The Cost of Clarity: Trade-offs to Public Investments in Rural Diagnostic Care

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Abstract

Rural hospitals face financial constraints that hinder investment in new medical technologies, contributing to disparities in health care quality between rural and urban areas. To address access gaps, recent policy efforts have funded investment subsidies for rural hospitals. By expanding access to advanced medical technologies, these policies can meaningfully improve clinical outcomes for underserved rural populations. However, housing high-cost technologies at low-volume rural hospitals may not be cost-effective. This paper examines the cost-access trade-off associated with deploying expensive diagnostic equipment in rural markets by studying the diffusion of 3D-mammography (3DM). My analysis focuses on the market for breast cancer screenings in rural Georgia, where a subsidy for rural hospitals alleviated financial constraints, facilitating the adoption of 3DM. I show that the subsidy increased the cumulative probability of adoption by 20 percentage points (140 percent). Leveraging changes in geographic access to 3DM over time, I demonstrate how distance to 3DM affects patients' technology choices and screening outcomes. Following the adoption of 3DM at a rural hospital, I estimate a 45 percentage point increase in the probability that local patients will screen with 3DM instead of 2D mammography (2DM). Increased 3DM uptake improves local screening outcomes, reducing the average likelihood of a false-positive scan by 1.8 percentage points (21 percent). To study the trade-off between access and cost, I estimate a structural model of demand for mammography. Counterfactual analyses show that a blanket investment policy funding 3DM upgrades at every rural hospital is inefficient, resulting in over-investment in high-access markets where adoption is socially redundant, or in sparsely populated markets that cannot sustain sufficient demand. Welfare is maximized by a targeted investment policy that allocates 3DM scanners to hospitals operating in midsize markets where patients are geographically isolated from incumbent 3DM providers.

1 Introduction

Rural hospitals face persistent financial constraints that hinder investment in physical capital. Declining cash flows have eroded profit margins, making it difficult for rural hospitals to acquire medical technologies that are commonplace in better-resourced urban facilities (Joynt et al., 2011; Adler-Milstein et al., 2015; Horwitz et al., 2018). This technology gap contributes to disparities in health care quality, particularly in capital-intensive service lines like radiology, where reliance on outdated equipment can impede the delivery of high-quality care (AHRQ, 2024).

The widening technology gap between rural and urban hospitals has prompted calls for increased public investment in rural health care infrastructure (Deryugina and Molitor, 2021). By reducing geographic barriers to care, technology adoption leads patients to substitute from lower-quality alternative procedures. As a result, these public investments have the potential to improve clinical outcomes for underserved rural populations (Scoggins et al., 2012; Syed et al., 2013). However, when the fixed costs of adoption are large, small rural hospitals may lack the patient volume needed to deliver upgraded services at a reasonable unit cost. Thus, publicly funded efforts to close technology gaps may not be cost-effective. These conflicting forces create a trade-off between expanding access and maintaining cost-efficiency.

This paper evaluates the cost-access trade-off in the market for breast cancer screening. As the second leading cause of death for women in the United States, biennial screenings for breast cancer are recommended for all women ages 50–74 (USPSTF, 2016). Traditionally, these have been performed using 2D-mammography (2DM). However, recent technological advances have brought a new tool to this market. Approved by the FDA in 2011, 3D-mammography offers clear clinical advantages over traditional 2DM screenings. By the end of 2017, 3DM supplanted 2DM as the predominant mode of screening for women in the United States. However, the diffusion of this technology has been slower in rural markets where hospitals are less likely to house expensive 3DM-scanners (Richman et al., 2019).

To explore the effects of 3DM adoption, I develop and estimate a model of demand for breast cancer screening where patients have preferences over hospitals, distance, and screening technologies. The model captures the effect of 3DM adoption on local screening patterns, distinguishing between marginal substitution (from 2DM to 3DM) and inframarginal substitution (from regional 3DM to local 3DM). I combine these structural substitution patterns with reduced form estimates of screening quality to quantify the effect of 3DM adoption on local screening outcomes. The model is estimated using a four-year panel of individual screening records for the entire state of Georgia. I use the estimated model to simulate counterfactuals that alter the distribution of rural 3DM supply. By varying the location of 3DM scanners across rural hospitals, I illustrate how the social returns to adoption vary across markets, providing insight into how public investments in rural health care infrastructure should be targeted.

My analysis focuses on the market for breast cancer screenings in Georgia, where a subsidy for rural hospitals reduced financial constraints on capital investment, facilitating the adoption of 3DM. To quantify the effect of the subsidy on Georgia's rural 3DM supply, I estimate an event-study model comparing adoption rates between subsidized Georgia hospitals and rural hospitals in other southern states. The subsidy sharply increased 3DM investment. I find a 20 percentage point increase in the probability of 3DM adoption over the first three years of the policy.

This quasi-exogenous variation in the supply of 3DM at rural hospitals in Georgia plays a key role in my analysis. Using patient-level screening records from 2016–2019, I exploit changes in geographic access to 3DM over time to measure the relationship between distance and technology choice. I find that distance strongly mediates access in this market. Following 3DM adoption at a rural hospital, I estimate a 45 percentage point increase in the probability that local patients screen with 3DM instead of 2DM. Moreover, I show that increased 3DM utilization meaningfully improves local screening outcomes. Leveraging variation in geographic access to 3DM to instrument for technology choice, I estimate that substitution toward 3DM decreases the average probability of a false-positive scan by 1.8 percentage points.

These reduced form estimates reveal a clear relationship between local access to 3DM and technology choice, but the mechanisms driving this pattern remain unclear. To investigate the underlying factors that affect patient choice, I estimate a structural model of demand for breast cancer screenings. Demand estimates show that while patients prefer higher-quality 3DM screenings, they have stronger preferences for screenings at local providers, where travel costs are lower. As a result, there is sharp substitution toward local 3DM screenings in the post-adoption period. The model predicts that in the absence of adoption, 60% of patients utilizing local 3DM would have received 2DM screenings. My estimates reveal substantial heterogeneity in the salience of travel cost; minority groups of lower socioeconomic status are more sensitive to travel, exhibiting a distance elasticity that is 25% above the baseline estimate. Thus, technology gaps likely exacerbate health inequities by limiting access for low-income and marginalized groups.

Finally, I quantify the welfare effects of rural 3DM adoption by comparing patients' willingness to pay for local 3DM to the fixed cost of adoption. I find that expanding geographic access to advanced mammography scanners generates meaningful welfare gains; however, these gains are highly heterogeneous and sometimes offset by cost inefficiencies. Counterfactual analyses show that a blanket investment policy funding 3DM upgrades at every rural hospital is inefficient, resulting in over-investment in high-access markets where adoption is socially redundant or sparsely populated markets that cannot sustain sufficient demand. Welfare is maximized by a targeted investment policy that allocates 3DM scanners to hospitals operating in midsize markets where patients are geographically isolated from incumbent 3DM providers. My results show that strategically targeted investments in rural healthcare infrastructure can promote access to high-quality rural healthcare services without sacrificing cost-efficiency.

This paper contributes to several strands of research. First, it adds to the literature on rural health care access. Prior work highlights the crucial role rural hospitals play in providing essential services to isolated communities. For example, Gujral and Basu (2020) show that rural hospital closures increase local mortality rates for emergency patients by eight percentage points, while Kozhimannil et al. (2020) documents the substantial gaps in obstetric care caused by such closures. I extend this literature by focusing on access to higher-quality diagnostic care. In particular, I examine how proximity to advanced screening technologies shapes screening patterns in rural areas, a key factor in assessing whether current diagnostic networks meet the needs of these populations.

Second, I add new evidence to the extensive literature on the impacts of provider entry, service adoption, and technology diffusion in health care markets. Much of this literature draws on theory from Mankiw and Whinston (1986), which shows that when fixed costs are present, the marginal entrant's effect on welfare depends on the size of the product diversity and business stealing effects relative to fixed costs. Horn et al. (2021) explore these effects in the context of robotic surgery. While they find evidence that the market for surgical interventions expands as more hospitals adopt this technology, adoption also leads to business stealing by changing the allocation of patients across hospitals. Similarly, Rosenkranz (2021) studies the repeal of entry regulation for dialysis centers in North Carolina and finds that marginal centers reduce patients' distance to higher-quality peritoneal dialysis, expanding the market for high-quality care. I contribute to this literature by focusing on the diffusion of medical technology in rural healthcare markets, where 3DM adoption may substantially reduce the distance local patients have to travel for advanced screenings. Following adoption, I find that the degree of business stealing versus technology substitution is directly related to patients' pre-adoption distance to incumbent 3DM providers, suggesting that the impact of rural technology adoption is dependent on proximity to the existing network of care.

Finally, by studying 3DM adoption, this paper provides new insight into the impact of service adoption at rural hospitals. Much of the literature in this area has focused on services that exhibit quality-returns-to-scale (Cutler and Kolstad, 2010; Trogdon, 2009; Yang, 2023; Dingel et al., 2023). However, less evidence exists regarding the impact of rural service expansions in clinical settings without strong quality-returns-to-scale. By studying the adoption of a high-cost medical technology with clear clinical advantages, this paper isolates the trade-off between duplicating fixed costs and improving geographic access to care. My results show that there are large potential welfare gains from increasing the supply of advanced diagnostic services at rural hospitals; however, these effects are tempered by reductions in cost efficiencies, creating a risk of over-investment in small markets that cannot sustain sufficient demand for these services.

The remainder of the paper is organized as follows. Section 2 provides institutional details and introduces my data. Section 3 shows reduced form analysis of the effect of the policy on the rural 3DM supply and the impact of adoption on screening patterns. Section 4 outlines the model and the estimation strategy while Section 5 presents results. Section 6 shows welfare and counterfactual analysis. Section 7 concludes.

2 Setting and Data

2.1 Technology Gaps in Rural Health Care Markets

Over time, rural hospitals have faced mounting financial challenges. Depopulation and increased competition from urban providers generated demand volatility, resulting in lower profit margins. From 2008–2010, 60 percent of rural hospitals reported negative annual profits, and since 2013, 8 percent of rural hospitals have closed (Sheps Center, 2024). This financial fragility hampers investment in new technology, as hospitals may lack the necessary liquidity for capital investments (Hegland et al., 2022). Moreover, financial uncertainty increases borrowing costs, as lenders view rural hospitals as high-risk investments. These factors deter rural hospitals from purchasing expensive diagnostic equipment, limiting rural communities' access to certain imaging services (AHRQ, 2024).

A notable rural-urban technology gap exists in the market for breast cancer screenings. While urban hospitals have rapidly integrated 3DM, it is less likely to be offered at rural providers (FDA, 2025; Lee et al., 2021). This disparity is attributed to the fact that rural facilities often lack the liquidity required to finance the fixed cost of upgrading to this advanced technology. Due to the limited availability of technology among local providers, rural patients are often geographically isolated from 3DM. This paper centers on the mammography technology gap in rural Georgia. My analysis leverages variation in access to 3DM following a subsidy that spurred 3DM adoption at rural hospitals in Georgia.

2.2 Georgia's Rural Hospital Tax Credit

In 2017, Georgia implemented the Rural Hospital Tax Credit (RHTC), an innovative funding mechanism that effectively turned private donations to rural hospitals into 100% state tax credits. In 2017, RHTC funds were available to non-profit or public hospitals in counties with populations of less than 35,000. In 2018, the state raised the population limit to 50,000, making nine additional hospitals eligible for the program. From 2017-–2019, hospitals received an average of $650,000 per year. Table A1 shows eligibility for the program and the evolution of donations received over the first three years of the policy.

