent work explores innovation's impacts on product markets, arguing the endogenous direction of innovation results in products aimed at higher-income households (Faber and Fally, 2022; Jaravel, 2019). This directed technological change is also prevalent in healthcare, where market size and patient incomes drive entry decisions for pharmaceuticals, medical devices, and clinical trial funding (Acemoglu and Linn, 2004; Moradpour and Hollis, 2020; Ji and Rogers, 2024). The flow of health innovations is also sensitive to market features such as insurance coverage (Agha et al., 2022), procurement environments (Clemens and Rogers, 2020), and tax incentives (Gamba et al., 2021; Yin, 2008).

My work highlights previously overlooked spillover effects of innovation, including the effects of skill degradation and capacity constraints on allocative inefficiencies and health inequities. These effects arise because economies of scale cause an innovation shock in one sector to affect technological returns in another, reducing patient welfare in possibly unequal ways. Recent work has studied how innovations may change incentives and endogenous behaviors, such as the decision to join a waiting list for an organ transplant post-innovation (Callison et al., 2023). In contrast, my work identifies how the features of innovations and the supply thereof may affect returns to care, exacerbating inefficient allocations of resources and disparities in accessing treatment. Finally, my work is related to a broader discussion on

how physicians respond to medical innovation (DeCicca et al., 2024; Barrenho et al., 2024).

I present the first theoretical framework for considering equity impacts of health innovations, contributing to literature on both health innovation and equity. Recent work has explored policies to equitably improve access to high-value services through physician payments (Kaarboe and Siciliani, 2023) or limiting geographic variation in service provision (Chandra et al., 2022). I argue technological advancement contributes to these disparities, modeling responses to susceptible innovations. These disparities in access to healthcare have been shown to cascade into other forms of inequality, including educational and income inequality and allocative inefficiencies (Chandra and Staiger, 2016; Kotschy, 2022). I examine how these spillover effects from innovation are related to typical measures of allocative efficiency, including new methodologies estimating market-specific value added in healthcare (Einav et al., 2022; Olenski and Sacher, 2024; Hull, 2020) and education (Abdulkadiroğlu et al., 2020; Koedel and Rockoff, 2015).

Health disparities have increased in recent years, with some groups even experiencing disproportionate decreases in life expectancy (Case and Deaton, 2015; Olshansky et al., 2012). I find procedural innovations are not guaranteed to improve efficient and equitable access; this is related to previous work studying the spillover effects of health events (Fadlon and Nielsen, 2019; Hoagland, 2024) and differences in policy outcomes across patient groups, including race and ethnicity (Singh and Venkataramani, 2024). Policymakers aiming to improve equitable access to innovative care may widen their focus beyond accessing innovations alone, considering broader protections to limit unintended spillovers. Rather than reducing or regulating the flow of welfare-improving innovations, policies supporting appropriate infrastructure to scale up an innovation without skill degradation or crowding out older procedures may limit these effects, particularly in the short run. For example, promoting thicker markets for interventional cardiologists or investments in catheterization labs may have helped to offset the spillover effects of TAVR's adoption.

Using TAVR as a case study underscores that inequities arise primarily when innovations compete with older technologies for scarce inputs. These results are therefore generalizable to a broader class of innovations, including procedural healthcare innovations, which are understudied relative to pharmaceutical developments (Dranove et al., 2022; Trajtenberg, 1989). However, results may also apply to a more expansive set of innovations, such as developments in education (Biasi et al., 2021; Biasi and Ma, 2022).[2] Finally, my work is related to discussion of identification of treatment effects across multiple margins of impact

[2]For example, recent work considers detrimental effects of broadband internet in primary schools (Belo et al., 2014), noting that technology is not equitably accessible (Supovitz and Manghani, 2022; Bacher-Hicks et al., 2021). If innovations in classrooms directly compete for other resources—e.g., teacher attention—expanded internet-based learning may inequitably disrupt student learning.

(Mountjoy, 2022).

2 Setting and Data

2.1 Adoption of TAVR

Aortic stenosis is a serious condition affecting 1.5 million people in the US; untreated, its 5-year survival rate is roughly 20% (Rosalia et al., 2023). It is the most common heart valve condition and the third most common cardiovascular disease (after hypertension and coronary artery disease) in the world. Subsequently, more than 80,000 surgical aortic valve replacements (SAVRs) were performed annually in the US prior to TAVR's adoption in 2011. During SAVR, a cardiothoracic surgeon removes the damaged or diseased aortic valve in an open heart surgical procedure, and installs a new valve; this process typically requires a 5-7 day hospital stay and a prolonged recovery period.

TAVR is a minimally-invasive alternative to SAVR, relying on transfemoral placement of an expandable valve instead of open-heart surgery. Numerous randomized trials have indicated that TAVR is noninferior among patients at intermediate or high risk for mortality from SAVR (Leon et al., 2016) and, subsequently, low-risk patients (Mack et al., 2019). The first TAVR device (Edwards-SAPIEN) received approval from the Food and Drug Administration for high-risk patients in November 2011 (Dvir et al., 2012); over time, TAVR's use has expanded to include lower-risk patients, outpacing SAVR as the leading surgical approach in 2017 (D'Agostino et al., 2018). Conditional on risk, TAVR is considered a cost-effective alternative to SAVR (Baron et al., 2019). However, important access gaps persist, with fewer than half of patients needing a valve replacement receiving either type (Li et al., 2022).

The adoption of TAVR is ideal for studying the potentially unequal impacts of innovation for two reasons. First, TAVR was market-expanding: the total number of valve replacements in the US increased by two-thirds between 2010 and 2017, with the number of operating surgeons nearly doubling (Appendix Table A.1). This increase in the total addressable market provided incentives for physicians to alter practice styles, similar to expansions of PCIs in the 1990s (Cutler and Huckman, 2003).

Second, TAVR disrupted the supply of valve replacement surgeries and procedures: whereas SAVR could be performed only by cardiothoracic surgeons, TAVR is performed by a team of surgeons and interventional cardiologists (Adams et al., 2014). Importantly, these two specialists receive differentiated training: after residency, interventional cardiologists complete three years of cardiology fellowship and an additional year specific to interventional cardiology, while cardiac surgeons complete six to seven years of cardiothoracic

surgery fellowships (Huckman and Stern, 2022). These unique training paths allow surgeons to hyper-specialize in different approaches at the expense of other skills. By 2017, 20% of TAVRs were performed by interventional cardiologists (Appendix Figure A.1), highlighting the comparative advantages of the two interventions (Breg, 2022).

2.2 Data

I assess the impact of TAVR adoption for traditional Medicare patients seeking cardiology care using fee-for-service (FFS) claims data from 2010 to 2017. I identify the receipt of SAVR, TAVR, and other interventional cardiology care using 100% of the Inpatient Encounters and 20% of the Outpatient and Carrier Encounters. I also use 100% of the Beneficiary Summary Files and the Medicare Data on Provider Practice and Specialty (MD-PPAS) files to obtain information on the patients, their providers, and the local markets in which they reside; this includes patient risk and demographic information including race, sex, dual eligibility, area-level disadvantage scores, and risk score (Ellis et al., 2022).[3]

Procedure Definitions. I define both valve replacement procedures and valve support procedures, in keeping with the model presented below in Section 3. Valve replacement procedures include procedures where the aortic valve is fully replaced, including SAVR (the original open-heart surgical method) and TAVR (the innovative, minimally-invasive alternative). Valve support procedures include all valve-related cardiac procedures to treat patients who are not candidates for a complete replacement. The most common of these procedures are angioplasty (also referred to as percutaneous transluminal coronary angioplasty, or PTCA), coronary artery bypass grafting (CABG), and cardiac catheterization. Pre-TAVR, these revascularizations and other interventions were used as a lower-intensity alternative for patients too high-risk for open surgical replacements (Goel et al., 2012b). Appendix Table A.2 defines the relevant codes used to identify both valve replacements and valve supports. For market-level analysis, I restrict the relevant procedures to those performed by interventional cardiologists, in order to most closely match the predictions of the model; when performing analysis at the patient level, I include all procedures regardless of physician specialty.

Healthcare Market Definitions. I define local markets at the commuting zone (CZ) level. CZs are geographically contiguous groups of counties within which residents typically commute (for example, to work), and are constructed based on Census commuting flow data. I assign CZs based on patient residence to avoid problems of market definitions should

[3]Note that this data excludes individuals enrolled in Medicare Advantage plans. See Appendix Table A.2 for the relevant procedure codes. Disadvantage scores are from the Neighborhood Atlas' Area Deprivation Index, which ranks zip codes by socioeconomic disadvantage given income, education, employment, and housing quality (Kind and Buckingham, 2018).

patients travel to another market to receive a preferred procedure (Dingel et al., 2023).[4] There are roughly 700 CZs commuting zones in the 2020 definition (Fowler et al., 2016); of these, 452 are included in my sample, as I require a market to perform at least 5 interventions annually. Similar work in this area has used commuting zones as reasonable definitions of local labor markets for hospitals and physicians (Prager and Schmitt, 2021; Rinz, 2018). Within each market, I define the timing of TAVR adoption based on the first documented procedure in the CZ.

Patient Definitions. I observe the full volume of patients receiving care in inpatient settings, but only 20% of outpatient procedures. Although TAVR, SAVR, and other PCIs were typically performed in inpatient settings between 2010–2017, more recent years have seen these procedures trending to outpatient settings. In part, this was intended to reduce the costs of these procedures, with initiatives such as the Recovery Audit Program and the 2-midnight rule providing incentives to switch these procedures to outpatient settings in conjunction with fee changes for PCIs (Blankenship and Marshall, 2013). However, it wasn't until after outcome differences were rigorously examined with the EXCEL trial—published in 2021, well after my analytical sample—that this change began in earnest (Gaba et al., 2021). To accommodate potential bias from excluding unobserved interventions, I conduct analysis at two levels: the market level using the universe of inpatient encounters, and the patient level across the entire 20% sample of Medicare beneficiaries.[5]

For patient level analysis, I measure intervention rates per 1,000 beneficiaries, using the full 20% subsample; I do not attempt to limit the denominator to only patients who are candidates for intervention, as identifying medically-managed patients with aortic stenosis is difficult in claims data. Aortic stenosis is a common condition among elderly patients, but typically is of minor severity; hence, patients may not have appropriate diagnostic information included on claims, as it may be undiagnosed or superseded by other conditions (Chiang et al., 2016; Hoagland et al., 2024). Furthermore, many of the patients with aortic stenosis on their chart may not realistically be candidates for interventions, given that their condition is likely not severe enough to warrant the risks of a procedure. Despite these concerns, my results are robust to limiting patient-level denominators to patients with an observed aor-

[4]Note, however, that roughly 0.68% of interventional cardiology procedures in the sample occur outside a patient's home CZ. I discuss robustness checks accommodating both potential for patient and physician migration in Section 5. For reference, the commuting zones providing the average number of PCIs in the sample are Appleton-Oshkosh-Neenah, Wisconsin; Bloomington, Indiana; and Springfield, Massachusetts. These regions provide roughly 300 PCIs each quarter over their complete patient population, roughly 50 of which are for patients enrolled in fee-for-service Medicare.

[5]I observe no significant relationship between the timing of TAVR's adoption and shifts to outpatient settings in my data, providing reassuring evidence that the parallel trends assumption needed for identification is likely not violated. However, I report both market- and patient-level analysis as a robustness exercise.

tic stenosis diagnosis prior to interventions. My main sample includes 10,874,161 Medicare patients, of whom 1,343,580 have an aortic stenosis diagnosis.[6]

2.2.1 Summary Statistics.

Table 1 presents relevant summary information across valve replacements and supports. Valve replacements are roughly four times costlier than valve support procedures, including for both SAVR and TAVR. Note that TAVR is performed on riskier patients than SAVR (a difference of 0.72 percentage points, or 15.8%), with the average risk of a TAVR patient more comparable to the average risk of a PCI recipient. TAVR is also performed on older patients (an average age of 82.8 years for TAVR compared to 78.6 years for SAVR), but otherwise there are few observable differences in patient demographics across valve replacements during the year of adoption. Despite these differences in patient risk and age, TAVR achieves comparable outcomes to SAVR even in the first year of adoption.

The table also highlights the inherent complexity of defining "alternative" treatments in this context. I use valve support procedures—including PTCA, CABG, and cardiac catheterization—as lower-intensity treatments compared to SAVR and TAVR. This comparison is imperfect in several ways. First, not every observed PCI is directly treating aortic stenosis; many PCIs are performed for patients with stable or unstable angina or following an acute myocardial infarction (AMI) (Goel et al., 2012a). Some valve supports, such as balloon valvuloplasty, are integral procedures required in performing TAVR; balloon valvuloplasty or coronary angioplasty were also commonly-performed even pre-TAVR for high-risk patients. Throughout, I study a broad set of interventional cardiology procedures to capture overall shifts in accessibility of treatments beyond just aortic stenosis patients. Second, some valve support procedures are higher risk (and hence, costlier) than others, the clear example being CABG. In general, the set of all valve supports (of which CABG constitutes only 1.3%) is still used on lower-risk patients than SAVR, and with generally lower readmission and mortality risk. Finally, there may be evolving standards of care for performing these valve support procedures which are happening simultaneously with TAVR's diffusion. For example, the 2007 COURAGE trial found that PCI did not reduce the risk of death, acute myocardial infarction (AMI) or major cardiovascular events for patients with stable coronary artery disease (CAD) (Boden et al., 2007). This is credited with sparking a reduction in PCI use over the next several years (Almarzooq et al., 2021; Carpenter et al., 2022). I discuss the identification concerns surrounding these changes in PCI use in Section 5.

[6] Aortic stenosis diagnoses are identified in the data using ICD-9 codes 395.0, 746.3, 396.2, and 424.1, and ICD-10 codes I06.0, I06.2, I35.0, and Q23.0. Note that this is a prevalence rate of about 12.4%, roughly in line with estimated AS prevalence (Osnabrugge et al., 2013).

