Who Gains When Medicine Becomes More Precise?

Evidence from Genomic Testing in Breast Cancer*

Jasmin Moshfegh

November 27, 2024

[DRAFT - NOT FOR DISTRIBUTION]

Abstract

I study the efficiency and equity consequences of the entry of a precision medicine technology in the context of breast cancer treatment. Using administrative Medicare claims data, I leverage within-provider variation in the timing of technology adoption relative to a patient's breast cancer diagnosis in an event-study framework. On average, I find that patients who saw an oncologist in the year after the oncologist adopted the technology are more likely to avoid unnecessary treatments. More specifically, patients are less likely to receive chemotherapy at no increased risk in mortality. However, this welfare-improving impact is concentrated among white patients and patients with higher socioeconomic status. I find large differences in technology diffusion by race that exist even among patients seeing the same physicians, suggesting that differences in use are not solely driven by differences in patient access to different physicians. Moreover, using linked cancer registry data I show that differences in medical appropriateness for the test only explain 40 percent of the within-provider Black-white gap. Overall, the results highlight the possibility of precision medicine to improve healthcare efficiency at a potential risk of widening health disparities.

*Stanford University. Email: moshfegh@stanford.edu. This paper benefited from incredible support and guidance from Laurence C Baker, Petra Persson, and Maya Rossin-Slater. I would also like to thank Dominique Araya, Alex Chan, David Chan, Mark Duggan, Caroline Hoxby, Suhani Jalota, Johan Ljungkvist, Maria Polyakova, Kurt Sweat, and seminar participants at Stanford. This research is supported by an R36 award ('The Causes and Consequences of the Diffusion of Precision Medicine: Evidence from Innovations in Breast Cancer Medicine') and grant T32HS026128 from the Agency for Healthcare Research and Quality. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality. This research is also supported by the Sweden-America Foundation and the Stanford Institute for Economic Policy and Research George P. Shultz Dissertation Fund. Data for this project were accessed using the Stanford Center for Population Health Sciences Data Core. The PHS Data Core is supported by a National Institutes of Health National Center for Advancing Translational Science Clinical and Translational Science Award (UL1TR003142) and from Internal Stanford funding.

1 Introduction

The United States healthcare system has increasingly prioritized investing in the research and delivery of precision medicine, defined as an approach to medicine that uses patients' unique genes, environments, and lifestyles to tailor disease prevention and treatment (FDA, 2018). Accordingly, spending on genetic tests has increased (Phillips et al., 2018). Medicare – the largest US public health insurance program covering individuals aged 65 and older and those who are disabled – spent $1.9 billion on genetic tests in 2021, four times the amount spent just five years earlier (Office of Inspector General, 2022). At the same time, evidence on the diffusion and impact of precision medicine is scant, with an active debate surrounding its potential to change healthcare delivery (i.e., does it create value?) as well as its equity consequences (i.e., if so, for whom?).[1]

In this paper, I study the consequences of the diffusion of one of the earliest genomic tests to reach the market in the United States[2] – the 21-gene recurrence score.[3] The setting is that of breast cancer – a disease that afflicted 254,744 individuals in 2018 in the US and that has been subject to substantial technological progress as well as health inequity.[4] Similar to an increasing number of medical technologies in precision oncology, the 21-gene recurrence score addresses a classification challenge typical in medicine - whom to treat and whom not to. While chemotherapy is generally effective in treating breast cancer and preventing its recurrence, the marginal benefits of treatment can be low in cases where the risk of recurrence is low, especially given the side effects of chemotherapy.[5] The 21-gene recurrence score assesses the expression of 21 genes present in tumor tissue to estimate the risk of recurrence, to help determine the subset of patients who are likely to benefit, or not benefit, from chemotherapy treatment.