Over this time period, nearly every qualifying hospital received RHTC funds. The statewide cap on donations was raised by $50 million in 2018, which led to a sharp increase in total and average funds received. Importantly, these funds were unrestricted in use, effectively boosting liquidity at participating hospitals. Table A2 reports aggregate information on reported use of RHTC funds in 2018. On average, hospitals spent 80% of funds available and held the remaining 20% as cash reserves. The bottom half of Table A2 shows that on average $250,000 of subsidy funds were spent on medical equipment in 2018, roughly 30% of all spending. Many hospitals reported using RHTC funds to purchase a 3DM unit. My analysis is consistent with these reports, as I find that by the end of 2019, 22 of the 58 subsidized hospitals acquired a 3DM scanner.

2.3 Data

This analysis relies on two primary datasets. To measure changes in the supply of 3DM across Georgia, I use technology adoption records. To measure changes in mammography utilization patterns, I use screening records for the entire state of Georgia.

Technology Adoption Records: I use administrative data from the FDA's X-Ray Installer database, which records every new installation of radiology equipment at U.S. health care providers. Each record contains the facility's name and location, the type of equipment installed, and the date of installation. Importantly, the records indicate whether the equipment is for mammography and whether it has 3D capability. I use these records to construct a panel of 3DM adoption at hospitals across the southeast from 2014–2019.

Breast Cancer Screening Data: I incorporate patient-level data to observe mammography utilization. This data comes from the health care Cost and Utilization Project (HCUP), which records outpatient discharge records for all hospitals and ambulatory surgery centers in Georgia.[1] Each of these records includes information on when a patient visits a given facility and which procedures were performed during the visit, which allows me to observe whether a patient received a 2DM or 3DM screening. Each record lists a patient's home zip code and demographic information on race, age, and insurance type. Records also include a unique patient identifier, allowing each encounter to be linked to a patient's care history over time. I use HCUP data from 2016–2019 to measure changes in hospital mammography service offerings and patient treatment patterns over time. I use the CPT procedure codes listed in Table A4, and the service identification algorithm introduced by Richman et al. (2022) to identify the type of technology used in a screening encounter. In the HCUP data, I observe 22 subsidized rural hospitals that started offering 3DM between 2017 and 2019. This aligns exactly with the 22 new installations recorded in the FDA data for rural Georgia, giving confidence that the adoption events are measured consistently across data sources. My analysis focuses exclusively on screening mammography encounters.

Supplementary Data: I use information on hospital size and financial health from Medicare Cost Reports. To measure the cost of 3DM adoption and utilization, I rely on data from the Center for Medicare and Medicaid Services' Practice Expense Files. These files provide itemized estimates of the expenses associated with mammography service lines, which I use

[1] I do not observe screenings in office-based imaging centers. However, I validate my data coverage against aggregate claims counts from Medicare Claims data in Table A5. Subsetting my data to match the FFS population, I capture 87% of 3DM screenings and 76% of 2DM screenings at the state level.

to measure the marginal cost of mammography procedures. Finally, I use the American Community Survey for information on zip code demographics.

3 Reduced Form Evidence

This section first explores regional differences in geographic access to mammography and screening patterns across Georgia. I then measure the impact of Georgia's RHTC on the rural 3DM supply. I exploit geographic variation resulting from the adoption of 3DM at subsidized rural hospitals to identify key factors influencing 3DM utilization. Specifically, I estimate the impact of changes in relative distance to 3DM, defined as the difference between a patient's nearest 2DM and 3DM providers, on technology utilization among women in rural areas. Finally, I explore the effect of adoption on screening outcomes, leveraging variation in rural access to 3DM over time to estimate the impact of technology choice on the probability of false-positive screening results.

3.1 Descriptive Screening Patterns

Before the subsidy, rural women were isolated from 3DM. Table 1 shows that in 2016, the year before the subsidy, there were significant disparities between these groups. The average rural patient would have to travel 22.5 miles to reach the nearest 3DM provider, nearly double the distance for non-rural patients. This difference persists across the 25th and 75th percentiles of the distribution. In contrast, there is a small difference in the distance to 2DM between the two groups, which is not statistically distinguishable from zero. Furthermore, the share of rural women receiving screenings that use 3DM is considerably lower at 12.1%, compared to 30.6% for non-rural women. At 25th percentile, the 3DM screening rate is low for both groups, but there is a sharp gap at the 75th percentile, where 45% of non-rural screenings are performed with 3DM compared to 30% of rural screenings.

Figure 1 shows how distance shapes screening technology choice among the sample of rural women receiving mammography screenings in 2016. The left plot shows how the probability of screening with 2DM or 3DM varies across bins of travel distance.

Table 1: Disparities in Rural 3DM Access (2016)

Sample Characteristics	Rural	Non-Rural	***p*-value**
Distance to 3DM (mi)			
Mean	22.5	12.5	0.000
25th %	13.5	8.5	
75th %	35.5	23.3	
Distance to 2DM (mi)			
Mean	14.6	11.1	0.450
25th %	8.9	8.2	
75th %	20.75	14.95	
Share of Screenings Performed with 3DM			
Mean	12.1%	30.6%	0.000
25th %	3.4%	5.1%	
75th %	30.0%	45.5%	

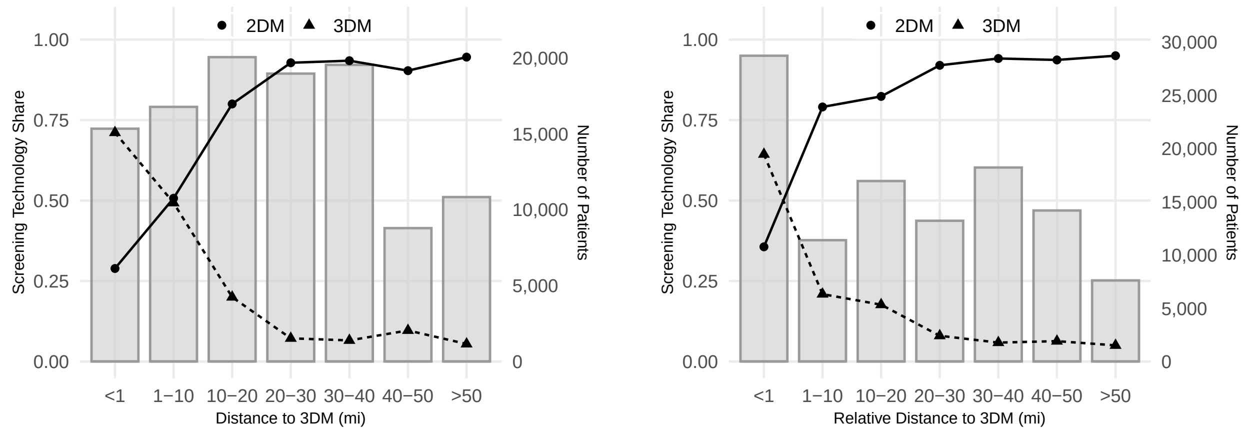
Notes: Table reports mean, 25th, and 75th percentiles of distance to nearest mammography provider and the share of screenings performed with 3DM. Sample includes all Georgia women screened in 2016. Distances are calculated at the zip code level using patient residence and provider location. p-values test for differences in rural versus non-rural means. Data source: HCUP screening records.

There is a steep but continuous decrease in the share of screenings performed with 3DM across the first four distance bins. Interestingly, beyond distance bin four, the share of women screening with 3DM remains constant at roughly 10%, suggesting that some patients are willing to travel significant distances to access 3DM. The x-axis of the right plot shows relative distance bins, defined as the additional distance in miles that patients must travel to reach the nearest 3DM provider relative to the nearest 2DM provider. The share of women screening with 3DM declines as the differential distance to 3DM increases. However, there is a sharp drop between distance bin zero, where a patient's closest provider already offers 3DM, and the subsequent distance bin where 3DM is not locally available. This non-linear relationship suggests that slight differences in proximity to 3DM can strongly influence screening decisions.

3.2 Policy-Driven Expansion of 3DM Supply

Next, I measure variation in the supply of 3DM driven by Georgia's RHTC, which began subsidizing technology upgrades at financially constrained rural hospitals in 2017.

Figure 1: Cross-Sectional Variation in Technology Choice (2016)



Notes: The plots show the average probability of screening technology choice across bins of distance. The x-axis of the left plot shows absolute distance. The x-axis of the right plot shows relative distance, defined as the difference between the closest 2DM and 3DM. Probabilities are calculated at the zip-code level using all mammography screenings in rural Georgia, 2016.

I compare the sample of subsidized rural hospitals in Georgia to a comparable set of control hospitals drawn from other southeastern states.[2] To select control hospitals, I identify the set of hospitals in each state that would be eligible to receive RHTC subsidies if an analogous program were to exist in their state. Table A3 shows 2016 summary statistics for treated and control hospitals. Both are similar in size and baseline financial health.

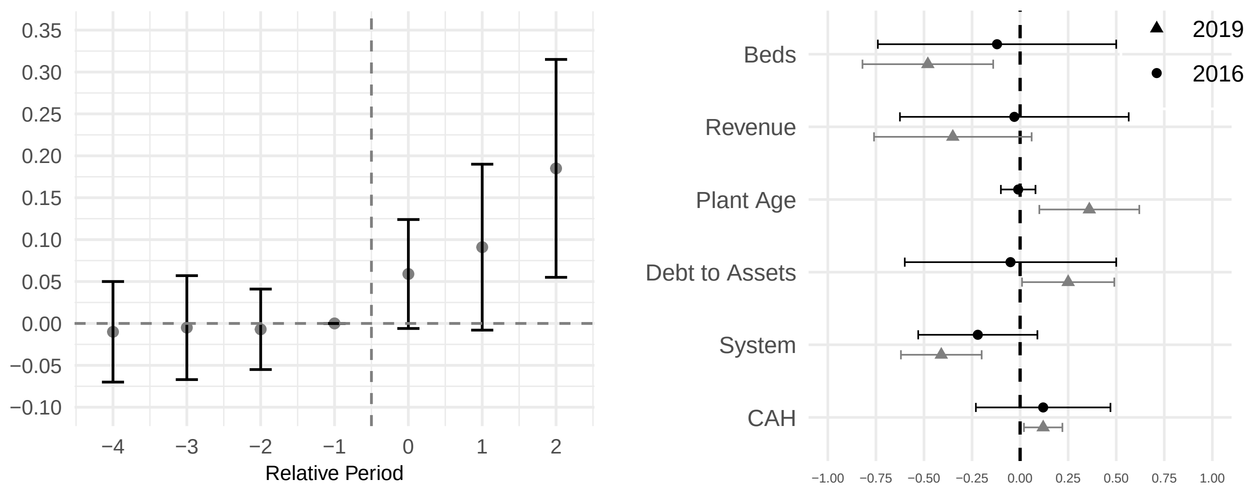
$$Y_{ht} = \sum_{k \neq -1} \beta_k \, GA_h \cdot D_{kt} + \lambda_t + \mu_h + \epsilon_{ht} \tag{1}$$

I estimate the event study model in equation 1 where Y_{ht} is an indicator for whether hospital h offered 3DM in year t. Coefficients β_k measure the change in the cumulative probability of 3DM adoption relative to the period before subsidy receipt. The estimates are plotted in Panel A of Figure 2 and show no distinguishable difference in adoption trends between these groups across the pre-periods. However, post-period estimates reflect a sharp break in trend across the groups.

[2]Including: Alabama, Florida, Mississippi, North Carolina, South Carolina, and Tennessee. Georgia did not expand Medicaid during this period, so I limit my sample to other non-expansion states.