	Valve Replacements			Valve Supports			
	All	SAVR	TAVR	All	PTCA	Cath.	CABG
Panel A: Procedure Costs and Risks							
Billed Cost	$62,542	$65,999	$60,018	$14,973	$16,870	$9,549	$41,718
	($562)	($965)	($657)	($31)	($41)	($33)	($440)
Patient 30-day Mortality Risk	5.02	4.61	5.33	5.75	5.50	5.90	4.58
	(0.076)	(0.108)	(0.104)	(0.013)	(0.019)	(0.025)	(0.076)
Readmission	20.48	20.11	20.77	13.79	15.28	16.41	11.98
	(0.790)	(1.193)	(1.052)	(0.078)	(0.131)	(0.150)	(0.632)
Mortality	5.02	5.05	5.17	4.79	2.91	3.39	3.91
	(0.427)	(0.652)	(0.574)	(0.048)	(0.061)	(0.073)	(0.377)
Panel B: Patient Demographics							
Age	81.0	78.6	82.8	73.0	72.5	71.5	71.9
	(0.17)	(0.27)	(0.20)	(0.02)	(0.04)	(0.04)	(0.15)
Female	0.43	0.41	0.45	0.44	0.39	0.49	0.29
	(0.010)	(0.015)	(0.013)	(0.001)	(0.002)	(0.002)	(0.009)
Black Non-Hispanic	0.03	0.03	0.02	0.10	0.07	0.12	0.06
	(0.003)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Hispanic	0.00	0.00	0.00	0.01	0.01	0.01	0.01
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)
Other Minority Race	0.02	0.03	0.02	0.03	0.03	0.03	0.03
	(0.003)	(0.005)	(0.004)	(0.000)	(0.001)	(0.001)	(0.003)
Dually Eligible for Medicaid	0.12	0.10	0.13	0.23	0.20	0.26	0.12
	(0.006)	(0.009)	(0.009)	(0.001)	(0.001)	(0.002)	(0.006)
Total Volume, Adoption Year	2,612	1,129	1,488	196,514	75,530	60,858	2,637
Total Volume, Full Period	42,194	5,166	37,075	1,441,703	1,019,417	502,077	18,833

Notes: Table shows summary statistics from relevant cardiology procedures from 2010–2017, with standard errors in parentheses (Procedures are defined in Appendix Table A.2). Means and counts are shown for the year of TAVR adoption (defined at the CZ level) to illustrate differnces at the time of innovation. Cath. refers to cardiac catheterization. Patient risk is predicted using the STS-PROM model with 30-day mortality as the outcome; patient readmission and mortality rates are also reported at the 30-day level.

Table 1. Summary Statistics: Procedures

3 Model

Suppose there is a continuum of patients suffering from a single disease. Patients and physicians—acting jointly—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 ($s = 2$).[7] Empirically, $s = 2$ corresponds to valve replacements (SAVR/TAVR) while $s = 1$ corresponds to valve supports (PCIs).

A procedure's patient-specific appropriateness depends on a risk index θ_{is} for patient i, where increasing θ_{is} indicates higher levels of predicted surgical risk.[8] Hence, individuals with lower levels of θ_{is} receive more intensive treatment. The expected utility of a procedure U_{is} is given by

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

where P_s represents the fraction of a patient's market receiving treatment s and ε_{is} represents an idiosyncratic, unobserved shock affecting patient-procedure matches. Equation 1 incorporates productivity spillovers in the second term, in the style of Chandra and Staiger (2007); if $\alpha_s > 0$, increased local use of s improves average outcomes regardless of θ_{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.[9] Patients then choose treatment only along two margins: a choice between valve replacement and valve supports, or a choice between supports and no intervention. 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 distribution of θ_i, this probability is given by:

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

[7] The model can be enriched to study physicians as imperfect agents (Chandra et al., 2011), as discussed below.

[8] Note that θ_{is} can also include additional clinical information outside of mortality risk, such as diagnostic severity, the presence of comorbidities, or other indicators for clinical appropriateness of treatment. In practice, θ_{is} is not perfectly observed, but may be proxied by a set of observable characteristics Z_{is}; the results of the model are not dependent on the choice of θ_{is} or Z_{is}.

[9] That is, I assume $|\partial U_{i2}/\partial\theta_2| > |\partial U_{i1}/\partial\theta_1| > |\partial U_{i0}/\partial\theta_0|$. This implies steeper indifference curves for more intensive treatments, all things equal.

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

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

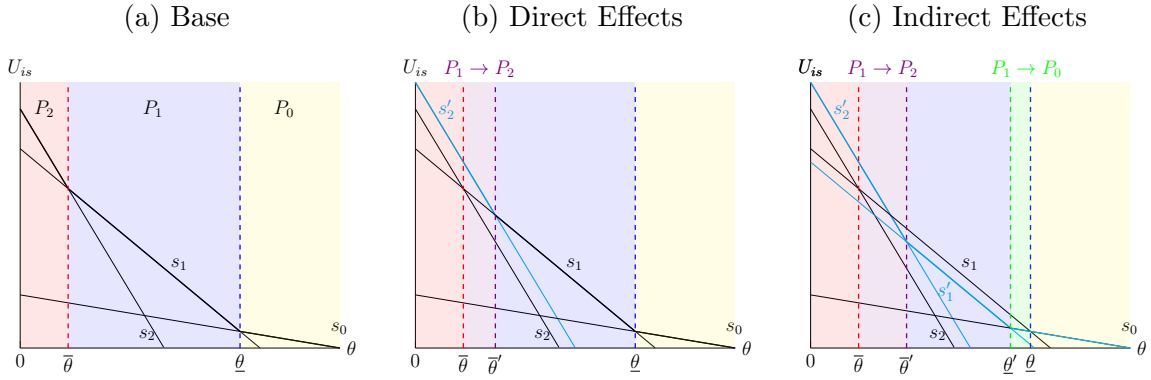
The equilibrium at the market level is therefore defined as a fixed point that solves the system of equations:

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

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

An equilibrium can be conceptualized in a 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, further shifting patients and returns until a stable equilibrium is reached.

Figure 1. Treatment Decisions Based on Patient Risk



Notes: Graphical illustration of model equilibria pre- and post-innovation. Panel (a) presents treatment utilities given θ prior to innovation, which define treatment regions for s_2 (red, P_2); s_1 (blue, P_1); and s_0 (yellow, P_0). Panel (b) presents direct effects of innovation, which changes the threshold between high- and low-intensity interventions (captured in purple). Panel (c) highlights indirect effects, where spillover externalities result in movement from s_1 to s_0 (captured in green).

Figure 1 (a) plots $U_s(\theta_i)$ for each s, illustrating the allocation of patients to treatments. Overall, utility is declining in risk, with steeper declines for more intensive interventions by assumption. This creates three well-defined treatment regions: low-risk patients select s_2, moderate-risk patients select s_1, and high-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, $\{\overline{P}_0, \overline{P}_1, \overline{P}_2\}$.

This simple setup for the model can easily be extended in a number of ways. Most importantly, in addition to returns from physician skill, one can incorporate capacity constraints in the model by augmenting the system in Equations 4 and 5 to include a constraint of the form $\lambda_1 \cdot P_1 + \lambda_2 \cdot P_2 \leq c$, where λ_i indicates the relative time cost associated with each intervention type and c indicates some upper limit on the total availability of care, measured in physician hours. Immediately, one can see that imposing these constraints will only serve to exacerbate the effects of innovations discussed below. Second, abstracting the model away from physicians as perfect agents is straightforward. Partially altruistic physicians may respond to a weighted average of expected patient outcomes (Equation 1) and additional incentives, including financial remuneration and non-pecuniary incentives such as hospital policies. However, incorporating these results are not critical to the main findings.

3.1 The Effect of Innovations

Consider an innovation—such as TAVR—in high-intensity treatments, s_2. TAVR's adoption can be characterized as a uniform cost reduction across θ without affecting survival utility (Section 2); hence suppose U_2 shifts by a fixed τ.[10]

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 to s_2' directly attracts patients who switch from low-intensity intervention (shown in purple). This flow changes the returns to s_1, lowering expected returns even for inframarginal patients who continue to receive valve supports.[11]

Importantly, these spillover externalities result in further increases in U_2 and decreases in U_1. Panel (c) shows these indirect effects as two separate flows out of s_1: some into s_2 ($P_1 \to P_2$, shown in purple) and others into s_0 ($P_1 \to P_0$, shown in green). These indirect effects may be further exacerbated depending on the presence of capacity constraints, as mentioned above. The new equilibrium has updated risk thresholds $(\overline{\theta}', \underline{\theta}')$.

Notably, the shift in $\underline{\theta}$ defines a share of patients who now forego treatment. To quantify this crowd-out, note that the risk thresholds $\overline{\theta}$ and $\underline{\theta}$ are defined, in expectation over ε (and

[10] τ need not be constant for results to hold, but is assumed to be fixed here for ease of exposition.

[11] In general, an innovation might provide productivity benefits even for adjacent incumbent technologies; for example, performing TAVR might enhance surgical skill for other PCIs. In practice, these procedures are fundamentally different within interventional cardiology: for example, TAVR involves the inflation and placement of a new aortic valve in a patient's heart, while catheterization requires using guide wires from a different insertion site to remove blockages. Given that spillovers *across* interventions are likely significantly smaller than spillovers *within* an intervention type, these can be differenced out in the model without loss of generality. I test directly for these types of effects empirically in Section 5.2.

in the absence of capacity constraints), by

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

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

This system of equations defines comparative statics measuring how risk thresholds change with an innovation's value τ:

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

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

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 represent post-innovation reductions in productivity spillovers for both s_0 and s_1. The right side captures differences in the marginal utility of each treatment. Hence, crowd-out occurs when the marginal utility gains from receiving any surgical intervention (the switch from s_0 to s_1) outweigh the losses from diminished productivity spillovers for s_1. As utility gains from treatment tend to be large relative to provider specialization, this condition is likely to be met in many cases.[12]

3.2 Allocative Efficiency & Equitable Access

These spillover effects of an innovation may indicate allocative inefficiencies, where either some patients were receiving too much care prior to an innovation's arrival, or too few patients received care following its adoption. Alternatively, the changes in volume may simply reflect changes in productive efficiency, including the comparative advantage of a specific market or its operators. Identifying whether patients affected by crowd out were being overtreated prior to adoption or are losing access following it is important for understanding the

[12] For example, however, innovations requiring extensive physician re-training with uncertain clinical benefits may not generate these effects.

normative implications of these spillover effects; this is particularly relevant if the affected patients differ systematically from unaffected patients, potentially affecting differences in allocative efficiencies across patient groups.

Separating out allocative efficiencies from these alternative explanations typically requires additional parametric assumptions (Chandra and Staiger, 2016). However, an informative, assumption-free test for the effect of an innovation on allocative inefficiences uses the fact that an innovation's impact will be different across markets, as each market will have a different equilibrium allocation of patients across treatments. By comparing, then, the effects of an innovation on crowdout across markets with different underlying thresholds for treating patients, one can determine the *direction*—if not the level—of allocataive inefficiencies. Formally, given that patients select interventions based on the condition in Equations 2 and 3, a patient in market CZ receives any intervention if

$$\begin{aligned} U_{i1} - U_{i0} &\geq 0 \\ \Rightarrow \beta_{10}\theta_i + \underbrace{\alpha_{10}P_{1,CZ} + \alpha_0 P_{2,CZ} - \alpha_0}_{\varphi_{CZ}} &\geq \varepsilon_{10}. \end{aligned} \tag{12}$$

That is, patients receive interventions based on a combination of their own clinical needs or underlying risk and market-specific factors dictating returns to treatment.[13] Denote by φ_{CZ} the value of these productivity spillovers and any additional market-specific differences in treatment thresholds; these values represent risk-adjusted treatment rates after controlling for patient characteristics in θ_i. Then, considering only the extensive margin decision of receiving any intervention, the coefficients $\vec{\varphi}_{CZ}$ in Equation 13 indicate market-level differences in treatment propensity, conditional on patient characteristics:

$$\Pr(s_i \in \{1,2\}) = \Pr(\text{Any Treatment}_i = 1|\theta_i) = F(\beta\theta_i + \varphi_{CZ}). \tag{13}$$

In Equation 13, local markets with a higher treatment threshold conditional on patient risk would have a positive value for φ_{CZ}, while negative coefficients would indicate a lower probability of treatment.[14] In the context of the spillover effects of innovation, the correlation between crowd-out propensities and φ_{CZ} coefficients is particularly informative: if they trend positively (meaning that the crowd out region grows for markets with higher treatment

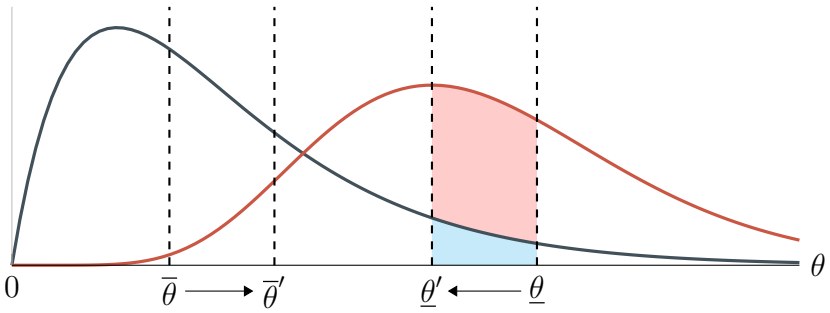
[13]Recall that one can expand θ_i to be a vector of clinical characteristics as well as surgical risk.

[14]This estimation is a simple version of the value-added estimation methods used to identify the value of healthcare facilities (e.g., SNFs, hospitals) or teachers in the education literature (Hull, 2020; Einav et al., 2022; Koedel and Rockoff, 2015). Previous work has expanded this framework to isolate levels of allocative inefficiencies across markets (Chandra and Staiger, 2016). Here, I simply use relationships between these estimated treatment thresholds and market characteristics (as well as to the estimated effects of TAVR's adoption) to identify how innovations change the direction of allocative efficiency in a market.

thresholds), innovation adoption may be reducing already existing over-utilization in some markets. On the other hand, if patients are more likely to be crowded out of care in markets with already low treatment thresholds, the observed spillover effects may constitute nontrivial reductions in access, potentially perpetuating allocative inefficiencies.

Inequalities and Inequities in Crowd-out. Any loss in efficient access to specialty care may be considered a market distortion. However, these losses may differ substantially across patient groups, particularly if groups have heterogeneous risk; losses may be further exacerbated if some groups have systematically misperceived risks.

Figure 2. Inequities in Crowdout



Notes: Graph shows potential differences in which patients forego 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).

Figure 2 presents the intuition for potential inequalities arising from the spillover effects of an innovation's adoption.[15] The figure illustrates two hypothetical patient groups with different distributions of risk, θ_i. The figure also shows the crowd-out region affected by an innovation (Figure 1). Even when risk is correctly measured, these groups have different likelihoods of losing access to specialty treatment, simply by virtue of having different underlying risk distributions. However, these inequalities may further correspond to *inequities* in access when risk distributions are imperfectly or incorrectly observed.[16]

3.3 Empirical Implications

The model predicts that innovations may generate spillover health inequities in two steps. First, innovations affect technological spillovers and create "crowd-out regions," shifting high-risk patients out of interventions. Second, these affected patients may be systematically different from the overall population, particularly if risk is incorrectly proxied. This loss in

[15] Appendix Section A.3 formalizes these results.

[16] Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019). See Appendix Section A.3 for further discussion about the effect of imperfect risk proxying on crowd-out.

access, particularly in relationship to a market's propensity to treat patients conditional on their risk, may leave some patients differentially unable to access specialty care.

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; this is done by examining intervention volume both overall as well as by intervention type. Second, I then identify *which* patients are affected based on their risk, paying particular interest to the existence and magnitude of crowd-out regions. I examine whether crowded-out patients are inequitably made up of different demographic groups, including patient race, income, and ADI. Finally, I identify the potential normative implications of this crowd-out by relating treatment effects to estimated treatment thresholds across markets.