I begin by assessing the potential impacts of the diffusion of the 21-gene recurrence score. Using Medicare claims data for a 20 percent random sample of beneficiaries, I leverage within-provider variation in the timing of a patient's breast cancer diagnosis[6] relative to the initial adoption of the

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[1] This issue has also received considerable media attention (New York Times, 2015b; New York Times, 2015a).
[2] In 2018, the test was among the top ten tests in terms of Medicare spending.
[3] Also known as OncotypeDX.
[4] As a case in point, while, breast cancer death rates fell by 40 percent between 1989-2020, 40 percent is also the magnitude by which death rates in black women were higher than that of white women between 2013-2017 (American Cancer Society, 2022).
[5] This includes temporary side effects such as nausea and infections, as well as long-term organ damage.
[6] More specifically, I leverage within-provider variation in the timing of a patient's breast cancer surgery which

technology by the provider, to estimate the impact of increased patient access to the technology in an event-study framework. The findings suggest substantial changes in treatment decisions. On average, patients who saw an oncologist three years after the oncologist adopted the technology are twice as likely to be tested and approximately 15 percent less likely to receive chemotherapy. These effects are concentrated to patients who saw providers who prior to adoption had the highest rates of chemotherapy use. Thus technology adoption appears to have led to a reduction in treatment intensity variation across providers.

If chemotherapy use prior to technology adoption represents overtreatment, or unnecessary use, the reduction should not be associated with an increased risk of long-term mortality or cancer recurrence. Consistent with prior overtreatment, I find no increase in five-year all-cause mortality or cancer metastasis. If anything, patients are *less* likely to die or have a metastasis. These effects may be driven by a reduction in the long-term side effects from chemotherapy as well as an overall better targeting of chemotherapy to patients. Patients are also less likely to experience common side effects associated with chemotherapy treatments, such as nausea, as measured by a decline in the use of anti-nausea prescriptions.[7]

To gauge the efficiency gain, I leverage insights from prior literature measuring productivity in healthcare (Abaluck et al., 2016; Abaluck et al., 2020) and Chan et al. (2022), in particular. More specifically, the previous results are viewed through the lens of a classification problem in which providers first observe patient risk types with noise and based on this information classify patients as low-risk or high-risk. The classification in turn determines whether or not a patient receives treatment. Imperfect information results in diagnostic errors or inefficiencies, such as false positives which occur when a low-risk patient is classified as high-risk and receives treatment. Under the assumption that the true distribution of patient risk-types does not change before and after provider technology adoption, the event-study design can be used to gauge the impact of adoption on the true and false negative rates. Overall, the results suggest the performance of the classification problem improves with genomic testing. This represents the efficiency gain from genomic testing.

Thus, the findings so far suggest the potential for substantial patient welfare gains from testing. To what extent are patients of different socioeconomic backgrounds and race likely to

occurs shortly after diagnosis.

[7] I focus on one of the most common classes of drugs used in conjunction with chemotherapy - anti-nausea drugs, although there are many other treatments that cancer patients may undergo to treat or avoid the side effects of chemotherapy.

benefit from testing? A large body of previous literature has shown how medical innovation can be both inequality-increasing initially (e.g., Aizer and Stroud, 2010; Lleras-Muney and Lichtenberg, 2005; Glied and Lleras-Muney, 2008; Cutler et al., 2006; Jayachandran et al., 2010), as a result of selective uptake by more educated and affluent individuals, as well as inequality-decreasing (e.g., Alsan et al., 2021). Several features of the 21-gene recurrence score make the disparity implications a priori unclear. First, the technology is fully covered by Medicare. Hence, differences in patient financial constraints cannot explain any differences in uptake. Second, the technology is primarily used as an aid in provider decision-making. Hence, differences in patient awareness or education also play a limited role in technology use.

In spite of this, the findings suggest sharp socioeconomic and racial gradients in genomic testing at the population-level. More specifically, Black patients are less likely to be tested compared to white patients over the 10 year time period following Medicare coverage of the technology, regardless of their income status as measured by dual enrollment in Medicaid – the US public health insurance program for people with low income – and regardless of where they live. These results are in line with a growing medical literature documenting disparities in test use (e.g., Peethambaram et al., 2017; Zhang et al., 2020; Chen et al., 2023), although findings have been mixed (Roberts et al., 2016; Dinan et al., 2015a).