Figure 2: Effects of Subsidization on 3DM Supply

Panel A: Cumulative Adoption Probability Panel B: Characteristics of Rural 3DM Suppliers



Notes: This figure in panel A shows event study estimates for the 3DM investment outcome. This model is estimated using radiology equipment installation records from 2014–2019 for RHTC hospitals (N = 58) and a group of rural hospitals in other southern states (N = 95), creating a total of 918 hospital-year observations. Relative year zero corresponds to 2017, the first year Georgia hospitals received subsidy funds. All estimates are relative to the year preceding the first receipt of the subsidy. I cluster standard errors at the hospital level. The coefficient plots in panel B show estimated differences in mean characteristics between rural hospitals offering 3DM in GA vs control states in 2016 and 2019. Source: FDA / HCRIS.

Over the first three years of the policy, I estimate that subsidization increased the cumulative probability of adoption by approximately 20 percentage points.

Panel B of Figure 2 reports coefficients from differences-in-means tests comparing characteristics between rural hospitals offering 3DM in Georgia and control states. In 2016, the two groups were statistically similar in size, financial structure, and facility age. However, by 2019, the group of rural hospitals offering 3DM in Georgia was on average smaller, with fewer financial resources, suggesting that the subsidy enabled adoption at resource-constrained hospitals.

3.3 The Effect of Adoption on Local Screening Patterns

I exploit the staggered timing of 3DM adoption at rural hospitals to measure the effect of distance to 3DM on rural patients' screening decisions. To quantify the relationship between local access and screening patterns, I use screening records from all Georgia patients whose nearest mammography provider is an RHTC hospital over the four-year period from 2016–2019. My analysis exploits changes in patients' access to 3DM following its adoption at subsidized rural hospitals. I construct a time-varying, zip code-level measure of local access based on relative distance to 3DM. Specifically, I define local access as a binary indicator equal to one for zip code z in period t if 3DM is offered at the mammography provider nearest zip code z. To precisely measure changes in access over time, I define calendar time periods in 6-month intervals. I supplement these results in Appendix B.2, which considers the effect of changes in absolute distance.

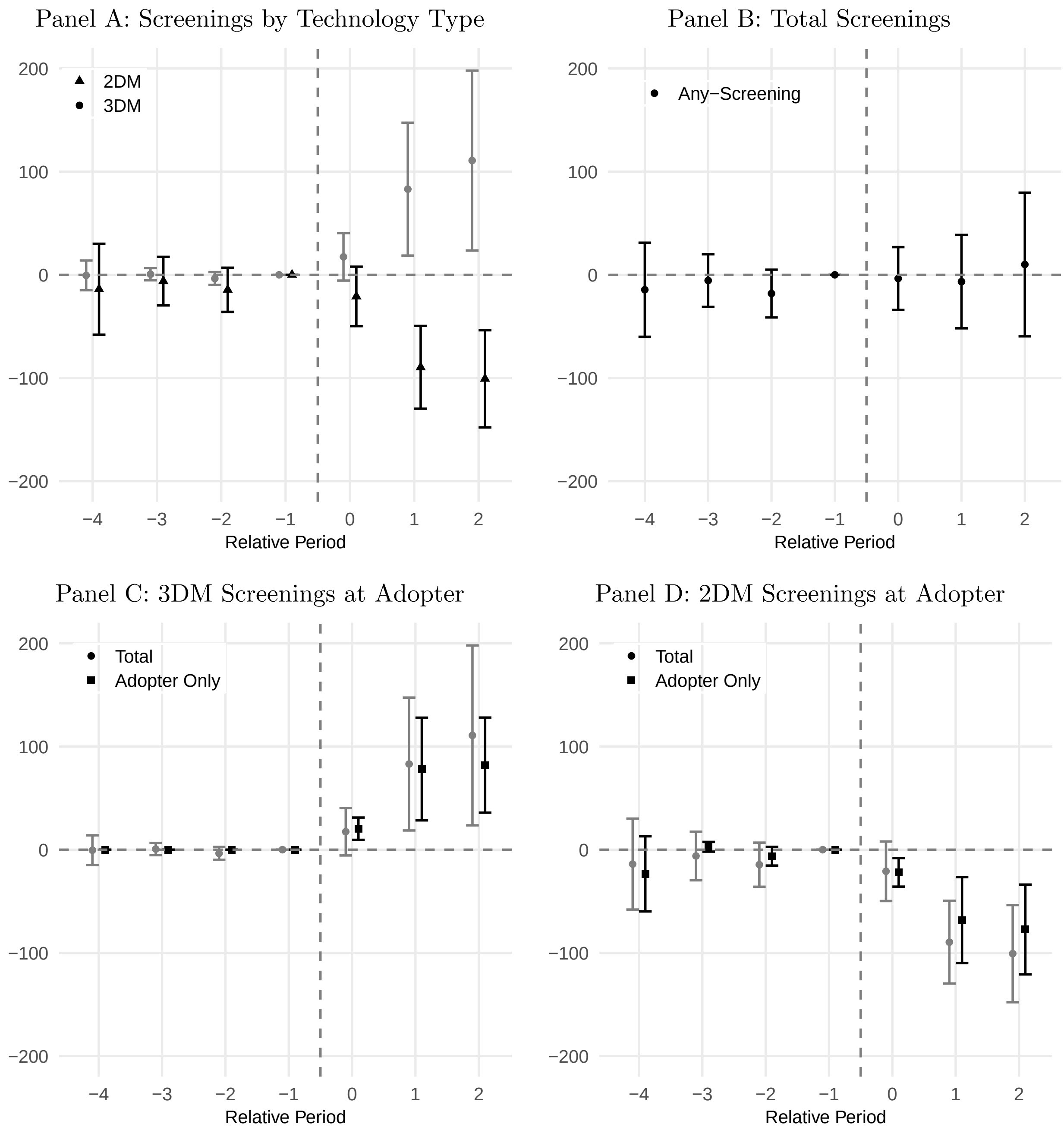
To measure changes following the adoption of 3DM, I estimate the event study regression:

$$Y_{zt} = \sum_{k \neq -1} \phi_k \cdot \mathbb{1}(t - e_z = k) + \lambda_t + \mu_z + \epsilon_{zt} \tag{2}$$

where Y_{zt} is the zip code's screening volume, measured separately for each technology type. Treatment begins during the event period (e_z) when 3DM becomes available at the provider nearest zip code z. Equation 2 is estimated using the imputation method proposed by Borusyak et al. (2024). To avoid compositional bias, I restrict attention to the set of hospital adoptions for which I observe at least 18 months of pre- and post-adoption data within my sample window. The final sample comprises 78 treated zip codes that gain local access and 94 control zip codes that do not gain local access during my sample period, allowing treatment effects, ϕ_k, to be identified through variation within and across zip codes over time. Identification hinges on the assumption that the timing of adoption is exogenous to short-run shocks in local screening demand. Alternatively, the counterfactual trends of zip codes with different degrees of access to 3DM would have evolved in parallel. I evaluate the plausibility of this assumption by testing for differences in pre-trends across groups.

Figure 3 presents ϕ_k estimates from equation 2. Panel A illustrates the estimated effect of local 3DM access on zip code-level screening volumes for both 2DM and 3DM. The flat pre-trends for both outcomes provide plausible support for the parallel trends assumption. Post-adoption, I estimate a sharp increase in 3DM utilization. By relative period 2, average 3DM volume increased by 110 scans in treated zip codes, representing a relative increase of 289% relative to the pre-treatment mean.

Figure 3: Effects of Gaining Local Access to 3DM on Screening Patterns



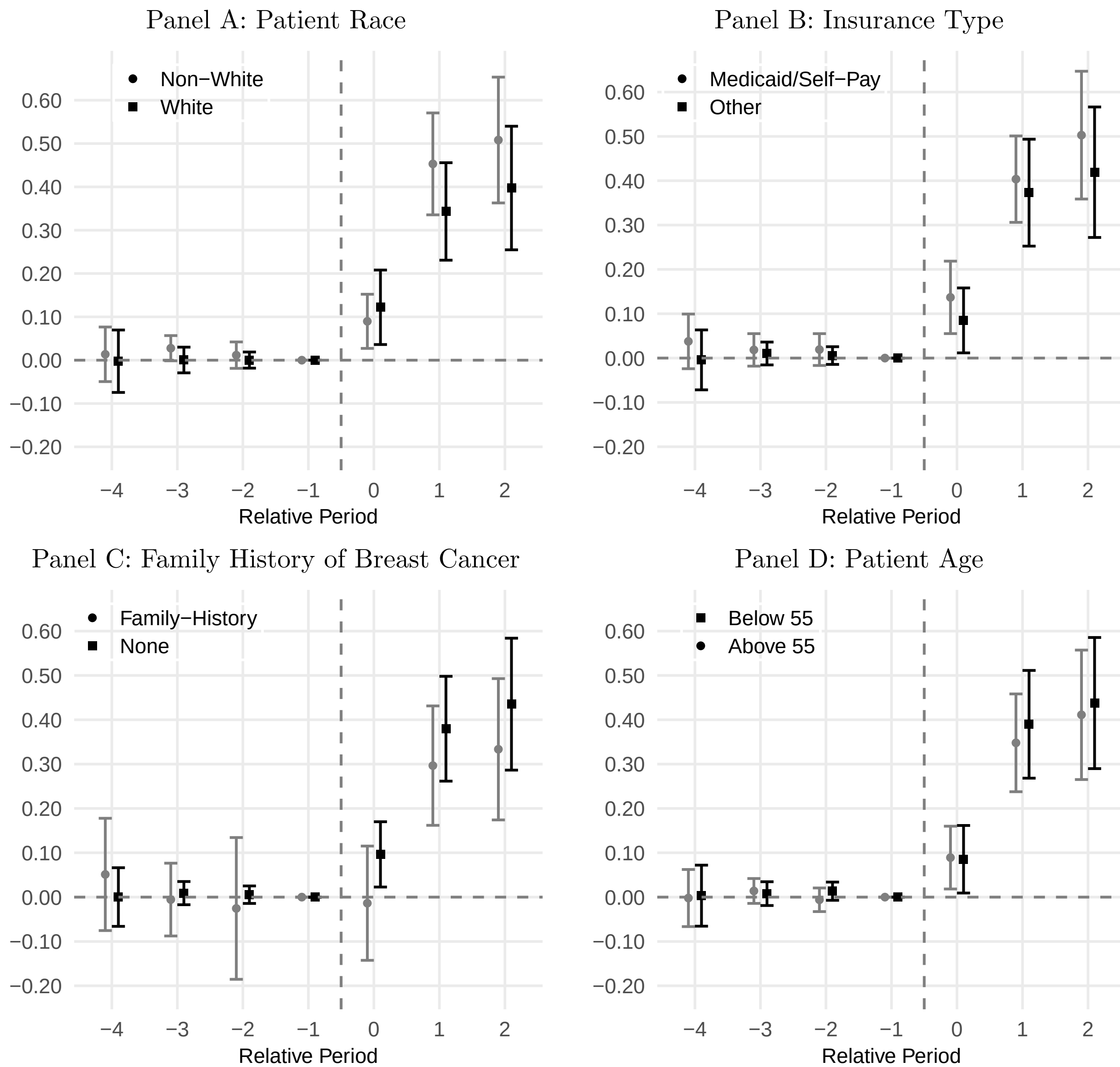
Notes: This figure shows estimates from model 2. Panel A shows estimated relative time coefficients for zip code screening volume across 2DM and 3DM. The respective means in relative period -1 are 2DM=210 and 3DM=38. Panel B shows estimates for overall screening counts. Each model is estimated using the sample of 172 rural zip codes from 2016–2019. Standard errors are clustered at the zip code level.