4 Methods

I assess the effects of TAVR's adoption on access to valve replacements (SAVR and TAVR) and valve supports (PCIs) within a local market. This adoption may change patient and physician decision-making in response to treatment availability and the (potentially market-varying) estimated returns to each procedure.

4.1 Estimating Patient Risk

Cardiac surgery risk is typically estimated using models constructed by The Society of Thoracic Surgeons (STS), accounting for pre-operative factors that influence surgical outcomes (O'Brien et al., 2009). I use the STS Predicted Risk of Mortality (STS-PROM) model, a logistic regression of mortality on demographics and clinical information (Appendix Table A.3). The model classifies patients into low risk (score $\leq$ 3%), moderate risk (score between 3% and 8%), and high risk (score $\geq$ 8%). Traditionally, SAVR is limited to low-risk patients, while PCIs can be done on higher-risk patients. The empirical distribution of predicted risk in my sample closely matches population STS-PROM predictions: 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 (Appendix Figure A.2).

4.2 Effect of Innovations

To estimate the causal impact of TAVR's adoption on treatment decisions, I use a local projections difference in differences (LP-DID) estimator (Dube et al., 2023), a "stacked" regression of treated units combined with their clean controls to estimate treatment effects without bias from naive staggered adoption designs with heterogeneous treatment effects

(Roth et al., 2023). The regression uses local projections methods to restrict the estimation sample so that previously-treated observations (which may be experiencing time-varying or heterogeneous treatment effects post-adoption) are not included in the control group, eliminating bias. The LP-DID regression performs similarly to other approaches in this context, including weighted stacked DID regressions (Wing et al., 2024; Cengiz et al., 2019) and imputation estimators (Sun and Abraham, 2020; Callaway and Sant'Anna, 2021). Formally, for h periods pre- and post-treatment, I estimate the equation

$$y_{CZ,t+h} - y_{CZ,t-1} = \beta_h^{\text{LP-DID}} \Delta D_{CZ,t} + \alpha_{CZ} + \tau_t + \varepsilon_{CZ,t}^h, \tag{14}$$

where the sample is restricted to newly treated ($\Delta D_{it} = 1$) or clean controls ($\Delta D_{i,t+h} = 0$). Outcomes include intervention volumes at the market CZ level and treatment decisions for patients i, with periods separated into quarters t. I cluster standard errors at the CZ level, and report pooled estimates of post-treatment effects with each regression.[17]

Throughout, the identifying assumption is that the timing of TAVR's adoption within a local market is exogenous for PCI operators, in the sense that there are parallel trends and no anticipatory changes in valve *support* procedures. That is, my approach requires the assumption that interventional cardiologists did not adopt TAVR due to underlying changes in the expected volume of patients seeking PCIs, or change PCI volumes preemptively anticipating adoption. While hospitals certainly made strategic decisions about TAVR adoption based on anticipated valve replacement volume, my estimation is well-identified provided there were no spillovers anticipating these events. This can be examined directly by assessing differential pre-trends between adopting and non-adopting markets.

This identifying assumption may be violated if, for example, contemporaneous changes to physician practice affected PCI volumes close to the time of TAVR adoption. This could arise from two channels: first, individual organizations may change their supply of procedures around the time of TAVR adoption. For example, facilities responding to TAVR's adoption in their market may change the volume of PCI procedures offered in anticipation of future demand for procedures ocurring in a catheterization lab. I examine this directly in the data and do not observe such anticipatory behavior, either for a market's first adopters or those that adopt later (Appendix Figure A.3).

Second, PCI takeup may have declined contemporaneously with, but independently of, TAVR's onset. For example, a critical 2007 randomized control trial (the COURAGE trial) indicated PCIs did not meaningfully reduce mortality or cardiovascular risk for patients

[17]Effects were estimated using the LPDID package in Stata (Busch and Girardi, 2023); this also allows for using an average of pre-treatment observations as the baseline reference period to avoid the inefficiencies associated with using a single pre-treatment period as the baseline, as discussed in Dube et al. (2023).

with stable coronary artery disease (Boden et al., 2007). This led to declines in PCI utilization over the next decade (Almarzooq et al., 2021; Yeh et al., 2015). If these reductions occurred in tandem with TAVR's adoption, this could bias regression estimates. Several factors, however, make this trial—or other general trends in PCI provision—unlikely to drive my observed results. First, shifts in practice began immediately following the COURAGE trial, with the bulk of changes occurring prior to 2010 (TAVR was adopted beginning in 2012). Second, given the staggered adoption design, PCI volume declines would need to be observed in tandem with TAVR's adoption; this is unlikely as it would require markets to be simultaneously late adopters of the PCI practice change and early adopters of TAVR. Finally, I show in the next section that my results are robust to excluding patients with stable coronary artery disease, the patient population affected by this change.

4.3 Heterogeneity & Inequities in Post-Innovation Access

After assessing the impacts of TAVR on access to interventions both at the market and patient levels, I examine how treatment effects varied across three dimensions: geography, socioeconomic status, and race and ethnicity. I use the Area Deprivation Index (ADI) score for 9-digit zip codes to define differences in geographic vulnerability both across and within markets. I also measure how many enrollees are dually-eligible for Medicaid to proxy for socioeconomic status, and measure racial diversity in a market as the fraction of nonwhite enrollees in a region. To identify heterogeneous treatment effects, I bin markets and estimate traditional difference-in-differences regressions, adjust these results for multiple inferences using sharpened false discovery rate control methods (Anderson, 2008).[18] Where applicable, I smooth these results using weighted local nonlinear regressions.

5 Results

5.1 Effects of TAVR's Adoption on Overall Intervention Volumes

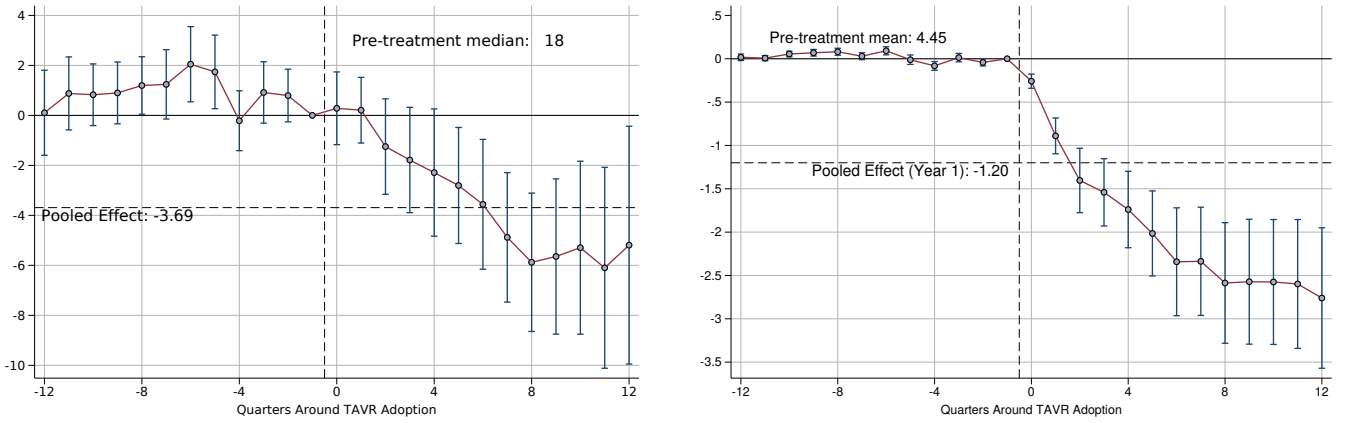
Figure 3 presents the dynamic effects of TAVR adoption on interventional cardiology procedures at the commuting zone and patient levels. Prior to adoption, I observe no meaningful variation in procedure volumes: the pre-treatment pooled LP-DID estimate at the CZ level is 0.558, with a 95% confidence interval of $[-0.576, 1.692]$. However, post-adoption I observe a marked decline in total intervention volume, with average volume dropping by 3.7 interventions quarterly in a market, or 14.8 interventions annually. This is roughly 7.8% (20%) of

[18] Results are robust to using average "pooled" LP-DID effects instead of DID coefficients.

the total volume of the average (median) commuting zone, which performs 47.3 (18) procedures per quarter. These effects are first observed one year after TAVR's adoption, becoming more pronounced within the first three years post-innovation. I observe similar effects at the patient level: an individual's probability of receiving any interventional cardiology procedure in a given quarter declines by 27.0% in the first year, or by a rate of 1.20 per 1,000 patients from a baseline of 4.45 per 1,000. The patient-level analysis includes outpatient procedures as well as inpatient interventions, suggesting that the observed results are not driven by unobserved shifts of PCIs to being performed in outpatient settings during my analytic period; if anything, the market-level results are a lower bound for true declines in volume.

Figure 3. Effect of TAVR Adoption on Total Intervention Volumes, Commuting Zone Level

(a) Market Level (# of Inpatient Procedures) (b) Patient Level (Rate of Interventions/1,000 patients)



Notes: Estimated impact of TAVR adoption on (a) total volume of intervention interventions performed by interventional cardiologists in a local market and (b) the rate of any valve intervention at the patient level per 1,000 patients (both follow Equation 14). Both outcomes include all valve interventions performed including valve replacements (SAVR/TAVR) and valve supports (PCIs). Markets performing fewer than 5 inpatient procedures quarterly are dropped from estimation. Rates in panel (b) are calculated using the full population from the 20% subsample of Medicare beneficiaries as the denominator. Standard errors are clustered by commuting zone in both panels.

Overall changes in intervention volume conflate both increases in valve replacements post-TAVR and changes in PCI availability. In Appendix Figures A.4, I disaggregate these overall effects across specific interventions at the market level.[19] Valve replacement takeup increased by 1.48 valve replacements quarterly on average; this is in keeping with the model's predic-

[19]The figure shows results for valve replacements (SAVR/TAVR), angioplasty (PTCA), cardiac catheterization, and all other PCI interventions; each of these last three groups constitutes roughly one-third of all valve supports in our sample. Note that only 213 patients in my sample (.02%) received more than one valve replacement; hence, the observed results are unlikely driven by repeat patients. Importantly, only 5.6% of SAVR patients in the sample required a follow-up PCI prior to TAVR's adoption; this indicates that the declines here are unlikely to be driven by TAVR's adoption reducing the need for follow-up PCI interventions following a valve replacement. Patient level results are similar.

tions (Figure 1). As predicted, this expansion moved the threshold for valve replacements down the patient risk distribution, with TAVR's adoption expanding replacement procedures to patients that were 4.1 years older and 1.5 percentage points higher-risk on average.

On the other hand, TAVR's adoption led to overall declines in other intervention volumes that outpaced the takeup of valve replacements. I observe average reductions of 3.7 PTCAs and 2.6 other PCI interventions per quarter, with no significant effects on cardiac catherization.[20] This implies that between 4 and 5 valve supports were eliminated for each TAVR procedure adopted by the average CZ, roughly consistent with the cost differential across PCIs and TAVR.

One might be concerned that the observed results may be driven, at least in part, by differential migration of patients or physicians in response to TAVR's adoption. For example, if patients begin flocking to early-adopting regions to receive TAVR, these regions may experience sharp declines in availability of other procedures; on the other hand, if interventional cardiologists move their practice to take advantage of TAVR, their home CZ may experience short-run declines in surgical availability. In Appendix Figure A.5, I document a strong negative relationship between a CZ's total TAVR volume post-adoption and changes in total intervention volume over time. This suggests two things: first, TAVR's effects are concentrated in the CZ where it is taken up, with limited spillovers across geographies; and second, CZs which invested more heavily in TAVR experienced larger declines in intervention volume.[21] Second, Appendix Table A.4 estimates the impact of TAVR's adoption on both patient and physician migration as well as the likelihood of receiving interventional cardiology services outside of a patient's home market; I do not observe TAVR's adoption affecting any of these measures, which already occur infrequently even prior to adoption.

Another possible interpretation is that these results constitute only transitional, short-run effects. Initial declines in volume could represent time spent building up capacity to accommodate both TAVR and PCI patients in the long-run, after which these declines would dissipate. Although short-run effects are interesting and important in their own right—particularly to the extent that they exacerbate inequitable health outcomes across patient groups, as discussed below—I do not observe evidence to suggest that these effects are merely transitory. For example, long-run versions of Figure 3 indicate intervention volumes maintain or even increase their decline through five years post-adoption (Appendix Figure

[20]Note that there are significant pre-trends for PTCA effects; this may be related to either investment costs as TAVR is preparing to be deployed in a region, or strategic delays in valve replacements for some patients until after TAVR becomes available. These differences, however, appear to be anticipation effects that would serve only to understate true declines in overall volume that are highlighted here.

[21]I observe these reductions even for CZs with low TAVR takeup rates, suggesting that outliers are not driving my results. I discuss this more in the next two paragraphs.

A.6). Additionally, transitional effects driven by short-run capacity constraints would be expected to affect prices for interventional cardiology services, particularly driving them up for patients with more elastic demand or those who face more cost-sharing, such as commercially-insured patients (Anderson et al., 2024). In Appendix Figure A.7, I show that prices for these interventions do not change post-adoption, suggesting that my effects are likely not driven by short-run adjustments to PCI prices, or even to a potentially mis-priced initial payment for TAVR.[22]

These results are robust to multiple alternative specifications. First, I report regression estimates using Poisson regression to examine whether reuslts are driven by markets with excessive pre-TAVR volume (Appendix Table A.5). Second, I consider the possible effects of changes in PCI provision following the COURAGE trial (see Section 4). In Appendix Figure A.8, I show removing PCI patients affected by this trial does not change the main results.[23] Finally, one might be concerned that the dynamic effects presented in Figure 3 may be endogenous to market characteristics, with some markets potentially adopting TAVR earlier than others in anticipation of potentially time-varying returns from investment. In general, this is unlikely to be a critical issue as over 50% of adoption occurred within the first year and 75% within two years. However, as a robustness check, in Appendix Figure A.9 I report results from a dynamic difference-in-differences specification that does not leverage variation in adoption timing across markets, but rather compares intervention volumes between ever-adopting and never-adopting markets relative to TAVR's FDA approval in the last quarter of 2011. I observe similar declines in total intervention volume—particularly after the first two years of approval—even using this design.[24]

Finally, I test how TAVR's adoption affected patient-physician interactions and heterogeneity across patient severity. I highlight two facts in the Appendix: first, interventional cardiologists are roughly 72.5% more likely to screen patients for valve replacement appro-

[22]I use the Merative data on commercially-insured patients across the US to obtain commercial PCI prices (measured as the sum of insurer and enrollee payments). Average Medicare payments are based on the relevant DRGs for each procedure. Once adjusted for linear increases over time, neither commercial nor Medicare prices change meaningfully over the post-adoption period, particularly in the short run.

[23]The COURAGE trial led to reductions in the availability of elective PCI for patients with stable angina or stable coronary artery disease. These patients are identified based on diagnosis codes (ICD-9-CM: 413.9; ICD-10-CM: I20.8, I20.9) anywhere in the first ten diagnoses; this is likely a conservative approach, as this also removes patients with medical histories of stable angina.

[24]I also examine whether the effects may be driven by patients enrolled in Medicare Advantage (MA) plans, whose claims do not appear in the data. If adopting CZs also experienced the largest growth in MA enrollment, the observed decline in service provision could arise mechanically and independently of TAVR's adoption. Using Medicare Enrollment Dashboard data, I find weak *negative* relationships between MA enrollment growth and TAVR's adoption; after conditioning on a set of controls including the fraction of beneficiaries with aortic stenosis, average intervention volumes in the pre-period, and patient and provider demographics (including risk), these relationships are statistically insignificant.

priateness post-adoption, suggesting physicians adapt their diagnostic screening strategies to available interventions (Mullainathan and Obermeyer, 2021) or to information about treatment options (Hoagland et al., 2024) (Appendix Figure A.10). Second, I also show that while TAVR reduced the overall availability of PCIs, urgent PCIs—including angiography for patients immediately following a heart attack—were not delayed (Appendix Figure A.11).

5.2 Mechanisms Affecting PCI Availability

My results suggest strong effects of TAVR's adoption resulting in reduced availability of valve support procedures and interventional cardiology more generally. As the model suggested, these reductions may, in part, be driven by features of the innovation that compete with adjacent technologies for scarce inputs, including physician skill and operating room capacity.

Physician Skill Degradation. First, I examine potential changes in physician skill following TAVR's adoption. The intuition here is that as operators increase the time dedicated to learning a new procedure (TAVR), the returns to performing PCI may decline. Immediately following TAVR's adoption, I observe that interventional cardiologists adapt by hyper-specializing in either TAVR or PCI provision (Appendix Figure A.12). While TAVR's adoption leads to reductions in the average number of PCIs per operator by 0.66 PCIs (13.2%), operators who continue to perform PCI increase their volume by 3.44 procedures quarterly, or nearly 50%. This may be due to minimum-volume rules requiring PCI and TAVR operators and organizations to provide at least a certain number of procedures annually, providing an incentive for specialization (Yang, 2023; Rashid et al., 2016).

This bifurcated response to the innovation may affect the overall quality of PCIs, perhaps differently across operators (Kleiner, 2019). I investigate TAVR's effect on a suite of PCI outcomes including mortality, intervention complications, PCI failures, and readmissions. Table 2 presents the results. For each outcome, I report TAVR's effects in percentage changes, pooled across all interventional cardiologists and then stratifying based on an operator's relative intensity of TAVR adoption. Given that intervention complications are generally quite rare, the statistical power to detect small changes in these rare events is limited. Even still, several results stand out.

First, 30-day (all cause) mortality following PCI increases by 15% with complication rates increasing by 5%. Complication rate increases are driven almost entirely by increases in needed transfusions during a PCI.[25] Second, these effects differ across operators based on

[25]Transfusions during PCIs are linked to increased risk of other complicating events, including strokes and myocardial infarctions; the baseline rate of 4.8% is within the typical reported range for the incidence of transfusions for PCI among the elderly (Kwok et al., 2015). The overall 30-day mortality rate post PCI observed here (4.3%) is well within the range of previous work on PCI mortality among the elderly, which has found ranges between 1.6% and 17.9% (Tran et al., 2019; Hannan et al., 2023; Shanmugam et al., 2015).

	Baseline	Pooled	Quantiles of TAVR Specialization				
PCI Complication	(rate/1,000)	Effect	Q1	Q2	Q3	Q4	Q5
Panel A: Mortality							
30-day mortality	43.19	0.15*	0.05	0.28*	0.23	0.11	-0.01
		(0.060)	(0.105)	(0.118)	(0.139)	(0.106)	(0.261)
Panel B: Surgical Complications (0-30 days)							
Arterial embolism	5.80	0.10	0.25	0.18	0.26	-0.42	0.16
		(0.157)	(0.271)	(0.303)	(0.315)	(0.376)	(0.562)
Bleeding requiring transfusion	41.67	0.06*	-0.01	0.08	0.05	0.08	0.23***
		(0.027)	(0.047)	(0.059)	(0.046)	(0.064)	(0.061)
Cardiac tamponade	2.98	-0.05	-0.29	-0.17	0.13	0.17	0.09
		(0.175)	(0.365)	(0.427)	(0.247)	(0.354)	(0.462)
Cardiogenic shock	48.22	0.11	-0.08	0.23	0.24*	0.05	0.19
		(0.058)	(0.124)	(0.120)	(0.100)	(0.096)	(0.239)
Intracranial hemorrhage	16.96	-0.02	-0.12	-0.01	-0.06	0.02	0.29
		(0.095)	(0.129)	(0.141)	(0.206)	(0.290)	(0.347)
Readmission with heart failure	214.29	0.06**	0.04	0.10*	0.01	0.05	0.20*
		(0.022)	(0.040)	(0.042)	(0.046)	(0.046)	(0.096)
Readmission with myocardial infarction	259.12	-0.06*	-0.12**	0.02	-0.08	-0.01	-0.05
		(0.027)	(0.045)	(0.055)	(0.060)	(0.066)	(0.056)
Thrombosis	18.01	-0.08	-0.11	0.03	-0.12	-0.08	-0.13
		(0.084)	(0.170)	(0.208)	(0.131)	(0.141)	(0.351)
Panel C: Restenosis/Repeat Vessel Intervention (31-365 days)							
	45.69	0.03	0.09	-0.15	0.19	0.06	-0.33
		(0.066)	(0.100)	(0.160)	(0.151)	(0.127)	(0.175)
Panel D: Pooled Estimates							
All (panel A-C)	520.68	0.02	-0.11	0.05*	0.01	0.01	0.06*
		(0.014)	(0.026)	(0.026)	(0.032)	(0.030)	(0.030)
All, excluding readmissions	190.48	0.05*	0.001	0.07	0.07	0.05	0.09
		(0.022)	(0.044)	(0.047)	(0.046)	(0.039)	(0.065)

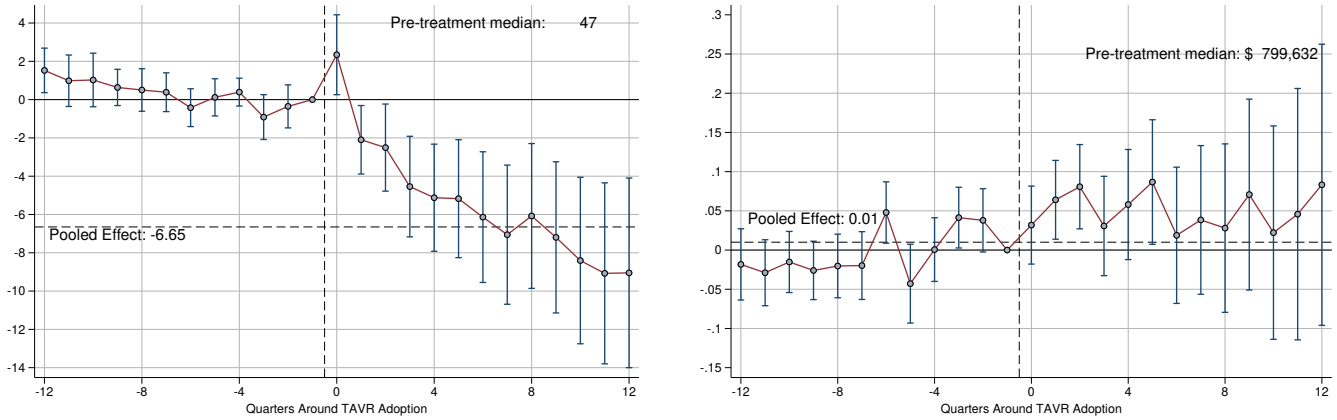
Notes: Table presents pooled LP-DID estimates of how TAVR's adoption affected a PCI operator's PCI outcomes for inpatient procedures (Table A.6 contains relevant codes used in defining complications). Effects are presented as baseline means (per 1,000 PCIs), pooled, and stratified by operators' specialization in TAVR (measured as the percentage of interventions devoted to TAVR post-adoption). Coefficients are rescaled relative to baseline means for comparability. Quantile ranges are: Q1 (0-1.7%), Q2 (1.7%-6.2%), Q3 (6.2%-13.8%), Q4 (13.8%-25.3%), and Q5 ($\geq$ 25.3%). Cardiogenic shock includes following myocardial infarction. "All, excluding readmissions" excludes readmissions within 30-days with diagnoses of heart failure or myocardial infarction. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

Table 2. Effect of TAVR's Adoption on PCI Outcomes

how much they specialized in TAVR post-adoption. For example, the increase in transfusions is concentrated entirely among PCI operators in the top quintile of take-up, with an increase of 23% in PCI transfusion rates. These operators also experience increases in patient readmissions for heart failure (20%); in contrast, PCI operators in the bottom quintile of adoption saw *reductions* in the rate of readmissions for AMIs. TAVR constitutes less than 2% of procedures for these operators, compared to over 25% for those in the top quintile. This divergent specialization appears to result in divergent outcomes for PCI patients.

Figure 4. Utilization of Catheterization Labs around Local TAVR Adoption

(a) Total # of Unique Patients Using Cath Lab (b) Total Utilization of Cath Lab (Medicare Charges)



Notes: Figure shows LPDID coefficients and 95% confidence intervals estimating the effect of TAVR adoption in a local market on utilization of catherization laboratories over time. Panel (a) measures the total number of patients receiving care in a cath lab in a given CZ-quarter; panel (b) measures utilization as the total volume of Medicare charges for patients receiving care in the cath lab (results here are robust to using Medicare payments or total Medicare inpatient days as alternative outcomes). Markets with fewer than 5 inpatient interventions per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

Physical Capacity Constraints. Second, I investigate differences in capacity constraints, estimating TAVR's effects on the utilization of catheterization labs in a commuting zone. These labs are examination and operating rooms where PCIs and TAVRs are typically performed; TAVR's adoption may consume valuable time in these labs and limit time for other procedures. Figure 4 illustrates that TAVR's adoption meaningfully reduced the total number of unique patients receiving care in a catheterization lab (panel a), while not affecting the total utilization of the lab (panel b).[26] The average number of patients receiving care in these labs declines by 14%, while total lab revenue is unchanged. This suggests capacity

Readmission rates are quite common in this population; hence, when estimating changes in all complications, I use a version of the outcome that omits readmissions to avoid overstating the results (Freites et al., 2023).

[26]Utilization is measured here in total charges; results are robust to using Medicare payments or inpatient days instead.

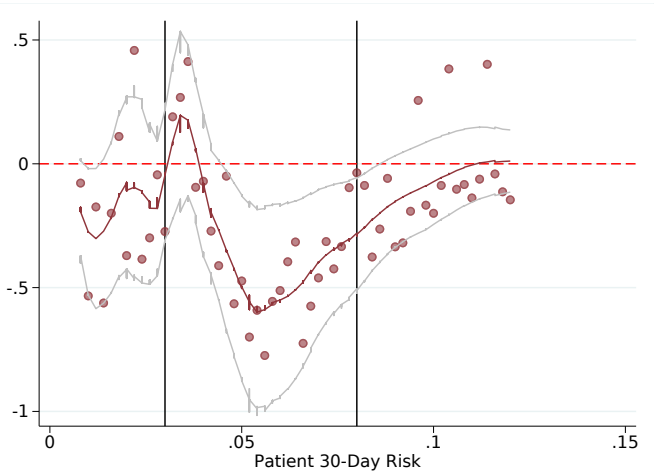
constraints, including for operating space, are binding in these markets, so that innovation adoption limits availability of other interventions.

Taken together, these results suggest that both changes to physician skill and physical capacity constraints may cause the overall declines in availability of PCIs following TAVR's adoption.

5.3 Which patients lose access to treatments?

These findings corroborate the model's predictions that patients will be crowded out from access to interventions. Next, I isolate which patients forgo interventions based on patient risk. Although TAVR increased the average risk of valve replacement patients, I do not observe corresponding increases in average risk for PCI patients. This suggests that the composition of PCI patients changed along *both* margins, with a corresponding exit of higher-risk patients as predicted by the model. I investigate this further, estimating treatment effects separately across bins of patient risk to identify the crowd-out region.

Figure 5. Effects of TAVR Adoption on Total Intervention Volumes by Patient Risk



Notes: Estimated effects of TAVR adoption on total intervention volume, stratifying patients by risk bin (width=0.2pp). Each point is a bin-specific difference-in-differences coefficient, with effects smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008; Benjamini et al., 2006). See Appendix Figure A.13 for non-smoothed version and Figure A.14 for a version scaled by overall decline in intervention volume. Vertical lines indicate STS-PROM delineation between low- and high-risk patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

Figure 5 shows the results across the distribution of 30-day risk. Each point in the figure represents an estimated DID coefficient; these effects are then smoothed using a local linear regression weighted by the number of patients in each bin, with standard errors corrected

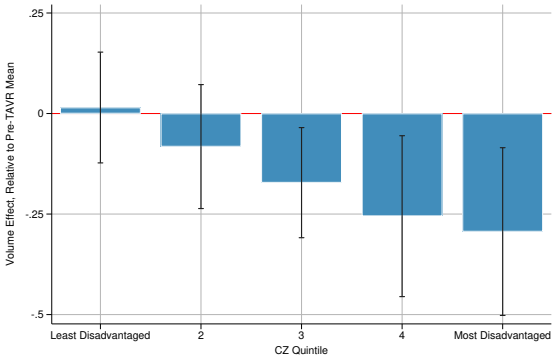
for multiple hypothesis testing.[27] The figure therefore identifies which patients experienced the largest declines in access to care following TAVR's adoption in their market.

The results corroborate the model predictions that patients on the margin between low-intensity procedures (valve supports) and maintenance care were more likely to forego care post-adoption. Figure 5 shows a clear region of patients crowded out from treatment, specifically those whose risk is between 4.5% and 9%. Patients in this group lost access to cardiac interventions at an average rate of 0.5 procedures per quarter per bin. I next consider how this lost access differentially affected vulnerable populations.

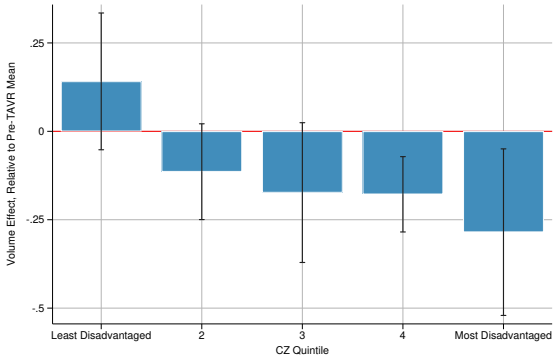
Market-Level Inequities. First, I consider how inequitable restrictions to access may propagate across markets, by considering market-level differences in patient populations. I sort CZs into quintiles based on the the share of nonwhite patients and the (population-weighted) average ADI across zip codes in a CZ, and then estimate TAVR's effects on total intervention volume within each quintile.