This rise in 3DM is mirrored by a decrease of similar magnitude in 2DM utilization, suggesting that the local availability of 3DM prompts patients to substitute between screening technologies, rather than encouraging individuals who previously did not screen to begin screening. Estimates in Panel B, which show the effect of adoption on total breast cancer screening counts, are statistically indistinguishable from zero and small across the entire pre- and post-period. Together, these outcomes show strong evidence that local access to 3DM primarily drives a shift in the choice of screening technology. Service volume means during the pre-access period equal 210 for 2DM and 38 for 3DM. Combining these totals with the event study estimates implies that by relative period two, treated zip codes experienced a 45 percentage point increase in the conditional probability of 3DM screening.

Panel C of Figure 3 includes level estimates of 3DM volume at adopting hospitals, which show that nearly all of the increase in 3DM utilization is attributable to screenings at adopting hospitals. Moreover, Panel D of Figure 3 shows that adopters experience a decline in 2DM volume that is similar in magnitude to the total zip code level estimates, suggesting that most patients who screen with 3DM in the post-adoption period are substituting away from 2DM to 3DM at their local hospital.

Next, I consider how these effects vary across patient characteristics. Figure 4 plots estimates from Equation 2 using the share of screenings performed with 3DM as the outcome variable. I find that the share of screenings performed with 3DM increases more for non-white patients and patients classified as Medicaid or self-pay. This suggests that lowering travel barriers to 3DM may have a greater impact on access for minority groups with lower socioeconomic status. Conversely, I estimate a smaller change in the share of 3DM screenings among women with a family history of breast cancer. The effects of increased access are muted for this group of women with observably higher health risk because they were more likely to travel to access 3DM before it became locally available. Panel D highlights heterogeneity across patient age by estimating the model for the subgroups of patients above and below 55 years old. I select this age threshold because empirical evidence shows that 3DM leads to a larger reduction in recall rates among younger patients (Conant et al., 2019; Sharpe et al., 2016). I find that substitution patterns evolve similarly in both groups.

Figure 4: Heterogeneity in Response to Local 3DM Access



Notes: This figure plots event study estimates using the conditional share of patients choosing 3DM in a given zip code as the outcome variable. Each Panel highlights heterogeneity in the effect of gaining local access to 3DM on screening patterns across patient characteristics. Standard Errors are clustered at the zip code level.

3.4 Technology Choice and Screening Outcomes

I use variation from the adoption of 3DM to estimate the effect of technology choice on the probability of false-positive screening results. For this analysis, I leverage individual data from the same balanced sample of rural zip codes to estimate the linear probability model:

$$\text{False}_{it}^{(+)} = \rho\, 3DM_{it} + \lambda_t + \mu_z + \epsilon_{izt} \tag{3}$$

Where $3DM_{it}$ is an indicator equal to one if i screened with 3DM at time t. The outcome variable $\text{False}_{it}^{(+)}$ is an indicator for i being recalled for a follow-up scan that does not result in a cancer diagnosis. Zip code and period fixed effects account for time-invariant differences in false-positive recall rates across localities, in addition to common changes in the prevalence of false positives over time.

Table 2: Effect of 3DM screening on False-Positive Rates

	OLS (1)	IV (2)	Sample Mean (3)
Panel A: False-Positive Rate			
Screened with 3DM	-0.034^{***} (0.002)	-0.018^{**} (0.003)	0.084
Panel B: 3DM Screening Rate			
Local Access		0.263^{***} (0.068)	0.275
Zip Code FE	Y	Y	
Period FE	Y	Y	
First Stage F		43.3	
Observations	250,200	250,200	250,200

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,. Panel A presents the effect of 3DM utilization on the probability of a false-positive test result. Column 1 reports the estimate from OLS while Column 2 reports the estimates from an IV where local access is used as an instrument for technology choice. Panel B reports the results from the first stage model. Column 3 shows mean outcomes for the dependent variables in each panel. Standard errors are clustered at the zip code level.

However, unobserved risk factors ϵ_{izt} may be correlated with a patient's decision to screen with 3DM. To address this endogeneity, I use changes in geographic access to 3DM to instrument for technology choice. Building on the approach from Section 3.3, I leverage variation in local access to 3DM following the adoption of the technology at subsidized rural hospitals. By conditioning on zip code and period effects in the first stage, this instrument isolates the variation in 3DM take-up resulting from adoption.

Panel B of Table 2 shows the results from the first stage regression. The model has an F-statistic of 43.3, suggesting that changes in local access to 3DM provide a relevant instrument. Panel A of Table 2 reports estimates of the effect of 3DM use on the probability of a false-positive. The OLS estimate in Column 1 shows that 3DM use is associated with a 3.4 percentage point decrease in the probability of a false-positive screening result. The estimate from the IV shows a smaller decrease of 1.8 percentage points. This local average treatment effect is similar in magnitude to estimates from the previous literature, reflecting a 21% reduction relative to the sample mean.[3]

4 Demand Model

4.1 Demand Specification

I model a woman's choice of breast cancer screening provider and modality as a differentiated product discrete choice problem. The utility that patient i in market m and period t receives from choosing technology s at hospital j is given by:

$$U_{ijsmt} = \underbrace{\delta_{jsmt} + \mu_{ijsmt}}_{V_{ijsmt}} + \epsilon_{ijsmt} \tag{4}$$

where δ_{jsmt} is the mean utility of screening service s at hospital j, in market m at time period t, which reflects vertical differentiation in individuals' preferences over hospitals and screening technologies. The idiosyncratic terms, $\mu_{ijsmt} + \epsilon_{ijsmt}$, capture individual-specific variation from mean utility. I specify μ_{ijsmt} as:

$$\mu_{ijsmt} = \gamma_1\, d_{ij} + \gamma_2\, d_{ij}^2 + \sum_{c=1}^{C} \kappa_c (d_{ij} * \underbrace{Z_{ic}}_{Demographics}) + \alpha_1 \mathbb{1}(Prev_{ijst} = 1) \tag{5}$$

where d_{ij} is round trip distance between i's zip code and provider j in ten-mile increments, enters utility nonlinearly. To capture heterogeneity in travel cost, I interact distance with Z_{ic}, a vector of observable patient characteristics, including race, an indicator for Medicaid

[3] Kerlikowske et al. (2022) find a 20% reduction from a baseline false-positive rate of 0.08 while Skaane et al. (2013) report a 15% reduction from an initial rate of 0.06.

or self-pay insurance status, and an indicator for family history of breast cancer. I include an indicator denoting whether i's last scan was with technology s at hospital j to capture inertia in patients' choices across time.[4]

Mean service utility is specified as:

$$\delta_{jsmt} = \beta_{3D}\, 3DM_{jmst} + \underbrace{\xi_j}_{Hospital\, FE} + \underbrace{\xi_{mt}}_{Marktet \times Period\, FE} + \underbrace{\Delta\xi_{jsmt}}_{\substack{\text{Unobserved} \\ \text{Taste Shock}}} \tag{6}$$

The mean utility of screening at hospital j varies with technology type. I define $3DM_{jmt}$ as an indicator for 3DM-technology so that parameter β_{3D} reflects the additive effect of 3DM on the mean utility from receiving a screening at provider j. I include fixed effects ξ_j to capture unobserved hospital quality and ξ_{mt} to capture time-varying market demand shocks. The remaining unobserved component $\Delta\xi_{jsmt}$ reflects hospital-service specific deviations in unobserved taste over time.

I do not model the choice to delay or forgo screening and thus assume the market size is equal to the total number of patients receiving scans. I choose to model this limited form of substitution because my model relies on variation resulting from changes in access to higher-quality services. While some patients do in fact choose to delay recommended screenings, I do not find evidence that this behavior is impacted by changes in local access to 3DM.[5] In each market, I define a particular hospital screening service combination as the outside good. Assuming ϵ_{ijsmt} follows a type one extreme value distribution, the individual probability of patient i in market m and period t choosing service s at hospital j can be written:

$$s_{ijsmt} = \frac{exp(\delta_{jsmt} + \mu_{ijsmt})}{\sum_{j,s} exp(\delta_{jsmt} + \mu_{ijsmt})} \tag{7}$$

4.2 Estimation and Identification

Sample and Market Selection: I estimate the model for Georgia hospitals that offer either 2DM or 3DM from 2016–2019. This includes 42 rural hospitals and 37 non-rural hospitals. When estimating taste for 3DM, I omit the group of hospitals that adopted 3DM after the end of 2018, ensuring adequate coverage both before and after adoption. To highlight the impact of changes in access to higher quality diagnostic care, I also limit this adoption

[4] I use data from 2014–2019 to define this variable, which ensures adequate coverage for my primary sample window 2016–2019.

[5] Appendix B.3 shows a null relationship between local screening compliance and 3DM adoption.

sample to hospitals that offered 2DM services by the start of the sample period.[6] Finally, I require that hospitals consistently report discharge data across each quarter year from 2016–2019. The final sample includes 16 rural adopters or 72% of all subsidized Georgia hospitals who adopt 3DM from 2017-2019.

Markets are constructed based on the Georgia Department of Community Health's defined state health planning regions. These designated regions encompass approximately 10 counties, with an average of seven mammography providers operating within each county. The providers located within these defined markets collectively capture an average of 92% of observed screenings for patients residing in these regions. I normalize the utility of screening with an out-of-market provider to zero. The health planning region corresponding to the Atlanta metro area is excluded from this analysis since it does not contain any subsidized rural hospitals.[7] The final sample includes a total of 79 hospitals with each operating in one of twelve unique markets.

Estimation: I estimate the model's parameters using a two-stage maximum likelihood procedure. Following Goolsbee and Petrin (2004), I estimate the idiosyncratic taste parameters θ=(γ, κ_c, α) in the first stage by maximizing the log-likelihood function (8). Where $I_{i,j,s,m,t}$ is an indicator for patient i in market m at time t choosing to screen at hospital j with technology s. Conditional on any candidate value of θ, I solve for the vector of service-specific mean utilities, $\hat{\delta}_{jsmt}(\theta)$, such that the observed market shares match those predicted by the model (Berry, 1994).

$$LL(\theta) = \sum_{i,j,s,m,t} I_{i,j,s,m,t} \cdot log\left(\frac{s_{ijsmt}(\theta)}{\sum_{j,s} s_{ijsmt}(\theta)}\right) \tag{8}$$

Travel cost sensitivity is identified by patients' substitution between local and more distant providers. An additional source of identification stems from variation in the timing of 3DM adoption at the local rural hospital, which changes the minimum distance to 3DM over time. This helps separate preferences for screening modalities and hospitals from travel sensitivity. Using patient identifiers to link patients' choices over time, α is identified by the tendency for patients to revisit the provider where they received their last scan. Identification is strengthened by variation in these patterns when new screening modalities are added

[6] This only excludes two adopting hospitals.

[7] Additionally, travel costs in this market may not be reflective of the broader state due to traffic patterns and the availability of public transit.

to the choice set. Accounting for inertia is crucial in identifying patients' preferences for screening technologies. By accounting for switching cost, I can distinguish patients' preferences for local 3DM from preferences for familiar providers.

After recovering mean utilities, at the optimal values of θ^*, I estimate the technology preference parameter β_{3D} in a second stage linear regression:

$$\hat{\delta}_{jsmt}(\theta^*) = \beta_{3D}\, 3DM_{jmst} + \xi_j + \xi_{mt} + \Delta\xi_{jsmt} \tag{9}$$

Hospital fixed effects, ξ_j, absorb all time-invariant differences across hospitals while market-by-period fixed effects ξ_{mt} control for common shocks that affect all hospitals in the same market at period t, such as changes in insurance coverage, screening campaigns, or demographic trends. The remaining variation that identifies β_{3D} comes from within-hospital changes in mean utility when a hospital begins offering 3DM, relative to other hospitals in the same market-year that have not yet adopted the technology. Consequently, β_{3D} captures the average incremental effect of 3DM availability on patient utility, net of average preferences over providers and market-wide demand fluctuations.

However, if the adoption of 3DM is influenced by hospital-level, time-varying demand shocks, $\Delta\xi_{jsmt}$, then the estimates from model 9 will be biased. To address this endogeneity concern, I employ an instrumental variables approach that exploits quasi-experimental variation from the disbursement of RHTC subsidies, which are targeted at financially constrained rural hospitals. These funds facilitated the adoption of 3DM equipment but are likely unrelated to contemporaneous local demand shocks after controlling for hospital and market-by-year fixed effects. Specifically, I instrument for the 3DM indicator with an indicator for whether a hospital received funds in year t, interacted with a 3D service dummy to create service-specific first-stage variation. This strategy isolates plausibly exogenous shifts in the propensity to adopt 3DM driven by subsidy timing and eligibility, rather than by endogenous investment responses to rising demand. Under the exclusion restriction that the subsidy affects patient utility only through its effect on 3DM availability, the IV estimates recover patients' taste for 3DM technology. Importantly, this IV estimate should be interpreted as a local average treatment effect reflecting the impact of 3DM adoption among the subset of marginal, financially constrained hospitals whose investment decisions were influenced by the subsidy.

5 Results

5.1 Preference Estimates

Results from the maximum likelihood stage of estimation are reported in Panel A of Table 3. Patients exhibit a distaste for distance, with a $\widehat{\gamma}_1$ coefficient of -0.668. This aversion to distance is stronger among Medicaid/Self-Pay patients and non-white patients. The positive estimate for $\widehat{\gamma}_2$ suggests that the incremental disutility of distance diminishes as distance increases. Patients demonstrate a strong preference for familiar providers, as reflected by a large positive value for $\widehat{\alpha}_1$.

Next, I quantify the elasticity of screening choice with respect to distance. Column 2A reports the average own-distance elasticities across sub-groups. Consistent with the results from Table 3, non-white patients insured by Medicaid are more sensitive to distance, exhibiting a distance elasticity that is 25% above the baseline estimate.

Panel B of Table 3 presents the results from the second-stage estimation procedure, which recovers preferences for screening technology. The estimates from the naive Ordinary Least Squares (OLS) regression are reported alongside the results from the two-stage least squares (2SLS) procedure. The instrument for 3D availability demonstrates a strong first stage, satisfying the relevance criteria with an F-statistic of 96.6, indicating that the policy created meaningful variation in the availability of 3DM. The larger point estimates for β_{3D} in Column 1B suggests that the OLS model likely overstates patients' preferences for 3DM. The adjusted estimate in Column 2B is equal to 1.93. This reflects a strong average preference for 3DM screening, indicating that patients are willing to travel an additional 30 miles round-trip to access 3DM, given the estimated costs of travel.

5.2 Patient Level Effects of Adoption

To quantify the effect of adoption on rural 3DM take-up, I use the model to construct choice removal diversion ratios. These diversion estimates predict patient demand in a counterfactual where 3DM is not available at rural adopters.

$$D_i(k_{3D} \rightarrow j_s) = \frac{(\hat{s}_{ijs})}{1 - \hat{s}_{ik\,3D})} \tag{10}$$

$$\Delta P_i(3D) = 1 - \sum_{j_{3D} \in J} D_i(k_{3D} \rightarrow j_{3D}) \tag{11}$$

Table 3: Utility Parameter Estimates

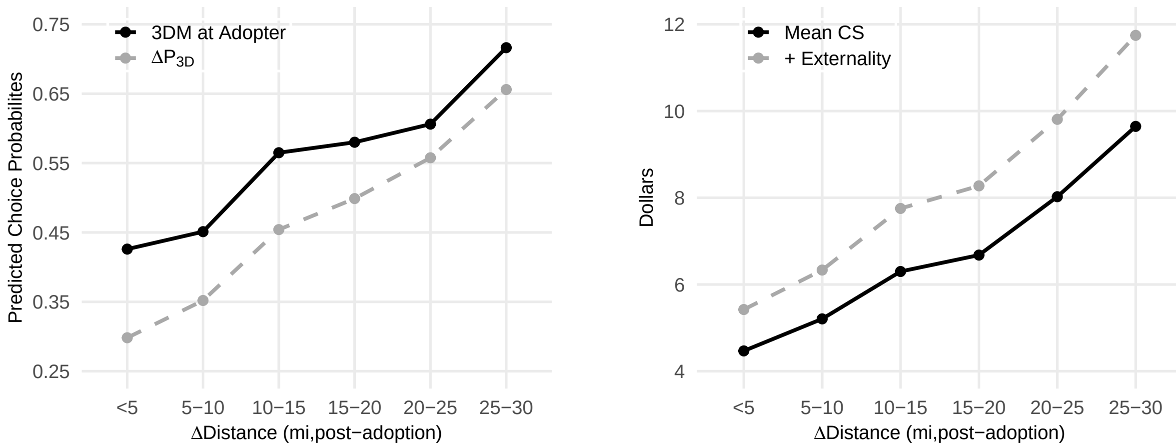
Parameter	Estimate	$\mathcal{E}_d$
Panel A:	(1A)	(2A)
Maximum Likelihood Estimation		
α_1 (Inertia)	3.238	
	(0.004)	
γ_1 Round Trip Distance (10 mi)	-0.668	
	(0.001)	-1.62
γ_2 Distance Squared	0.009	
	(0.000)	
Distance Interactions		
κ_{race} (White)	0.0221	-1.51
	(0.001)	
κ_{ins} (Medicaid/ Self-Pay)	-0.016	-1.75
	(0.004)	
κ_h (Family-History)	0.054	-1.40
	(0.001)	
Screening Observations	1,192,078	
Panel B:	(1B)	(2B)
Technology Preference Estimates	OLS	2SLS
β_{3D}	2.292***	1.93**
	(0.441)	(0.788)
Hospital FE:	Y	Y
Market×Period FE:	Y	Y
Hospital-Year Observations	1041	1041
First Stage F-stat		96.60

Notes: Panel A shows results of the logit choice model. Utility parameter estimates are shown in column 1A. Standard errors shown in parentheses. Column 2A reports the average marginal effects of a 10-mile increase in relative distance to 3DM on the probability of 3DM screening. The model is estimated using 1,192,078 unique screening observations from 2016–2019. Panel B reports the results from the regression that decomposes the effect of 3DM technology on mean utility. Column 1B reports the OLS estimates where the independent variable is a binary indicator for 3D. Column 2B shows the results from the 2SLS estimator where the subsidy is used as an instrument for 3DM availability.

Denoting the option to screen with 3DM at a given rural adopter as k_{3D} and omitting market and time notation for brevity, equation 10 gives the probability that patient i would be diverted to a given hospital screening alternative, j_s, if k_{3D} were removed from the choice set. Aggregating the set of alternative 3DM providers in a patient's choice set, I use equation 11 to measure how technology diffusion at subsidized rural hospitals impacted the likelihood of 3DM utilization.

The left plot of Figure 5 illustrates the effect of the adoption of 3DM utilization among patients who gain local access to 3DM. The solid black trend shows the average predicted probability of screening with 3DM at a rural adopter across distance bins. Specifically, the x-axis shows the change in minimum distance to 3DM post-adoption.

Figure 5: Technology Substitution and Consumer Surplus Gains Across Distance



Notes: This left plot shows average predicted probabilities from the model against reductions in travel distance. The black trend represents the predicted probability of screening with 3DM at the adopting hospital, while the gray trend reflects the total predicted change in probability of any 3DM screening. The right plot shows average consumer surplus gains from local 3DM adoption in black and the additional positive spillover attributable to reduced downstream costs from false-positive screenings in gray.

The trend increases across distance bins. This shows that on average, patients are more likely to choose 3DM at adopting hospitals when distances to alternative 3DM providers are large. For example, at the first distance bin, where adoption reduced distance to 3DM by less than 5 miles, the model predicts that 45% of patients will screen with 3DM at the adopting hospital, compared to 70% of patients at the furthest distance bin. The dotted trend line reflects the overall change in the predicted probability of 3DM screening from equation 11. The space between these trends demonstrates the degree of inframarginal substitution (between providers) versus marginal substitution (between technologies). The model predicts that adoption increased the probability of 3DM screening by 30 percentage points at the first distance bin. However, the gap between the trends at this bin implies that in the absence of adoption, 15 percent of patients would have screened with 3DM. Conversely, at the furthest distance bin, the predicted increase in the probability of 3DM screening is 65 percentage points, suggesting that nearly all of the demand for local 3DM is driven by substitution from 2DM. Intuitively, the screening decisions of patients who are further isolated from alternative 3DM providers are more responsive to adoption at the local hospital.

Next, I use the model to quantify the value patients in rural Georgia place on local access to 3DM. I use revealed preference estimates to calculate patients' willingness to pay for local access to 3DM. Equation 12 provides the change in travel miles required to compensate patient i for the expected utility loss between choice set J and J', excluding 3DM at the adopting rural hospital. I then average across patients and monetize $CV_i(J, J')$ to construct a measure of the average value patients place on 3DM at rural hospital k. I monetize this measure at a rate of \$0.77 per-mile to determine each patient's willingness to pay for local access to 3DM.[8]

$$CV_i(J, J') = \frac{1}{\tau_i} \left\{ \ln \left(\sum_{j,s \in J} \exp(V_{ijs}) \right) - \ln \left(\sum_{j,s \in J'} \exp(V_{ijs}) \right) \right\} \tag{12}$$

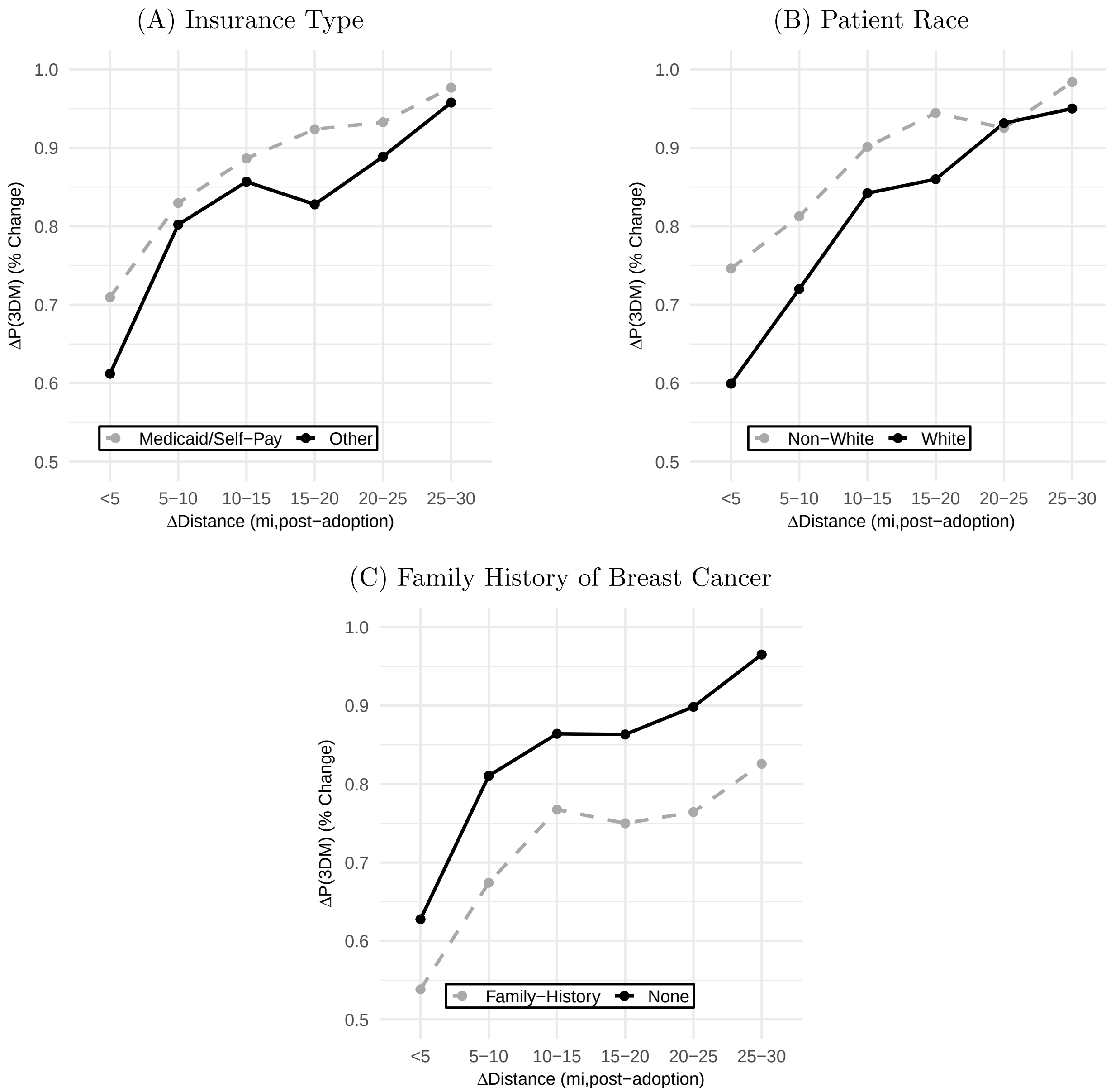
The solid line in the right plot of Figure 5 represents the average patient's willingness to pay for local 3DM across changes in distance to 3DM after adoption. I find a strong linear relationship between remoteness and willingness to pay. These values reflect the direct benefits attributable to increased product variety.