Figure 6. Inequities in TAVR's Effects on Local Access to Interventions: CZ Level

(a) % Non-white



(b) 9-digit zip code ADI



Notes: Heterogeneous effects of TAVR adoption on intervention volume across binned quintiles of CZs according to disadvantage, measured in (a) as the fraction of nonwhite patients, and in (b) as the average ADI in the market (based on 9-digit ZIP code ADI scores; results are robust to using 5-digit scores). Each point represents a "pooled" post-treatment LP-DID average effects, where the outcome is total intervention volume at the market level as in Figure 3. Outcome has be rescaled relative to pre-adoption mean for each quintile to facilitate comparisons (so coefficients represent percentage changes). In each regression, both treated and control groups are limited to the quantile of interest, so comparisons are between CZs within a specified category of (dis-)advantage. See Appendix Figure A.15 for results for dually-eligible patients. Results are robust to using standard difference-in-differences coefficients.

Figure 6 presents the results. In both panels, a clear gradient emerges: in panel (a), local markets with racial diversity above the median experience declines in volume over three times larger than the average decline, with a 25% reduction in total intervention volume relative to pre-TAVR levels. A similar result appears when examining local markets with limited

[27] Results are similar across 60- and 90-day risk. Appendix Figure A.13 presents a non-smoothed version.

employment, education, and housing, as measured by average ADI in panel (b).[28] If anything, I observe that the least disadvantaged markets may have experienced *increases* in total intervention availability, underscoring the importance of considering variation across markets as well as within them. Overall, vulnerable patient groups experienced larger declines in intervention volume post-adoption.

Patient-Level Inequities. Second, I consider how differences in patient characteristics may affect the dynamic treatment effects presented in Figure 3. In particular, the model predicts that even within a market, patients of different groups may be more or less likely to lose access to interventions. A within-market analysis limits the data to the 20% subsample of Medicare enrollees; I similarly stratify results on patient geography (zip-code level ADI), dual eligibility status, race/ethnicity, and sex (Section 2). Within each stratification, I report the pooled post-treatment from estimating Equation 14 separately across groups.

Table 3 presents the results. Overall, I observe a decline in total volume of 26.86% in the 20% sample of patients, consistent with the results presented in Figure 3. In general, patients in at-risk populations experience larger declines in access relative to majority populations. Patients living in areas of higher disadvantage in a CZ (panel a) experience larger effects from TAVR's adoption, with declines in intervention volume 4.4 percentage points larger for those living in the most disadvantaged decile of a CZ. I also observe that racial and ethnic minorities are 1.4 to 1.9 times less likely to receive interventions post-TAVR than non-Hispanic White patients; however, these differences are only significant for Hispanic patients (p=.037). I do not observe meaningful differences in TAVR's effects across patients based on their sex or dual eligibility for Medicaid.[29]

Overall, the estimates suggest that an innovation's adoption may affect equitable access to care within markets, particularly affecting patients living in geographically deprived regions or from marginalized racial and ethnic groups.

5.4 Allocative Inefficiencies

The relative impact of this crowd-out on patients depends, in part, on the degree to which care was efficiently allocated prior to TAVR's adoption. For example, if valve supports such as PCIs were over-used in some markets, the results in Figure 6 may not be welfare-decreasing (Chandra and Staiger, 2020). To address this, I examine differences in TAVR's effects across markets with different underlying propensities to treat patients of the same

[28] I also stratify markets by dual eligibility, finding little evidence of inequities along this dimension (Appendix Figure A.15).

[29] I also examined differences across patient age categories using quintiles, and did not find meaningful variation across patient age groups.

Group	Estimate	% Change	95% Confidence Interval	p-value, difference
Overall	-1.12	-26.86	[-32.59, -21.12]	—
Panel A: Patient Geography				
ADI: Lowest Decile	-0.12	-27.27	[-34.00, -20.55]	—
ADI: Highest Decile	-0.19	-31.67	[-38.89, -24.45]	0.050
Panel B: Patient Eligibility				
Not Dual Eligible	-0.84	-27.10	[-32.67, -21.53]	—
Dual Eligible	-0.29	-27.10	[-33.86, -20.34]	0.500
Panel C: Patient Race				
White	-0.54	-14.92	[-19.04, -10.80]	—
Black	-0.08	-23.53	[-31.66, -15.40]	0.133
Hispanic	-0.02	-28.57	[-51.25, -5.89]	0.037
Other Non-White	-0.03	-21.43	[-35.85, -7.01]	0.198
Panel D: Patient Sex				
Male	-0.67	-26.69	[-32.37, -21.02]	—
Female	-0.46	-27.71	[-33.63, -21.80]	0.454

Notes: Table presents estimates of Equation 14, stratified by patient groups. The outcome variable is the count of interventions performed within the patient group at the CZ level; markets with ≤ 5 procedures quarterly are dropped. Reported coefficients are pooled average post-treatment effects for the first year post-adoption. Patients and demographic information are identified based on the 20% carrier file. Standard errors are clustered at the CZ level. Percentage changes are relative to the mean CZ-quarter intervention volume for the indicated group and are used in hypothesis testing; results are robust to considering the median instead.

Table 3. Within-Market Inequities: Pooled LP-DID Estimates

clinical severity. Here, the intuition is that if patients are losing access to care in markets which already have lower than average propensities to treat patients, their lost access may be particularly inefficient.

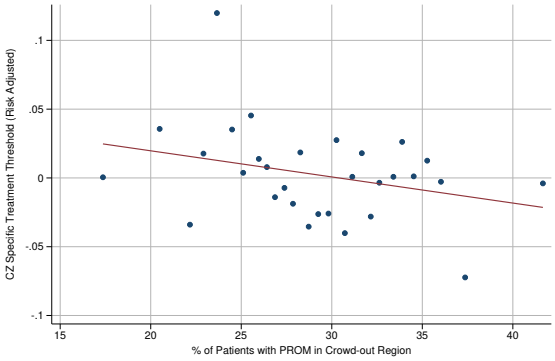
I therefore use the rich set of patient, physician, and geographic controls used in predicting patient risk (Appendix Table A.3) to calculate risk-adjusted treatment rates at the CZ level ($\hat{\varphi}_{CZ}$), following Equation 13.[30] I estimate these treatment propensities on the pre-adoption data, to evaluate how markets treated the same patient in potentially different ways prior to the spillover effects induced by TAVR. I then compare these market-level estimates of treatment thresholds to measures of crowd-out severity.

Figure 7 presents results highlighting the correlations between the $\hat{\varphi}_{CZ}$ coefficients and these measures, including the share of patients likely to be crowded out from care based on

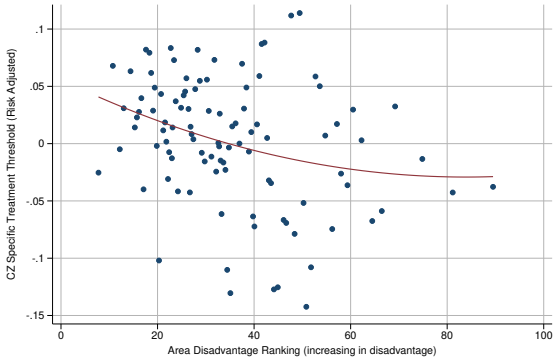
[30] Appendix Figure A.16 shows the distribution of these predicted values. In general, the distribution is centered around zero, as expected since treatment propensity is determined on average by included covariates.

Figure 7. Market Level Relationships between Treatment Propensity and Crowd-Out Risk

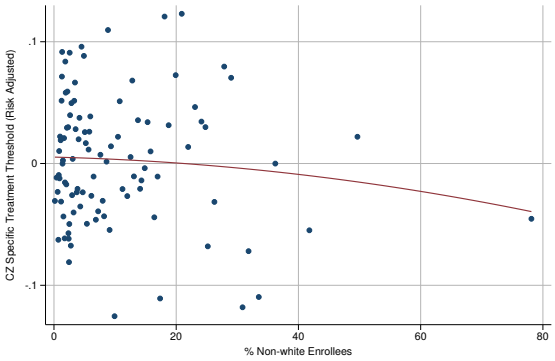
(a) % of Patients in Crowd-out Region



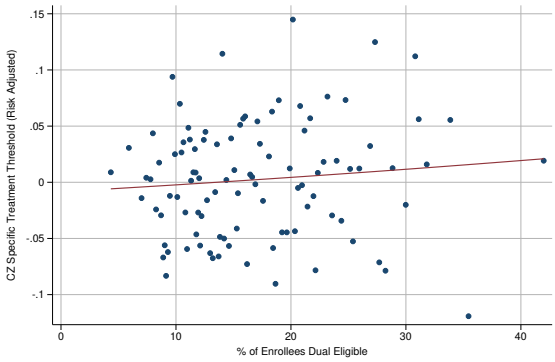
(b) ADI (9-digit ZIP code)



(c) % of Nonwhite Patients



(d) % of Dual-Eligible Patients



Notes: Figures show binscatter relationships between the estimated values of $\hat{\varphi}_{CZ}$ (using Equation 13) and CZ-levels of disadvantage, including: the percentage of patients with PROM risk levels between 4.5% and 9% (panel a; see Figure 5); the average ADI rank of the 9-digit ZIP codes in a CZ (panel b); the percentage of nonwhite Medicare enrollees in a CZ (panel c); and the percentage of dual-eligible Medicare enrollees in a CZ (panel d).

their risk (following Figure 5) and the relative disadvantage of a market, measured by ADI, the percentage of nonwhite enrollees, and the percentage of dual-eligible patients. I first observe that markets with a greater percentage of patients in the crowd-out region are also markets with lower treatment thresholds; to put this correlation into context, I estimate that a market increasing the share of these patients by 10% (roughly 3 percentage points) would move about 5 spots down in the ranking of $\hat{\varphi}_{CZ}$ (about a 1.5% decline). Similarly, I observe a strong negative correlation between the population-weighted average ADI of a CZ and its treatment thresholds—this relationship is particularly strong, with a one unit increase in the average ADI ranking of a CZ corresponding to a 2.5% decline in a market's treatment generosity. This is a particularly relevant finding, as I consistently observed that patients from more geographically disadvantaged regions—either across (Figure 6) or within (Table 3) markets—were more likely to lose access to care following TAVR's adoption. Negative

correlations are weaker for markets with a high share of nonwhite residents; in contrast, I observe a positive correlation between dual eligibility and treatment thresholds.

		Quartile, Risk-Adjusted Treatment Thresholds			
	Full Sample	Q1	Q2	Q3	Q4
$\hat{\varphi}_{CZ}$	–	[-0.46, -0.08]	[-0.08, -0.01]	[-0.01, 0.08]	[0.08, 0.51]
Treatment Effect	-3.87	-3.10	-4.38	-3.26	-5.44
	(1.673)	(1.613)	(1.915)	(1.715)	(7.907)
p-value	[0.021]	[0.056]	[0.024]	[0.060]	[0.493]
$N_{CZ-quarters}$	2,922	596	867	753	700

Notes: Table reports pooled effects from LP-DID regressions estimating the effect of TAVR's adoption in a CZ on total intervention volume per quarter (Equation 14; compare with Figure 3). Results are stratified based on each market's risk-adjusted probability to treat a patient with valve replacement or supports, conditional on patient characteristics ($\hat{\varphi}_{CZ}$ in Equation 13). Treatment thresholds are estimated using pre-adoption data only.

Table 4. Adoption Effects on Intervention Volume, by Pre-TAVR Propensity to Treat

To fully estimate how TAVR's adoption may have differentially impacted markets based on their underlying probability of treating patients, I estimate how TAVR's adoption effects differed across markets with different treatment propensities. Table 4 presents the results. In general, total intervention declines are concentrated in markets with the lowest risk-adjusted treatment thresholds. Areas with the most pronounced declines in intervention volume also had generally lower accessibility to treatment conditional on patient risk.

Taken together, these results suggest that rather than correcting over-use of PCIs prior to adoption, TAVR's arrival may reduce the availability of accessing treatment in markets where access was already limited. I observe that crowding out occurs in regions with already lower treatment thresholds; hence, the inequitable effects documented in the preceding section may serve only to exacerbate disparate access to treatment across groups.

6 Conclusion

Inequities in access to high-return health services have persisted for decades, leaving patients of lower incomes or marginalized groups with inferior treatments and, subsequently, health outcomes. Innovations in health treatments—despite their significant health benefits—may further entrench these differences if they inhibit access to older technologies.

I present a theoretical framework considering these implications. The model highlights a tension between innovation takeup and overall service availability, stemming from limited

physician capacity and productivity spillovers. This tension implies that an innovation may reduce overall availability of care. Importantly, these effects may differ systematically across the population and differentially affect vulnerable groups. Finally, these effects may further entrench differential access to care across markets.

I test these predictions empirically using aortic valve replacement surgeries as a case study. My results—which suggest that both capacity constraints and physician specialization may drive observed declines in volume—suggest the need for infrastructure to scale up innovative treatments without compromising availability of adjacent procedures (Hoagland and Kipping, 2024). Identifying these adjacent treatments and incentivizing their continued provision—for example, by adjusting physician reimbursement rates or centralizing access to innovations (Yang, 2023)—could maximize the social impact of technological change.

This framework and its empirical results may be useful in evaluating the potential spillover effects of a broader class of innovations. In general, innovative practices in healthcare may either augment or compete with existing adjacent technologies, potentially affecting the availability of a broad set of interventions or procedures and, therefore, overall (equitable) access to specialized care. To ensure procedural innovations maximize social welfare gains, it is important to carefully consider the potential for these spillover effects and how large changes in equitable access might be. These effects are likely context dependent; for example, the use of catheterization labs and the presence of minimum volume requirements for both TAVR and PCIs may influence the reported empirical results in this study. The constellation of physician skill, hospital policies, and other contextual factors such as prices or government interventions likely will influence evaluation of other innovations.

Future work examining the potentially unequal impact of technological change can build on this paper in several ways. As innovations like TAVR mature, future work can consider the long-run impacts of innovation on equity, including for harder to observe outcomes such as wait times, complications, and endogenous patient risk.[31] New research may also incorporate long-run physician entry, exit, and specialization decisions. Additionally, future work may consider how selection affects market outcomes, whether selective innovation takeup by providers (Huckman and Stern, 2022) or "cherry-picking" patients post-innovations (Cram et al., 2008; Desai et al., 2009). Finally, this framework can be extended to many other inequities and structural forces that worsen health outcomes for marginalized groups, including discrimination at the point of care and systematic gaps in seeking out healthcare due to eroded trust in the healthcare system (Webb Hooper et al., 2019).

[31] Wait times for SAVR/TAVR have increased in other countries, leading to higher rates of heart failure for those with severe aortic stenosis (Albassam et al., 2020). This might be due to high centralization of access. Additionally, this paper only examined years that TAVR was available for high-risk patients; as TAVR became more widely available, more structural market changes may have occurred.

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A Appendix

A.1 Tables

	All Procedures (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 intervention type performed by the type of medical professional in a given year. Sample is limited to all aortic valve replacements (TAVR/SAVR) procedures. Totals do not add up to 100% because some procedures are performed by a team comprised of both cardiothoracic surgeons and interventional 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."

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.2. Definitions of Interventional Cardiology Procedures

Notes: Table shows inpatient hospital procedure codes (ICD-9-PCS and ICD-10-PCS) used to identify valve replacements (TAVR and SAVR) and valve supports (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.3. 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 $N = 377,532$ cardiology patients, including all those who received valve replacements or supports in the analytical sample.

	(1) Patient Migration	(2) Operator Migration	(3) Traveling for Care
TAVR Treatment Effect, Pooled	-0.026	-0.026	0.012
	(0.0244)	(0.0137)	(0.0164)
p-value	[0.2950]	[0.0632]	[0.4648]
Baseline mean	3.23%	3.71%	0.68%

Notes: Table presents estimates of Equation 14 on three outcomes measuring the effects of TAVR's adoption on patient and physician migration. Column (1) indicates the probability that a patient moves CZs in a given year, using the BSF files to measure patient migration. Column (2) indicates the probability that an operating physician moves in a given year, using the MD-PPAS files to measure physician migration. Column (3) indicates the probability that a patient will go out of their home CZ to receive an intervention, using the Inpatient claims files. Note that regressions are estimated at the year level given data availability (column 3 can be estimated at a finer level of time variation without affecting the results, but is presented at the annual level here for consistency with the other models). Reported coefficients are pooled average post-treatment effects over 6 years post-adoption. Markets with ≤ 5 procedures quarterly are dropped, and standard errors are clustered at the CZ level.

Table A.4. Effects of TAVR Adoption on Patient and Physician Migration

Market Level Analysis: 100% inpatient claims	
All Interventions	-0.159***
	(0.0137)
Valve Replacements	1.857***
	(0.0745)
PTCA Only	-0.258***
	(0.0174)
Cardiac Catheterization	0.034**
	(0.0133)
All Other PCI	-0.123***
	(0.0117)
Individual Level Analysis: 20% Subsample (Inpatient + Outpatient)	
All Interventions	-0.968***
	(0.0139)

Table A.5. Robustness of Main Regression Results to Poisson Estimation

Notes: Table shows estimated regression coefficients from pooled DID analysis using Poisson regression. Compare with Figure 3. Panel A includes 100% of inpatient procedures, and measures total volume at the CZ-quarter level; panel B includes all interventional cardiology procedures for the 20% carrier file (inpatient and outpatient), and measures individual rates of interventions per 1,000 enrollees. Standard errors are clustered at the CZ level. Model is estimated using the `ppmlhdfe` package (Correia et al., 2020).

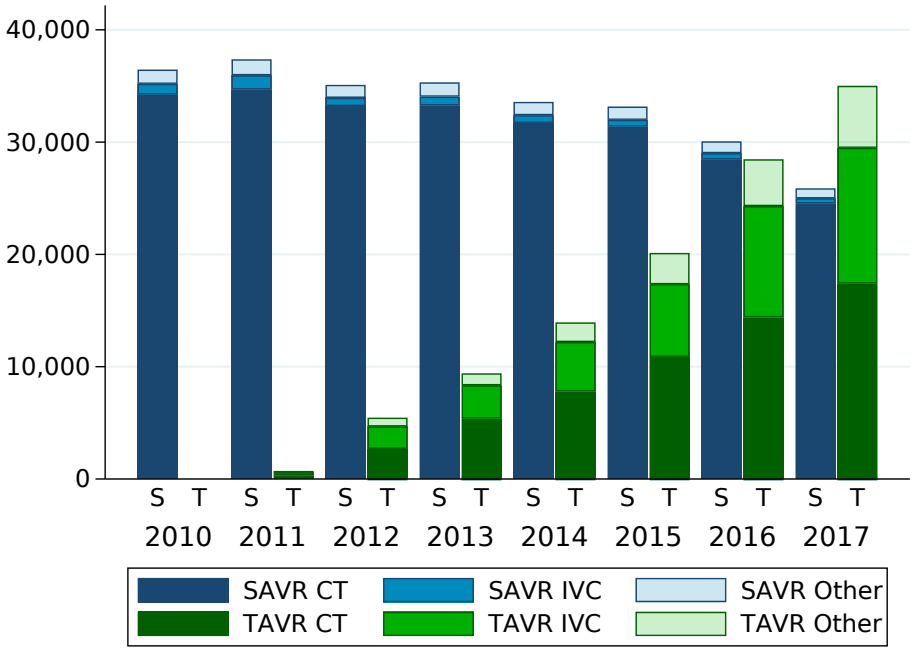
Complication	Codes
Arterial Embolism	444.*, 445.*, I74.*, I75.*
Bleeding Requiring Transfusion	36430 (CPT-4) or Revenue Center codes 039*
Cardiac Tamponande	423.3*, I31.31, I31.39, I31.4
Cardiogenic Shock	R57.0, 785.51
Heart Failure	428.*, I50.*
Intra-cranial Hemorrhage	430.*, 431.*, 432.*, 433.*1, 434.*1, I60.*, I61.*, I62.*, I63.*
Myocardial Infarction	410.*, I21.*, I22.*
Thrombosis	451.*, I80.*, 452.*, I81.*, 453.*, I82.*
Restenosis	36*.*, 02100ZZ, 021009Z, 021008Z, 02100YZ, 02100WZ, 02110ZZ 021109Z, 021108Z, 02110YZ, 02110WZ, 02120ZZ, 021209Z, 021208Z, 02120YZ, 02120WZ, 02130ZZ, 021309Z, 021308Z, 02130YZ, 02130WZ, 02703ZZ, 027034Z, 027035Z, 02703DZ, 02703EZ, 02713ZZ, 027134Z, 027135Z, 02713DZ, 02713EZ, 02723ZZ, 027234Z, 027235Z, 02723DZ, 02723EZ, 02733ZZ, 027334Z, 027335Z, 02733DZ, 02733EZ, 02300ZZ, 02303ZZ, 02304ZZ, 02310ZZ, 02313ZZ, 02314ZZ, 02320ZZ, 02323ZZ, 02324ZZ, 02330ZZ, 02333ZZ, 02334ZZ, 02V00ZZ, 02V03ZZ, 02V04ZZ, 02V10ZZ, 02V13ZZ, 02V14ZZ, 02V20ZZ, 02V23ZZ,02V24ZZ, 02V30ZZ, 02V33ZZ, 02V34ZZ, 02U00JZ, 02U03JZ, 02U04JZ, 02U10JZ, 02U13JZ, 02U14JZ, 02U20JZ, 02U23JZ, 02U24JZ, 02U30JZ, 02U33JZ, 02U34JZ, 02Q00ZZ, 02Q03ZZ,02Q04ZZ, 02Q10ZZ, 02Q13ZZ, 02Q14ZZ, 02Q20ZZ, 02Q23ZZ, 02Q24ZZ, 02Q30ZZ, 02Q33ZZ, 02Q34ZZ, 02Y00Z0

Table A.6. Definitions of Complications from Interventional Cardiology Procedures

Notes: Table shows inpatient hospital diagnostic (ICD-9-CM and ICD-10-CM) and procedure codes (ICD-9-PCS and ICD-10-PCS) as well as CPT-4 codes used to identify complications associated with interventional cardiology procedures, particularly PCIs. * indicates all relevant ICD codes with the listed prefix. Restenosis indicates a follow-up PCI intervention within 30-days.

A.2 Figures

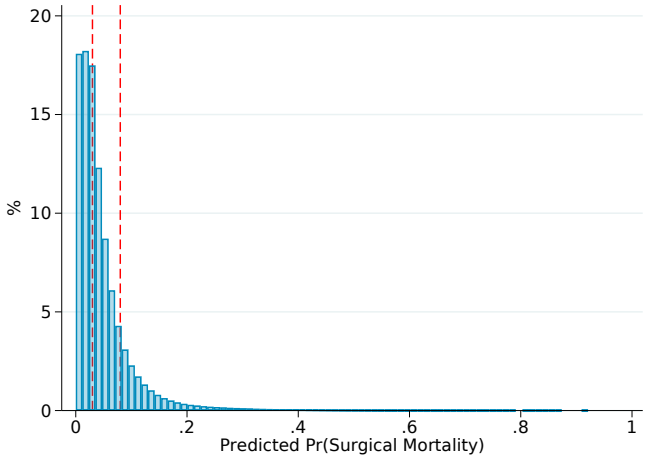
Figure A.1. Timeline of TAVR Adoption



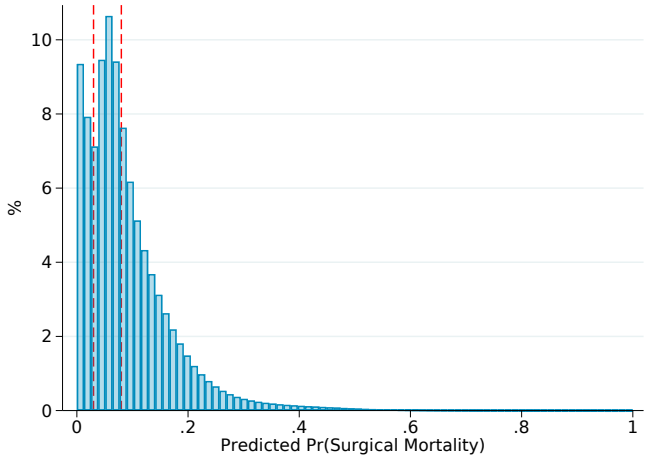
Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic 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.2. Predicted Patient Risk of Surgical Mortality (STS-PROM)

(a) Pr(30-Day Mortality)



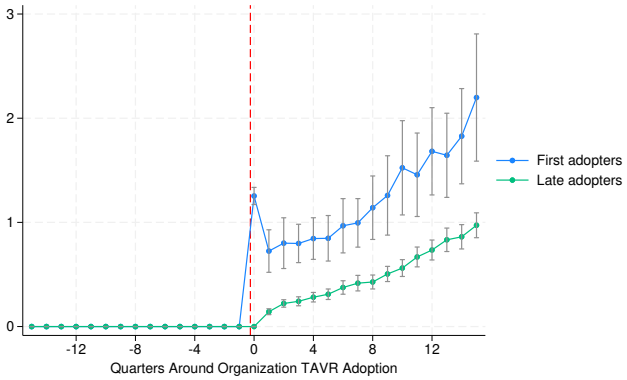
(b) Pr(90-Day Mortality)



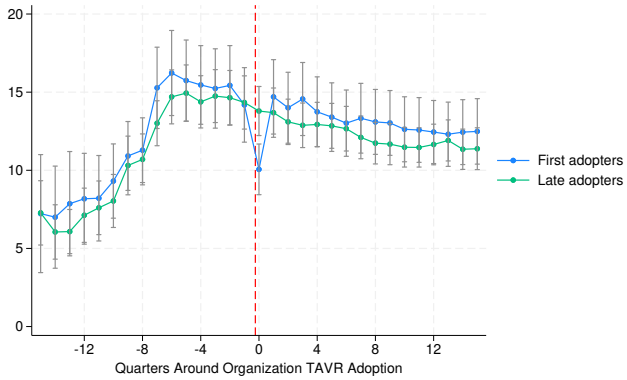
Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table A.3. The current STS-PROM model classifies a similar population as 33% low-risk, 42% intermediate-risk, and 25% high-risk (Kumar et al., 2018).

Figure A.3. Organization-level trends in utilization around TAVR adoption

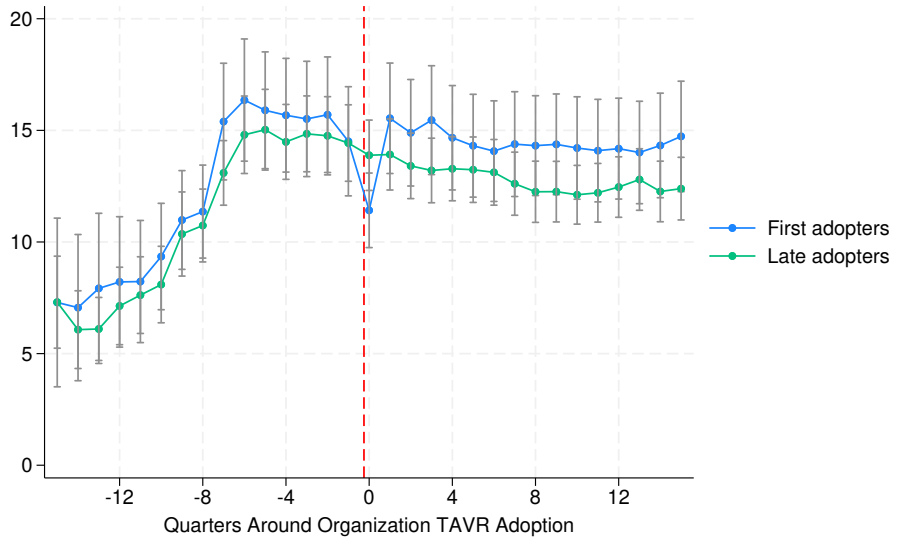
(a) TAVR Surgeries



(b) Other PCI



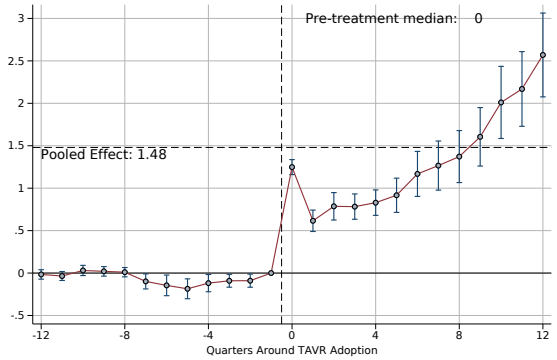
(c) All Interventions



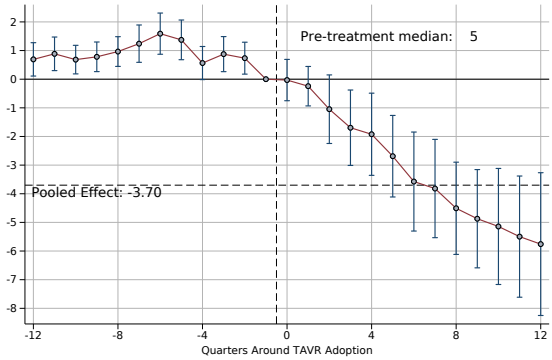
Notes: Figure shows recentered time series indicating average surgical volume at the individual organization level (identified using organization NPI) in the quarters around their own TAVR adoption in a local CZ. Panel (a) shows average TAVR volume; panel (b) average PCI volume; and (c) average total intervention volume. Results are stratified by those who were the first organizations to adopt in their local CZ.