However, because 3DM screenings are less likely to yield false-positive results, their adoption reduces the expected and downstream costs of unnecessary follow-up screenings. Thus, consumer surplus estimates likely understate the marginal social value of local 3DM. To reflect the positive spillover from technology substitution, I calculate the expected reduction in health care spending per marginal 3DM screening. I set the social cost of a false-positive at \$211.21, the 2019 Medicare reimbursement rate for a diagnostic scan. Combining this with the 1.8 percentage point reduction in the probability of a false-positive result from section 3 gives an expected savings of \$3.8 per marginal 3DM screening. The dotted gray trend in the right plot of Figure 5 illustrates the average incremental gain from this positive spillover.

[8]This value is based on the IRS's reimbursement rate for a mile of travel in 2017 \$0.53 times 1.417 driving miles per straight-line mile (Boscoe et al., 2012).

The divergence between the trends at points further along the x-axis reflects the fact that technology substitution is more prevalent when prior access to 3DM is lower.

Figure 6: Technology Substitution Across Distance Bins by Patient Characteristics



Notes: Panels show the predicted change in 3DM utilization after local adoption by patient subgroup. Each panel plots average percentage changes in the probability of 3DM screening across differential-distance bins. Estimates come from the structural demand model, which incorporates travel costs and heterogeneous preferences by insurance status, race, and family history of breast cancer.

Finally, Figure 6 highlights heterogeneity across patient types by plotting the average percentage change in the predicted probability of 3DM use across distance bins for subgroups of patients with different observable characteristics. Panel A shows this relationship for patients based on insurance status. Across each distance bin, the model predicts that adoption will increase the probability of screening more for self-pay and Medicaid patients. A similar pattern is observed in Panel B, where non-white patients experience a larger increase in the likelihood of 3DM uptake. Notably, the gaps between subgroups are pronounced at the first distance bin, suggesting that smaller absolute travel burdens have a more salient impact on non-white patients of lower socioeconomic status.

Panel C plots the same relationship based on whether patients have a family history of breast cancer. Consistent with the reduced form estimate, the model predicts that women with a family history of breast cancer are less responsive to distance when making screening decisions.

6 Welfare Effects and Counterfactual Simulations

6.1 Social Welfare

$$\Delta TS_k^0 = \sum_i \sum_t \beta^t (\underbrace{\Delta CS_{it}}_{\substack{\text{Revealed}\\\text{Preference}}} - \underbrace{\Delta c_{it}}_{\substack{\text{Marginal}\\\text{Resource}\\\text{Cost}}} - \underbrace{F_t}_{\substack{\text{Period}\\\text{Fixed-cost}}}) \tag{13}$$

I perform a simple back-of-the-envelope calculation to measure the welfare effects of 3DM diffusion in rural markets. Equation 13 quantifies the baseline change in social welfare per screening due to the availability of 3DM at a given rural hospital k. I define the impact of adoption on social welfare as the change in consumer surplus net of the change in marginal resource cost of screening and the fixed cost of 3DM adoption. I take estimates of the purchase price and annual service cost of 3DM equipment from CMS's Practice Expense File. Assuming a discount rate of 3 percent over a useful equipment life of 8 years gives a per-period fixed cost, F_t, of \$23,800. I assume the marginal costs of screenings are constant across hospitals. However, I allow j's marginal cost of screening to vary across technologies. Using estimates from the Practice Expense file, I set the relative incremental cost of performing a 3DM screening, Δc_{it}, at \$13.7.

$$\Delta TS_k^1 = \Delta TS_k^0 + = \sum_i \sum_t \beta^t (\underbrace{\widehat{\rho} \cdot \Delta P_i(3D) \cdot \mathrm{R(Diagnostic)}}_{\substack{\text{Downstream} \\ \text{savings}}} + \underbrace{\eta^{SV} \cdot \Delta \pi_{it}^k}_{\text{Profit transfers}}) \tag{14}$$

Equation 14 incorporates the potential positive spillovers associated with 3DM adoption. Since 3DM screenings are less likely to yield false-positive results, technology substitution is likely to reduce the incidence of unnecessary follow-up screenings. To reflect the positive spillovers from technology substitution, I calculate the expected reduction in health care spending by monetizing the change in the probability of a false-positive recall for patient i at the Medicare reimbursement rate for a follow-up diagnostic scan.

Finally, η^{SV} reflects the social value of screening profits at adopting rural hospitals, where $\eta^{SV} > 0$ relaxes the assumption that profit transfers between firms are welfare neutral. I calibrate this parameter using data on supplemental payments received by Georgia hospitals under the Medicaid Disproportionate Share Hospital (DSH) program, which reimburses hospitals for a portion of the financial losses incurred from providing care to indigent patients (Dranove et al., 2022). States have broad discretion in how they distribute these supplemental payments, often distributing funds based on hospitals' underlying financial health to mitigate the risk of closure. In 2016, rural hospitals meeting the criteria for the RHTC program received an additional \$0.19 in DSH payments for every dollar of uncompensated care, implying that the state of Georgia places a higher weight on their financial health. To reflect this preference, I set $\eta^{SV} = 0.19$.

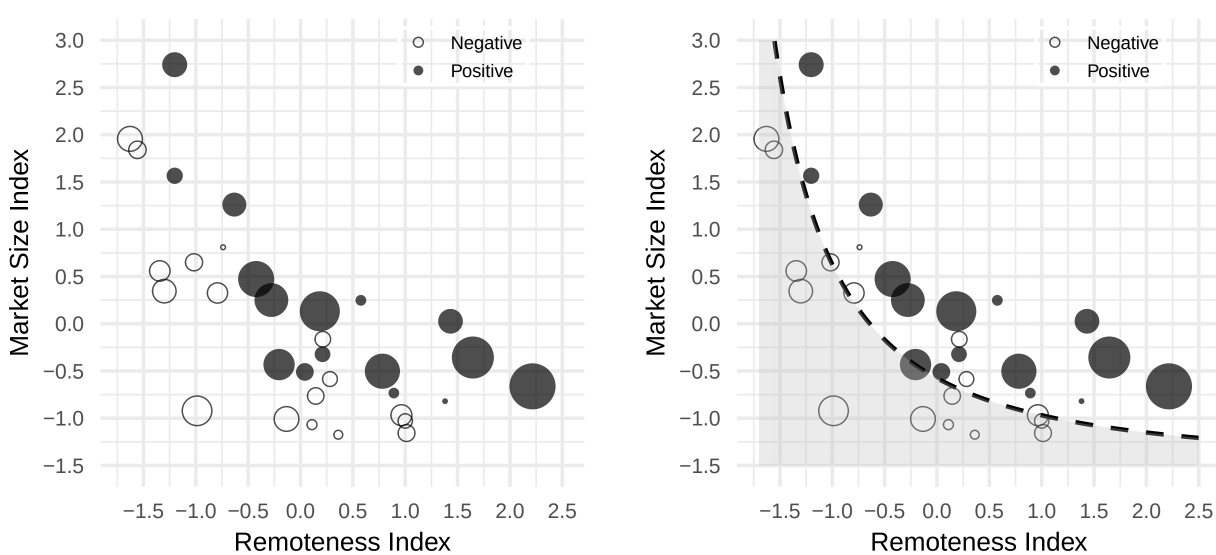
6.2 Counterfactual Simulations

Finally, I perform counterfactual exercises, using my model to simulate the effect of alternative distributions of rural 3DM supply from 2017-2019.

In this analysis, I consider the set of 33 rural Georgia hospitals that offered 2DM but not 3DM in 2016. This sample of potential rural adopters includes the rural hospitals that actually adopted 3DM after receiving subsidies as well as the never-adopters that only offered 2DM from 2016–2019. This analysis requires out-of-sample predictions for demand at hospitals not observed to adopt 3DM. I simulate counterfactual demand for 3DM at these hospitals using my technology preference estimates to predict service mean utilities via equation 6. To address concerns that non-adopters may have lower latent demand; I draw values of $\Delta\xi_{jsmt}$ from the bottom 10th percentile of the empirical distribution. For each counterfactual period, I draw 200 values of $\Delta\xi_{jsmt}$ for each non-adopter to compute the corresponding logit choice probabilities and report final counterfactual demand and welfare estimates as averages across the 200 simulation draws.

The left plot of Figure 7 plots the welfare effects of rural 3DM adoptions at each rural hospital across characteristic space. The y-axis represents the screening-eligible Hospital Service Area (HSA) population, a proxy for potential market size. The x-axis shows the distance between the adopting hospitals and the nearest incumbent 3DM provider, a proxy for horizontal differentiation. Both axes are normalized by z-scores. I plot the welfare effect of each adoption, with the color of each bubble reflecting whether the change in total surplus was positive (dark bubbles) or negative (transparent bubbles). The size of each bubble corresponds to the absolute value of the adoption's impact on total surplus. There is a clear concentration of welfare-negative adoptions in the left region of the plot, where rural adopters are relatively close to incumbent 3DM providers. Conversely, hospitals with low potential market sizes are also more likely to reduce social welfare since screening volumes are insufficient to justify the significant fixed cost of 3DM upgrades.

Figure 7: Welfare Effects Across Market Characteristics.



Notes: Each bubble represents a rural Georgia hospital in counterfactual adoption simulations. Bubble size is proportional to the absolute welfare effect, with color indicating sign (dark = positive, light = negative).

These patterns reflect the underlying trade-off between access and cost efficiency in rural health care markets. The right plot of Figure 7 illustrates this trade-off by tracing an iso-welfare frontier across distance–population space. This boundary approximates the combinations of distance and market size for which the incremental welfare effect of adoption is constant. Thus, its convex slope represents the marginal rate of substitution between remoteness and market size. The shape of this curve reflects the fact that the social value of adoption increases with both market size and differentiation, but at a diminishing rate. As a result, gains from adoption are concentrated among hospitals that are simultaneously far enough from incumbents and large enough in potential patient volume. This relationship between welfare and market characteristics suggests that allocation mechanisms that account for remoteness and potential market size can more efficiently direct funds to hospitals where welfare gains from adoption are largest.

Finally, use my model to simulate demand for breast cancer screenings in rural Georgia under alternative distributions of rural 3DM supply. First, I calculate the welfare effects of the observed 3DM upgrades at subsidized rural hospitals. I then use the model to calculate the effect of a blanket investment approach, where all rural hospitals in Georgia offer 3DM. Next, I solve for the optimal allocation of 3DM by simulating all combinations of 3DM adoption and find the set of providers that maximize social welfare. Finally, I consider selective allocation rules that limit 3DM adoption to hospitals above the 25th percentile of the distance or population distributions, and a two-part criterion combining a 25th percentile distance cutoff with a 25th percentile market size cutoff.

Table 4 summarizes the effects of each counterfactual allocation on total surplus. Column A reports the effects of adoption among the hospitals in the observed sample, where A0 reports the welfare effects under the baseline specification and A1 includes the potential spillovers. Under either specification, the net welfare effect of adoption across this observed sample of 16 adopters is positive, ranging from ($670,000–$982,000). However, there is substantial heterogeneity in these effects across hospitals. Under the baseline specification, 44% of adoptions reduce welfare.

Column B reports the effect of universal 3DM adoption. This allocation is poorly targeted. Under this blanket approach, two-thirds of adoptions have a negative effect on welfare. On net, these 33 adoptions reduce total surplus. In this counterfactual, the average patient values local 3DM at $5.2, suggesting that the variety gains from adoption are muted relative to alternative allocations. Moreover, under this allocation, utilization of the new 3DM equipment is relatively low. Average fixed spending per-scan totals $25.2 and is driven up by the deployment of 3DM in small markets.

Column C illustrates the welfare gains at the optimal set of rural 3DM suppliers. I solve for this set by iterating over all combinations of rural 3DM adoptions within each market, selecting the group of potential 3DM adopters that maximizes total surplus. Under either specification, this first-best allocation includes 12 rural adopters. These adopters all have a positive effect on welfare, increasing baseline total surplus by $1.9 million, which corresponds to a $1.19 social return on every dollar of investment in the rural 3DM supply. Under this perfectly targeted allocation, average consumer surplus is high, and average fixed spending per scan is low. This illustrates that well-targeted investments are those that meaningfully increase product variety while also ensuring sufficient scale.

Column D shows that the selective allocation rule based purely on distance increases social welfare relative to the observed and universal scenarios. These gains result from the improved targeting of funds toward hospitals that are horizontally differentiated from incumbents in terms of distance, highlighting the importance of product variety in this setting. However, 40% of adoptions in this counterfactual have a negative effect on welfare, suggesting that allocating investments solely based on distance is insufficient. This approach tends to select adopters with inadequate scale. Under this policy, equipment spending per-scan is relatively high compared to the optimal set.

Finally, I consider a two-part allocation criterion that targets funds based on distance and potential market size. This counterfactual combines the previous two conditions, targeting investments at hospitals above the 25th percentile of the distance and market size cutoff. Column E shows that preventing 3DM investment at hospitals at the tails of the characteristic distribution substantially increases the welfare effect of adoption, achieving nearly 80% of the welfare gains relative to the optimal allocation. This targeting mechanism reduces investment at hospitals that operate in sparsely populated markets, where screening volumes are insufficient to justify the large fixed cost of 3DM upgrades. However, average variety gains are lower under this two-part allocation rule relative to the distance-based approach, indicating that these efficiency gains come at the cost of reduced access in small markets where patients remain isolated from 3DM.

Table 4: Welfare Effects Under Counterfactual 3DM Allocations

	A		**B**		**C**		**D**		**E**	
	Observed		**Universal**		**Optimal**		**Dist >12 mi**		**Dist >12 mi & M>2.5k**	
	(A0)	(A1)	(B0)	(B1)	(C0)	(C1)	(D0)	(D1)	(E0)	(E1)
N	16	-	33	-	12	12	20	-	15	
$\overline{CS_i}$ (\$)	7.1	-	5.2	-	8.9	-	8.1	-	6.8	-
$\overline{F_i}$ (\$)	16.17	-	25.19	-	10.4	-	18.2	-	12.5	-
ΔTS_k <0	44%	32%	67%	60%	0%	0%	40%	40%	26%	26%
ΔTS (\$1,000s)	670	982	-1,033	-588	1,933	2,402	1,407	1,674	1,527	1,716
Social ROI	0.31	0.45	-0.23	-0.13	1.19	1.48	0.52	0.62	0.75	0.84

Notes: This table reports the welfare effect of simulated technology upgrades across alternative supply distributions. Columns A report the effects of the observed set of adoptions, Columns B reflect the counterfactual where every rural hospital adopts 3DM, Column C reflect the optimal allocation which maximizes total surplus. Columns D and E correspond to the counterfactual where 3DM is allocated using observable market characteristics. Cutoff values of 12 miles and 2.5 thousand correspond to the first quartiles of the distance and market size distribution. For each allocation, welfare results from the baseline specification (0) and the alternative specification that accounts for spillovers (1) are displayed. Row 1 shows the total number of rural adopters under each counterfactual. Row 2 shows the average consumer surplus gain across adoptions. Row 3 reports the average fixed cost per-scan, calculated as total fixed cost divided by total 3DM volume at adopting hospitals. Row 4 reports the share of welfare-negative adopters, while row 5 shows the net welfare effect across adoptions. Dollar values are reported in thousands. Finally, Row 6 reports the social return on 3DM investment, calculated as the change in total surplus divided by total fixed spending.

7 Conclusion

This paper studies the welfare consequences of 3DM adoption at rural hospitals in Georgia. Using quasi-exogenous variation from the state's Rural Hospital Tax Credit, I estimate both reduced-form effects of distance on screening choice and a structural model of patient demand. The results show that local access to 3DM substantially increases utilization of the technology, driven primarily by substitution away from lower-quality 2DM screenings. Patients exhibit strong disutility of travel, and the value they place on local adoption is highest in markets that were previously most remote from 3DM. Welfare analyses indicate that, on average, adoption improved total surplus. However, I find that the benefits of adoption vary widely across rural markets. While some adoptions generated substantial welfare gains, others resulted in net losses when placed in sparsely populated or already well-served markets. As a result, I find that an untargeted investment approach leads to large welfare losses. My results show that an allocation rule where eligibility is determined by a hospital's remoteness and market size substantially improves targeting, delivering larger net welfare gains without unnecessary public spending.

These results highlight a fundamental tension in rural health policy: expanding geographic access to advanced medical technologies generates meaningful welfare gains, but those gains are highly heterogeneous and sometimes offset by cost inefficiencies. My analysis shows that adoption of 3DM at rural Georgia hospitals improved patient welfare on average, with every public dollar invested yielding an additional $0.45 in total surplus. Yet, adoptions resulted in welfare losses when new scanners were placed in small markets with sufficient access to 3DM. These findings underscore that technology subsidies, while effective in relaxing financial constraints and facilitating adoption, can lead to over-investment if not carefully targeted. This suggests that blanket subsidies may not be the most effective way to close technology gaps. Instead, allocation mechanisms that account for observable market characteristics can more efficiently direct funds to hospitals where the welfare benefits of adoption are largest. The targeting rule I propose strikes a balance between serving isolated patients and ensuring sufficient scale, providing a transparent framework that can be applied to other rural service lines.

These findings contribute to broader debates in health economics and industrial organization. This study provides empirical evidence on how fixed costs, geographic frictions, and patient heterogeneity interact to shape welfare outcomes from technology diffusion. In particular, I complement prior work showing that provider entry often entails both beneficial increases in product variety and socially redundant business stealing. My results show that in rural markets, these forces can be balanced by targeting funds based on observable market characteristics.

My results have several caveats. First, the consumer surplus calculation assumes that the dollar value of time is constant across patients. Second, I use cost estimates from a national survey of hospitals that may not be reflective of my rural sample. Third, while I document meaningful heterogeneity across patient subgroups, data limitations prevent a full accounting of unobservable health risks that may shape willingness to travel. Finally, my setting focuses on breast cancer screening, and it is unclear whether the results would fully generalize to other diagnostic technologies where cost and quality differ.

Nevertheless, this analysis offers important insight into how financial constraints and public policy influence the allocation of medical technologies and access to care in rural markets. The findings in this paper directly address current federal efforts to modernize the rural health care supply. Under the recent \$50 billion appropriation to the Rural Health Transformation Fund, states have unprecedented flexibility in the allocation of funds to rural health care systems (CMS, 2025). My results show that public investments in rural health care capacity can yield significant improvements in access to high-quality diagnostic care, but efficiency depends on where the funds are targeted. This analysis provides a framework for designing allocation policies that better balance access and cost-efficiency. Overall, this analysis demonstrates that investments in rural health care quality can yield meaningful welfare gains by bringing services closer to those in need; however, maximizing those gains requires careful attention to where and how those investments are made.

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A Appendix Tables

Table A1: Program Information and Funding Allotments from 2017-2019

	2017	**2018**	**2019**
Eligibility			
County Population	35,000	50,000	50,000
Qualifying Hospitals	50	58	58
Participating Hospitals	49	58	58
Donations ($1,000s)			
Statewide Cap	10,000	60,000	60,000
Total	9,227	59,505	46,516
Mean	188.3	1,025.9	802.0
25th Percentile	59.0	634.2	340.5
50th Percentile	128.0	865.0	579.5
75th Percentile	243.0	1,268.5	918.2

Notes: This table shows eligibility for the program and the evolution of donations received from 2017-2019. In 2017, RHTC funds were only available to non-private hospitals in counties with populations below 35,000. In 2018, the population limit was raised to 50,000 and the number of participating hospitals increased to 58. Over this time frame, nearly every qualifying hospital received RHTC funds. The statewide cap on donations was raised by $50 million in 2018, which led to a sharp increase in total and average funds received. Source: Georgia Department of Community Health.

Table A2: Reported Use of Funds and Spending Across Categories in 2018

	Funds Available	**Funds Spent**	**Funds Reserved**
Mean	$1,080,189	$871,584	$208,604
25th Percentile	$684,623	$415,541	$0
50th Percentile	$904,350	$802,032	$0
75th Percentile	$1,292,252	$1,234,524	$386,388

Category	**Mean Spending**	**Median Spending**	**Frequency of Spending**
Operations	$383,898	$93,570	32
Personnel	$32,329	$13,125	16
Med-Equipment	$249,948	$82,409	36
Facilities	$219,484	$24,180	26
Other	$147,725	$35,741	53

Notes: This table shows summary statistics from hospital level reports on utilization of RHTC funds in 2018. Columns 2, 3, and 4 shows summary statistics for the amount of RHTC funds available to hospitals in 2018, funds spent in 2018, and unspent funds that hospitals kept as financial reserves. On average, hospitals spent 80% of funds available, and held the remaining 20% as cash reserves. The reported distribution shows that more than half of all hospitals spent all available funds in 2018. The bottom half of panel B shows a breakdown of hospital spending across categories. The largest share of RHTC funds were spent on regular operating expenses. The second largest reported expenditure category in 2018 is purchases of medical equipment. Source: Georgia Department of Community Health.