Figure A.4. Procedural Volume Responses to TAVR Adoption, by Intervention Type

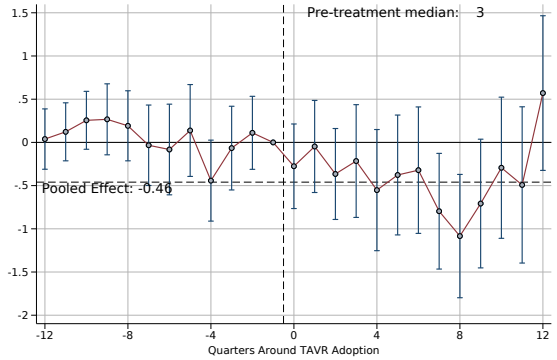
(a) SAVR/TAVR Surgeries



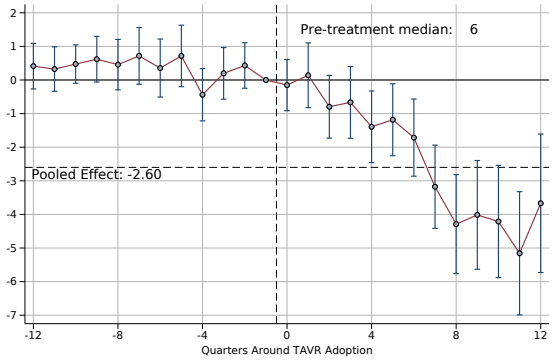
(b) PTCA



(c) Catheterization

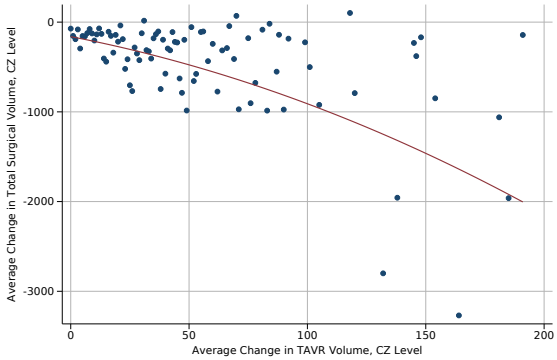


(d) All Other PCIs



Notes: Figure shows estimated impact of TAVR adoption on the total volume of valve interventions performed in a local market, divided into major service types. In each panel, the outcome variable is the total market volume of a given intervention at a CZ level. Panel (a) shows the effect on all SAVR/TAVR surgeries; panels (b) and (c) show the effects on PTCA and cardiac catheterization, the two major PCI procedures; panel (d) shows effects for all other PCI interventions. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

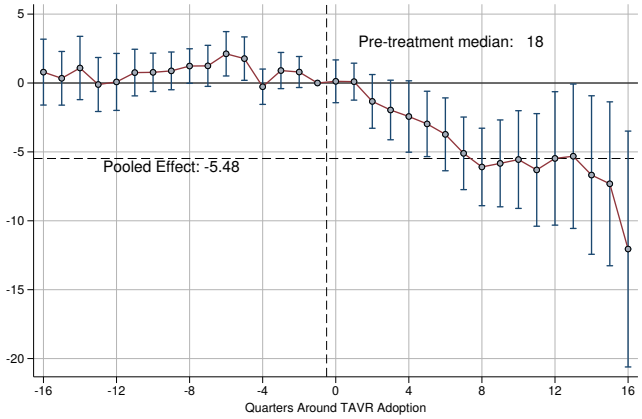
Figure A.5. Market Relationships Between TAVR Takeup and Overall Intervention Volume



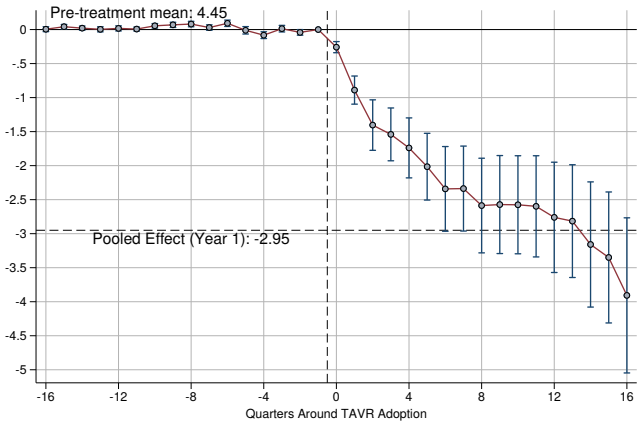
Notes: Figure shows a binscatter plotting the relationship between TAVR takeup in a local market (commuting zone) and changes in total interventional cardiology procedures performed. Each point is a CZ included in the analytical sample; the x-axis shows average quarterly TAVR volume in 2017, and the y-axis shows average differences in total IVC surgical volume (quarterly) between 2010 and 2017. 2 CZs with total 2017 TAVR volume exceeding 200 patients/quarter are dropped from view for visibility; binned regression results are robust to their inclusion/exclusion.

Figure A.6. Long-run Effects of TAVR Adoption on Intervention Volume

(a) Commuting Zone Level (100% Inpatient)



(b) Patient Level (100% Inpatient + 20% Outpatient)

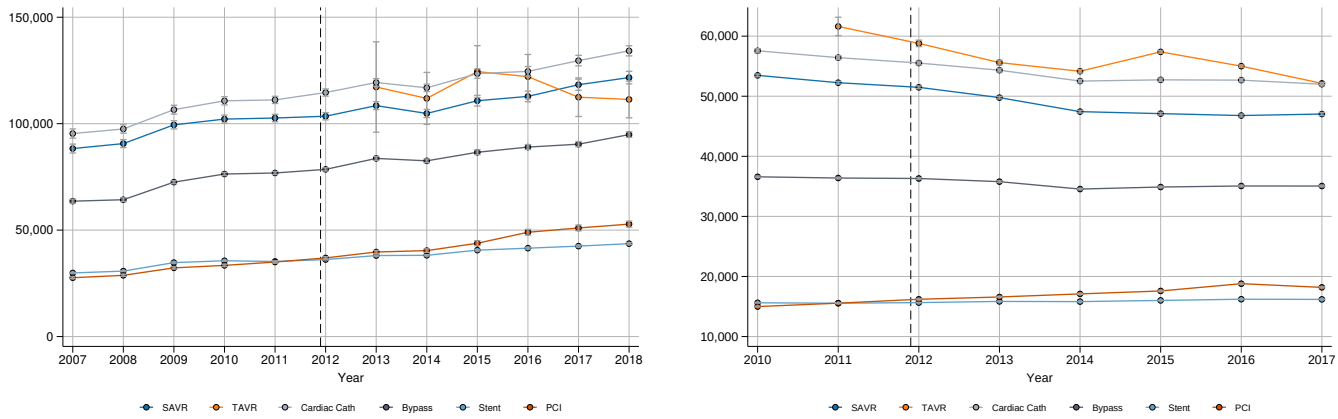


Notes: Figure shows LPDID coefficients and 95% confidence intervals estimating the effect of TAVR adoption in a local market on total intervention volume. Compare with Figure 3.

Figure A.7. Average Commercial and Medicare Prices for Interventional Cardiology Procedures and SAVR

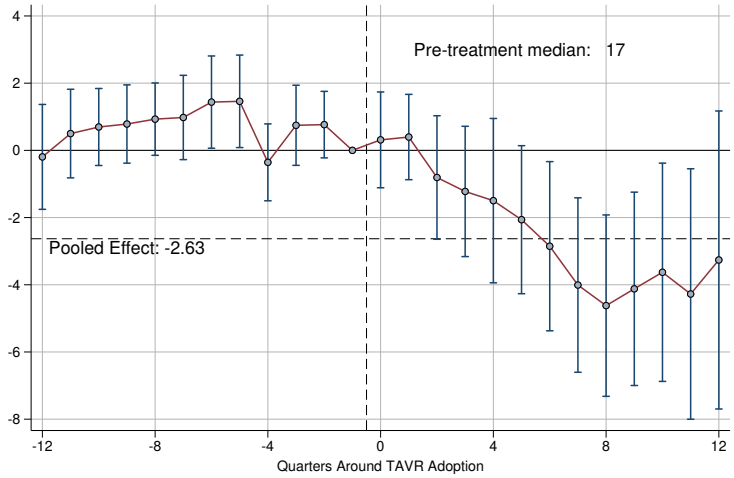
(a) Commercial Prices (Merative)

(b) Medicare Prices (DRG Payments)



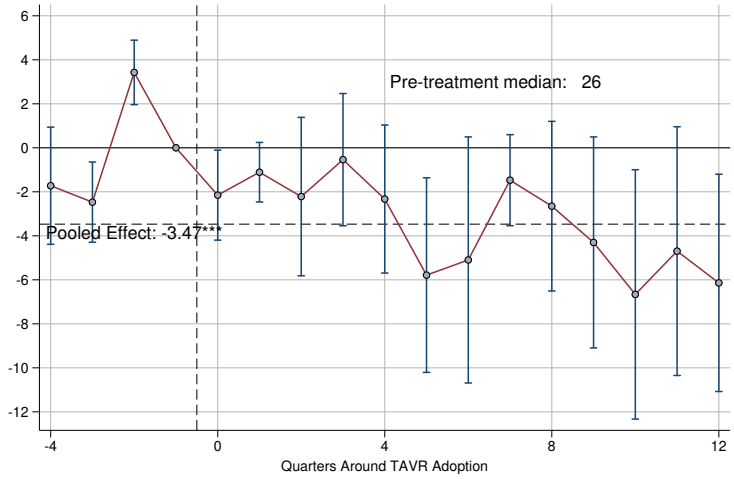
Notes: Figure shows average prices and 95% confidence intervals for key interventional cardiology services (as well as SAVR, which is typically performed by cardiothoracic surgeons instead of interventional cardiologists) around the time of TAVR's adoption. In panel (a), average prices for patients enrolled in commercial, employer-sponsored insurance, are reported using the Merative data (prices are measured as insurer + enrollee payments). In panel (b), the average Medicare payment amount for the relevant DRGs for each procedure are reported. Prices are reported in 2024 USD.

Figure A.8. Robustness: Total Intervention Effects, Excluding Patients with Stable Angina or Stable Coronaory Artery Disease



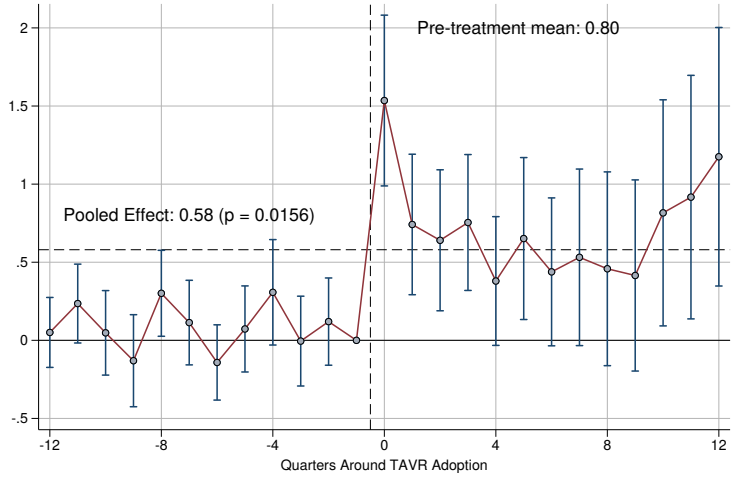
Notes: Compare to Figure 3. Sample excludes patients treated with stable angina or stable coronary artery disease, identified as patients with ICD-9-CM diagnosis code 413.9 or ICD-10-CM diagnosis codes I20.8 or I20.9 anywhere in the first ten diagnoses. Note that this likely a conservative approach, as this may remove patients with a history of stable angina but with new cardiovascular conditions; however, results are unchanged. 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.9. Robustness: Total Intervention Effects, Dynamic Difference-in-Differences Model Relative to 2011 Quarter 4



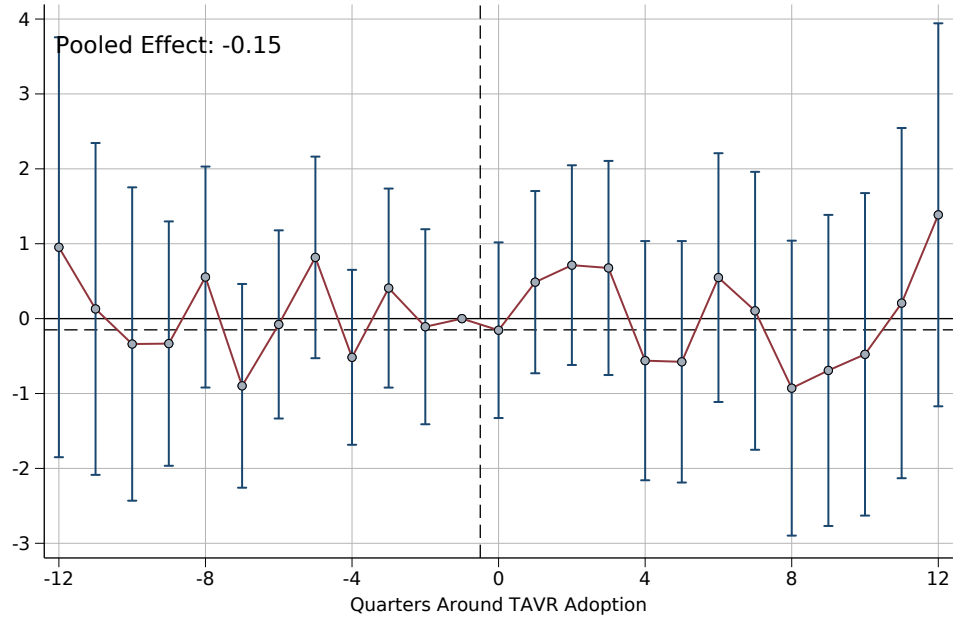
Notes: Compare to Figure 3. Instead of using a staggered adoption design, this specification reports estimates from a dynamic difference-in-differences model with 2011q4 as the reference period. Hence, regression coefficients compare intervention volumes averaged over all adopting markets compared to all non-adopting markets for each quarter. 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.10. Effect of TAVR Adoption on Screening for Surgical Viability



Note: Figure shows effect of TAVR adoption at the CZ level on the fraction of interventional cardiologists performing screening for aortic valve replacement appropriateness. Screenings include computed tomography angiography (CTA) screening for the chest (CPT code 71275), cardiac computed tomography (CPT code 75573), and CTA of the heart (CPT code 75574). Regressions are estimated as in Equation 14. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure A.11. TAVR Adoption Effects on Acute Angiography for NSTEMI Patients

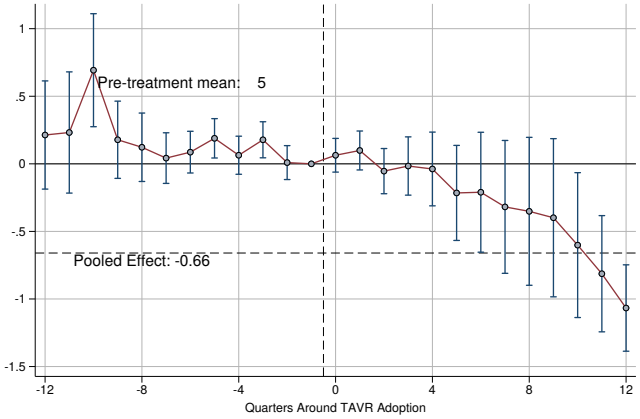


Note: Figure shows estimated treatment effects of TAVR's adoption on the percentage of Non-ST-Elevation Myocardial Infarction (NSTEMI) patients receiving an angiogram within 72 hours (the maximum acceptable wait time recommended by the European Society of Cardiology guidelines) (Hansen et al., 2018). Markets experiencing fewer than 5 NSTEMI patients quarterly are dropped from estimation.