Table A3: Summary Statistics

	Treated	Control	*p-value*
Panel A: Hospital			
Net Worth	14,417.7	16,359.51	(0.428)
	[21,544.1]	[29,247.45]	
Fixed Assets	14,537.8	13,876.4	(0.595)
	12,426.8	14,227.5	
Hospital Equipment	11,760.7	11,342.4	(0.59)
	[7,438.6]	[8,906.7]	
FTE	0.25	0.29	(0.37)
	[0.16]	[0.32]	
Inpatient Days	6.65	7.18	(0.475)
	[6.42]	[8.54]	
Beds	51.4	49.5	(0.80)
	[41.00]	[56.49]	
Government Owned	0.63	0.64	
Hospital Count	58	95	
Panel B: County			
County Population	23,808.9	27,623.9	(0.01)
	[13,700.7]	[17,244.8]	
Percent Uninsured	18.7	16.7	(0.01)
	[3.2]	[3.6]	
Percent Above 65	15.9	16.5	(0.05)
	[4.1]	[2.7]	
Percent Employed	89.6	87.5	(0.01)
	[2.9]	[3.9]	

Notes: This table displays mean 2016 characteristics for subsidized rural Georgia hospitals and rural control hospitals from other southern states. Standard deviations are shown in brackets and p-values are shown in parentheses. County demographic variables are taken from the American Community Survey. Source: HCRIS.

Table A4: Identifying Screening Mammograms from CPT Codes

Modality	Screening	Diagnostic
3DM	77063	G0279, G0204, G0206
2DM	77067, G0202, 77057, 77052	77065, 77066,77051, 77055, 77056, G0204, G0206

Notes: This table displays the procedure codes used to identify screening and diagnostic mammography encounters across imaging modalities.

Table A5: Comparing HCUP Screening Counts to Medicare Claims

Service	Medicare	HCUP	Percent
Screening 3DM	85,515	74,859	87
Screening 2DM	173,719	132,223	76

Notes: This table displays a comparison of screening mammography procedure counts between my primary data source and public-use Medicare aggregate files across Georgia in 2018. To match the Medicare population, I subset the HCUP data to individuals insured by Medicare FFS. At the state level, I capture 87% of 3DM screenings and 76% of 2DM screenings.

B Supplemental Analyses

B.1 Triple Difference Estimates of Subsidized Adoption:

I test the robustness of these results by estimating the triple difference specification presented in Equation 15. This model accounts for potential Georgia-specific factors that may be occurring concurrently with the implementation of the subsidy and could bias my estimated treatment effects. I address these potential confounding state-specific factors by comparing adoption rates among non-rural Georgia hospitals with those of non-rural hospitals located in control states. By differencing out adoption trends between these two non-rural groups this model is robust to time-varying state-specific confounders.

$$Y_{ht} = \beta_1(GA_h \cdot post_{ht} \cdot rural_h) + \beta_2(post_{ht} \cdot GA_h) + \beta_3(post_{ht} \cdot rural_h) + \lambda_t + \mu_h + \epsilon_{ht} \quad (15)$$

Table B1 presents the estimated effects from a standard difference-in-differences specification alongside the triple difference results. I find a significant 11 percentage point increase in the annual probability of 3DM adoption under the difference-in-differences specification that is significant at the 5% level. The triple difference estimate of 7.5 percentage points is significant at the 10% level. Though smaller in magnitude, the qualitative nature of these results suggests that the increased adoption of 3DM in rural Georgia hospitals is driven by the implemented subsidy. This increase in 3DM adoption at rural Georgia hospitals created plausibly exogenous variation in rural patients access to 3DM-technology. In the next section, I exploit these time-varying changes in access to the nearest 3DM provider to quantify the effect of distance on screening technology choice.

Table B1: Effect of Subsidy on 3DM-Adoption

3DM-Purchase	(DD)	(DDD)
Post x Subsidy	0.11**	0.075*
	(0.035)	(0.042)
Controls		
Hospital FE	Y	Y
Year FE	Y	Y
Hospital-Year Observations	918	3,627

Notes: Column 1 reports estimates from the difference in differences model estimated using the sample of rural hospitals in GA and control states. Column 2 reports estimates from the triple differences model estimated using the sample of rural and urban hospitals in GA and control states. Standard errors are clustered at the hospital level. Source: FDA

B.2 Marginal Changes in Distance to 3DM:

I exploit changes in rural patients' absolute distance to the nearest 3DM provider over time to estimate the elasticity of screening choice with respect to distance.

$$Y_{izt} = \rho\, d_{izt} + \lambda_t + \mu_z + X_i + County_i \cdot t + \epsilon_{zt} \tag{16}$$

Using the same sample of screening observations across 136 rural zip codes from 2016–2019, I estimate the model presented in equation 16. Outcome variable Y_{izt} is an indicator for whether individual i chooses to screen with 3DM. My preferred specification controls for zip code and period fixed effects, though I also test the robustness of results to patient level controls and county-specific time-trends. Explanatory variable, d_{izt}, is a continuous measure of distance to the nearest 3DM provider in miles, so that ρ reflects the marginal effect of a change in distance to 3DM on the probability of screening with 3DM-technology.

Table B2: Effect of Absolute Distance to 3DM on Technology Choice

	(1)	(2)	(3)
Panel A: Reduced Form—Dependent Variable: Screened with 3DM			
Distance to 3DM	-0.0058^{***}	-0.0059^{***}	-0.0063^{***}
	(0.0008)	(0.0009)	(0.0008)
N	216,544	216,544	216,544
Panel B: First Stage—Dependent Variable: Distance Traveled			
Distance to 3DM	0.6951^{***}	0.6851^{***}	0.6478^{***}
	(0.0938)	(0.0928)	(0.0953)
N	72,595	72,595	72,595
Mean outcome	27.730	27.730	27.730
F-stat	64.9	37.6	5.348
Panel C: Second Stage—Dependent Variable: Screened with 3DM			
Predicted Distance	-0.0084^{***}	-0.0086^{***}	-0.0096
to chosen provider	(0.0012)	(0.0013)	(0.0078)
Mean outcome	0.3352	0.3352	0.3352
Zip code FE:	X	X	X
Period FE:	X	X	X
Individual Controls:		X	X
County-Time-Trend:			X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,. This table displays the estimates from equation 16 quantifying the impact of distance to 3DM on 3DM utilization. Panel A reports the effect of distance to the closest 3DM provider in miles on the probability of 3DM screening. Panel B shows estimates of the relationship between minimum distance to 3DM and distance to the chosen 3DM screening provider. Panel C shows estimates from the second stage regression where predicted distance to the chosen 3DM providers is the explanatory variable. Each column includes period fixed effects. Column 1 includes zip code fixed effects, Column 2 adds patient level controls, Column 3 includes a linear time-trend at the county level. Standard errors are clustered at the zip code level, and bootstrapped using 500 iterations in Panel C.

To account for the fact that some women don't receive screenings at their nearest provider, I follow the approach of Gazze (2024) and supplement the results from equation 16 with a two-sample two-stage-least-squares (2SLS) model. This model is estimated using the sample of women who screen with 3DM, where first stage regresses distance to the chosen screening provider on distance to the nearest 3DM provider. I use estimates from the first stage to construct a measure of predicted miles traveled to 3DM for the full sample which is the explanatory variable in the second stage of estimation. This two-stage procedure scales the reduced form estimates of distance's effect on screening decisions by the share of compliers, that is, the individuals who change screening technology choice in response to a reduction in distance to 3DM. Standard errors for the second stage estimates are constructed via bootstrap.

Estimates in Panel A of Table B2 show that a one mile increase in distance to 3DM lowers the probability of 3DM-take-up by -0.58 percentage points, equivalent to a 1.7% change in the mean outcome. This baseline estimated from column (1) is robust to alternative specifications including individual controls and time-varying trends. Panel B shows a strong first-stage relationship between minimum distance to 3DM and distance to the chosen provider for all specifications except column 3. This estimate implies that a one mile drop in distance to the nearest 3DM provider decreases the average distance traveled for 3DM screening by seven-tenths of a mile. Finally, I use the predicted distance estimate from the first-stage regression to estimate the scaled effect for the entire sample. Estimates in Panel C show that a one mile increase in predicted travel distance to 3DM reduces the probability of 3DM screening by -.084 percentage points. Together, these results show strong evidence that distance to 3DM-technology is a key determinant in 3DM take-up.

Distance has a clear impact on screening decisions, but thus far, it is unclear whether these effects differ systematically across patient types. To quantify how changes in distance impact selection into 3DM screening, I estimate equation 16 on the sample of patients who choose to screen with 3DM, using patient characteristics as the outcome variable. These estimates measure changes in the average characteristics of rural 3DM screeners that result from marginal changes in distance to 3DM-technology. Table B3 reports the results of this analysis across observable patient characteristics. Column 1 shows that women who opt into 3DM screenings at larger distances are more likely to have a family history of breast cancer, suggesting that patients' willingness to travel to access 3DM is positively related to underlying health risk. Column 2 tests for differences in willingness to travel to 3DM across age. Qualitatively, younger women are more likely to travel further to access 3DM screenings, but the estimated effect is not distinguishable from zero. In columns 3 and 4, I find that women screened with 3DM when travel costs are higher are less likely to be non-white or classified as Medicaid/Self-Pay. This suggests that lowering travel barriers to 3DM may have a larger effect on access for minority groups of lower socioeconomic status, but that the effects for women with observably higher health risk will be more muted.

Table B3: Changes in Mean Characteristics of 3DM Patients as Distance Varies

	Family History (1)	Age (2)	Non-White (3)	Medicaid/Self-Pay (4)
Distance to 3DM	0.003^{***}	-0.006	-0.002^{***}	-0.001^{***}
	(0.001)	(0.009)	(0.000)	(0.001)
Sample Mean	0.115	62.07	0.244	0.092

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,. This table shows the effect of distance to 3DM on the average characteristics of patients who select into 3DM screening. The model is estimated using the sample of rural patients who screen with 3DM (N=72,595). Each column shows the average change in patient characteristics for a one-mile increase in distance to the nearest 3DM provider. All regressions include zip code and period fixed effects. Standard errors are clustered at the zip code level.

B.3 Alternative Measure of Screening Compliance:

This section tests for evidence of the effect of rural 3DM adoption on county level mammography screening compliance. I use two measures of screening compliance in this analysis, the first is constructed using Georgia HCUP data from 2016-2019. Over this sample period, the United States Preventative Service Taskforce recommended women ages 50 and up receive a screening mammogram every two years. I calculate two-year screening compliance at the county level using patient identifies in the discharge data to construct a measure of the number of unique screenings given to women in each Georgia county over a two year interval. I then scale this count by the ACS estimate of female county population for women 50 and up. I supplement this analysis with an additional county level compliance measure from the Dartmouth Atlas Dataverse's Selected Primary Care Access and Quality Measures Data set. This data contains county level two year mammography screening compliance rates for women ages 67-69 in the fee-for service Medicare population. For each data set, estimate the following two-way fixed effects model:

$$Y_{ct} = \beta_0 + \beta_1 * Rural * Post_{ct} + C + \tau + e_{ht}$$

Where Rural is an indicator for whether county c is defined as rural by the RHTC eligibility criteria, and $Post_{ct}$ is an indicator that equals 1 if any hospital in county c provides

3DM at time t. I estimate this model using county and year fixed effects. β_1 captures the average effect of rural 3DM adoption on county screening compliance rates, and is identified by differences in compliance trends between rural adoption counties all other counties in the state before and after adoption. Column 1 of Table B4 reports estimate of β_1 using the HCUP compliance measures while column 2 shows the estimate from the Medicare FFS sample. Both estimates are small and statistically indistinguishable from zero, suggesting that rural 3DM adoption leads to substitution across screening types rather than an increase in screening compliance.

Table B4: County Screening Compliance and Rural 3DM Adoption

	(1)	(2)
$Rural * Post_{ct}$	0.0103	0.002
	(0.809)	(0.953)
Data Set	HCUP	Dartmouth Atlas
Sample Mean	0.68	0.71
County FE	Y	Y
Year FE	Y	Y
County Year Observations	415	415

Notes: This table shows estimates from a model regressing county level screening compliance rates on an indicator for rural 3DM adoption. Source: HCUP/Dartmouth Atlas.