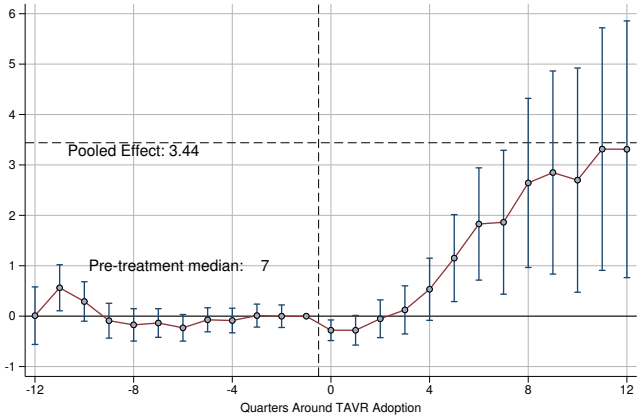
Figure A.11 considers the case of urgently required PCIs, using the case of Non-ST-Elevation Myocardial Infarctions (NSTEMIs). These are less severe heart attacks that typically require angioplasty to reduce patient risk of future, more serious, heart attacks or strokes. The American and European Society of Cardiology guidelines both state that angiography should be performed on NSTEMI patients within 72 hours, in preparation for subsequent angioplasty (Hansen et al., 2018). The figure shows that the percentage of NSTEMI patients meeting this target is not affected by TAVR's adoption, suggesting that the reductions in PCI availability may be for less severe patients.

Figure A.12. Impact of TAVR Adoption on PCI Volumes, Individual Operator Level

(a) PCI Volume: All Operators

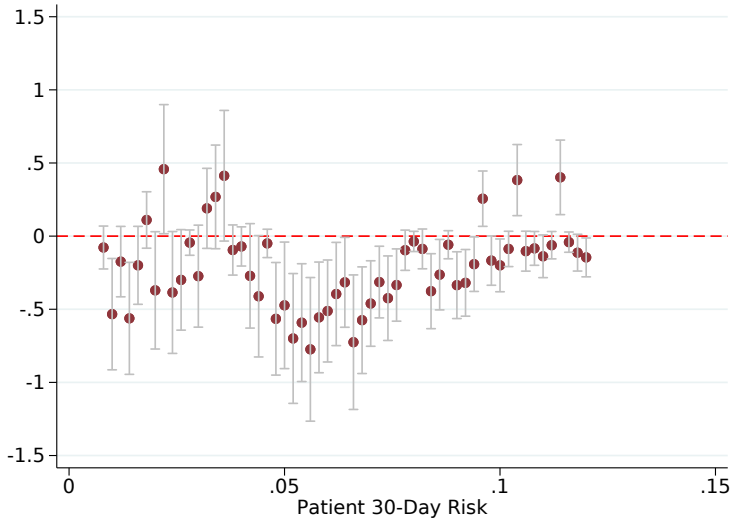


(b) PCI Volume: Only PCI Operators



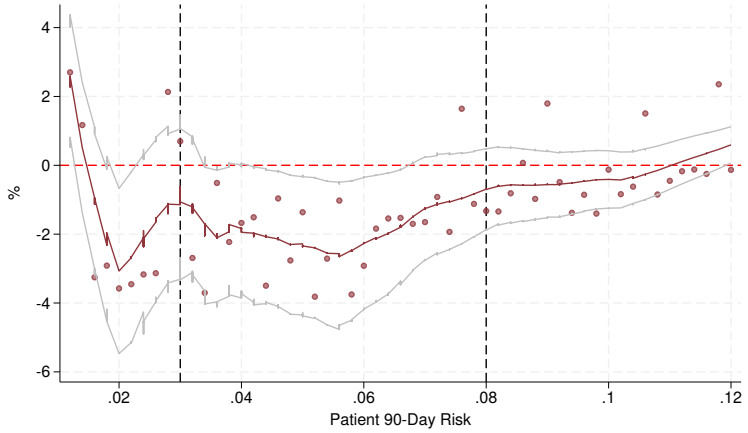
Notes: Figure shows LP-DID coefficients and 95% confidence intervals estimating the effect of TAVR's adoption at the commuting zone level on the average number of PCIs performed per operator (identified using operator NPIs in the Medicare claims data). Panel (a) reports the unconditional average, while panel (b) reports averages after conditioning on operators performing at least one PCI in that quarter. Standard errors are clustered at the market level.

Figure A.13. Heterogeneous TAVR Effects on Procedural Volumes by Patient Risk



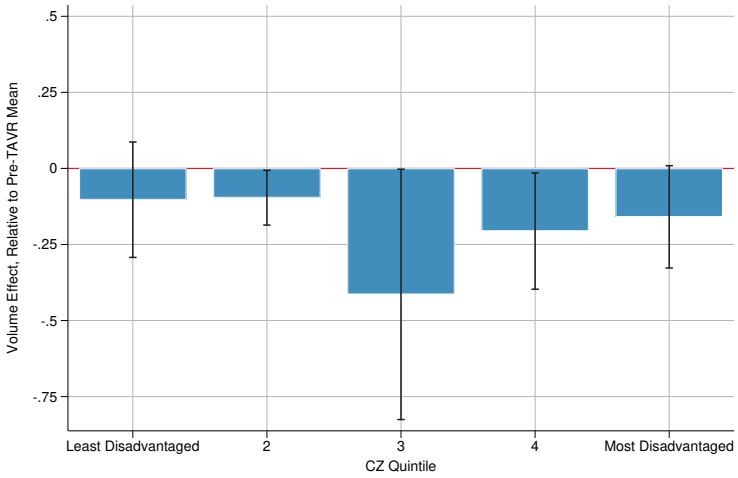
Note: Figure shows estimated heterogeneous treatment effects of TAVR's adoption on total surgical volume for patients in different risk bins. STS-PROM risk is binned (width=0.2 percentage points); each point represents a difference-in-differences coefficient of TAVR's adoption on surgical volume within 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 5.

Figure A.14. Effects of TAVR Adoption on Total Intervention Volumes by Patient Risk: Effects as % of Overall Decline



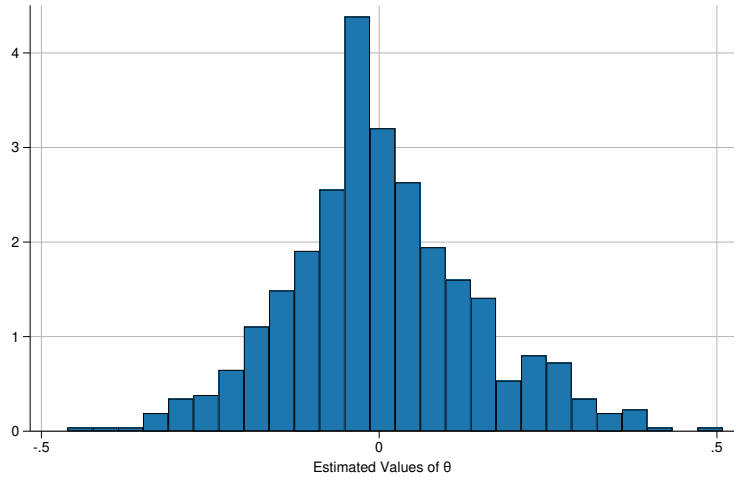
Notes: See Figure 5 for estimation details. In this figure, coefficients are normalized to be percentages of the total decline in intervention volume, with each coefficient divided by the overall DID estimate. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008; Benjamini et al., 2006). Vertical lines indicate STS-PROM delineation between low- and high-risk patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

Figure A.15. Effects of TAVR Adoption on Procedural Volumes by Dual-Medicaid Eligibility



Notes: Compare to Figure 6. Effects of TAVR adoption on surgical volume across binned quintiles of CZs according to disadvantage, measured in the fraction of patients in a market who are dually-eligible for Medicaid (results are robust to defining dual-eligibility at the month or year level). Each point represents a "pooled" post-treatment LP-DID average effects, where the outcome is total surgical volume at the market level as in Figure 3. Appendix Figure A.15 for results for dually-eligible patients. Results are robust to using standard difference-in-differences coefficients.

Figure A.16. Distribution of Risk-Adjusted Treatment Thresholds, CZ Level ($\hat{\varphi}_{CZ}$)



Note: Figure shows distribution of estimated values for ($\hat{\varphi}_{CZ}$), following Equation 13. Regression is estimated using a mixed-effects logistic regression, with controls including the full set of patient, clinical, and geographic characteristics used to predict patient risk in Appendix Table A.3.

A.3 Additional Model Results

This section formalizes the discussion in Section 3.2, concerned with identifying potential inequalities and inequities arising from an innovation's impact on the total volume of interventions provided in a market. The analysis identifies the relative share of patients from two groups likely to be in the "crowd-out region" of patients losing access to interventions as a result of the innovation.

Inequalities in Crowd-out. 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 post-adoption ($C = [\underline{\theta}, \underline{\theta}']$). However, suppose that clinicians do not observe θ directly but a proxy $\hat{\theta}$.[32] Assume $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} correctly predicting θ except for an idiosyncratic, mean-zero error ν_{is}:

$$\theta_{is} = \underbrace{Z_{is}\gamma}_{\hat{\theta}} + \nu_{is}. \tag{15}$$

Group membership can be represented as a binary variable $d_{ig} \in Z_{is}$ indicating if patient i is a member of a group g. Groups may include demographic (e.g., low-income) or clinical indicators (e.g., patients with diabetes, smokers); such indicators routinely inform patient risk calculations (van Ryn and Burke, 2000). The coefficient γ_d captures discrete shifts in predicted risk across groups.[33] If membership is informative (so that $\gamma_d \neq 0$), patients in different groups constitute different shares of the crowdout region, $s_{C,g}$, determined by the underlying distributions of θ and $Z_{is}\gamma$ and Bayes' rule:

$$\begin{aligned}
s_{C,g} = Pr(i \in g | i \in C) &= Pr(i \in C | i \in g) \frac{Pr(i \in g)}{Pr(i \in C)} && (16)\\
&= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\gamma_{-g} + \gamma_g \in [\underline{\theta}, \underline{\theta}']] \right. && (17)\\
&= \frac{s_g}{s_C} \left[\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g}) \right] && (18)\\
&= s_g \frac{\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g})}{\int_{\underline{\theta}}^{\underline{\theta}'} f(\theta) d\theta}. && (19)
\end{aligned}$$

Here, s_g indicates the share of group g in the population, and $s_C = F(\underline{\theta}) - F(\underline{\theta}')$ is the relative size of C. As these are not equal in general, C may over- or under-represent g.

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

[33] For ease of exposition, assume d_{ig} is independent to all covariates $Z_{is,-g} = Z_{is} \setminus d_{ig}$.

Inequities in Crowd-out. These inequalities in access may correspond to *inequities* in access when risk distributions are imperfectly or incorrectly observed. Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019). This 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" $\hat{\gamma}_g$:

$$\hat{\gamma}_g = \gamma_g + \nu, \tag{20}$$

where ν is an idiosyncratic error in group risk measurement.[34] Consider how this term changes the representation of group g in the crowd-out region C (that is, $s'_{C,g}(\nu)$) relative to the original representation, $s_{C,g}$. Define this ratio to be $I(\nu)$ and notice:

$$I(\nu) = \frac{s'_{C,g}(\nu)}{s_{C,g}} \tag{21}$$

$$= \frac{1}{s_{C,g}} \int_{\underline{\theta}-\gamma_d-\nu}^{\underline{\theta}'-\gamma_d-\nu} f(X_{i,-g}\gamma_{i,-g}) d(X_{i,-g}\gamma_{i,-g}). \tag{22}$$

Importantly, this ratio changes in keeping with the size of the measurement error, ν:

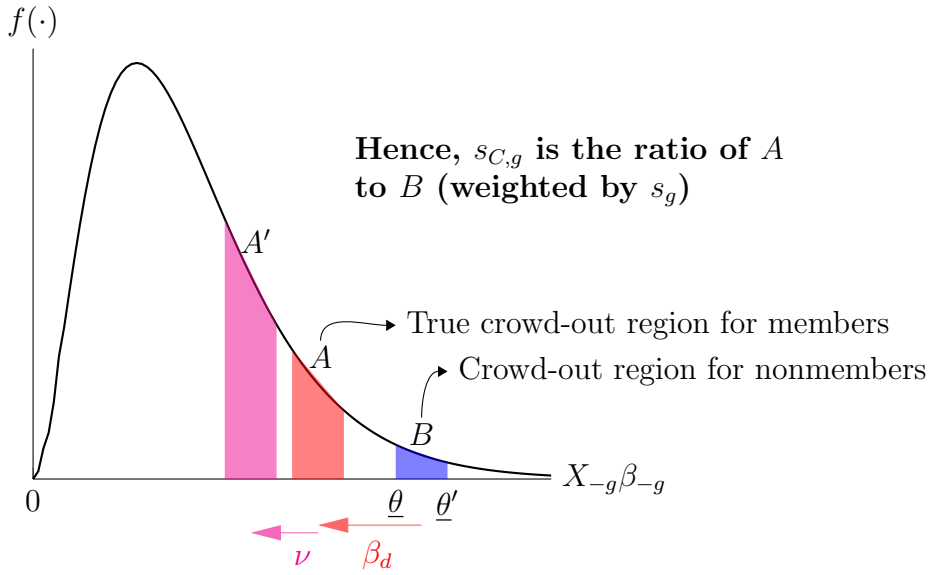
$$\frac{\partial I}{\partial \nu} = \frac{\left[f_{X_{-g}\gamma_{-g}}(\underline{\theta}-\gamma_d-\nu) - f_{X_{-g}\gamma_{-g}}(\underline{\theta}'-\gamma_d-\nu)\right]}{s_{C,g}}. \tag{23}$$

That is, risk perception error ν affects group-specific crowd-out proportionately to the initial composition of g in C. Figure A.17 presents the intuition behind this result; intuitively, ν incorrectly shifts patients of one group up or down along the risk distribution, θ, leading the "over-estimated group" more likely to lose access to care.

The figure shows, for a given distribution of observable *non-group* characteristics $X_{-g}\gamma_{-g}$ 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 γ_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).

[34] ν is not classical measurement error or necessarily centered around 0. In addition, ν can be allowed to vary across providers or patients.

Figure A.17. 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 shift the region A', ultimately affecting the relative representation of members of group g in the crowd-out region.