Racial disparities in health between Black and white Americans are not unique to this setting. Prior literature has shown how differences in the types of providers that Black and white patients see can explain racial disparities in health, especially historically (Chandra et al., 2022; Skinner et al., 2005). To what extent does *allocation* explain differences in testing across Black and white patients? That is, are Black patients less likely to see an adopting provider? The previous event-study models, which leverage variation in testing *within* provider, reveal testing to be concentrated to certain patient populations, and in particular white patients and patients with higher incomes, as proxied by the absence of Medicaid enrollment. This suggests that the previously documented racial gradients in technology use are not solely driven by differences in patient access to adopting providers.

The equity consequences, and the policy implications that follow, depend on the causes underlying the observed within-provider gaps in technology use between Black and white patients. For instance, Black patients may be less likely to be tested due to unobserved (to the econometrician)

patient characteristics that make them less likely to benefit from the technology. This would be true if Black patients generally present with more advanced stages of cancer making chemotherapy a necessity, and hence a test that guides in the decision to forgo it, irrelevant. In light of an extensive literature on racial differences in cancer characteristics, including staging (see for instance, Iqbal et al., 2015; Chatterjee et al., 2013; Li et al., 2003), potentially attributable to racial gaps in the use of mammograms (Smith-Bindman et al., 2006), differences in medical appropriateness across Black and white patients likely explain part of the gap. If by contrast, a within-provider gap exists for two medically identical patients, this could be suggestive of racial differences in provider testing behavior potentially stemming from discrimination (Chandra and Staiger, 2010).

To distinguish between these two mechanisms as drivers of the within-provider racial gap, I turn to detailed cancer registry data from the Surveillance, Epidemiology, and End Results (SEER) Program. Between 2010-2015, Black patients were approximately 40 percent less likely to be tested than white patients, conditional on seeing the same provider. Controlling for measures of medical appropriateness, including but not limited to cancer staging, hormone status, and the size of the primary tumor, reduces the gap by 35 percent. This leaves a substantial portion of the gap unexplained and should be the focus of future research and policy efforts.

These results highlight how the extent to which different population groups eventually gain from the arrival of a new technology depend on various distinct margins. Cutler et al. (2010) show that (induced) innovation can cause a widening of health disparities between majority and minority groups as a result of research targeting the diseases most common in the former. The findings of this paper highlight how the same implication may arise when research targets earlier stages of a disease, where minority groups may be underrepresented, e.g., due to existing disparities in health behaviors or screenings.

In particular, a disparity in the gains from innovation across two groups emerges and amplifies when the technology 1) is more appropriate in one group because it targets a disease more prevalent in one group ("differential appropriatenes"), 2) conditional on appropriateness is accessed to a greater extent by one group ("differential access or allocation"), 3) conditional on appropriateness and access, is used more intensively in one group ("differential testing or discrimination"), and conditional on all of the above, 4) is of greater value in one group ("differential treatment effects"). When this is true, and groups are defined along the lines of socioeconomic status or race, the arrival of a new

technology gives rise to, or worsens, an existing health disparity. A back-of-the-envelope calculation in the setting of my study highlights the role of differential appropriateness and testing as driving the overall gap in testing, as opposed to differences in access.

Overall, the findings suggest that in the context of breast cancer, the arrival of genomic testing for chemotherapy treatment was associated with substantial efficiency gains, in the form of a reduction in unnecessary treatments. However, the gains from the diffusion of precision medicine were borne by some groups more than others. In the short-run, identifying causes behind the within-provider racial gap in testing for medically similar patients is important. Moreover, addressing potential existing gaps in the use of preventive medicine such as mammograms continues to be an important issue in and of itself, but also because the value of catching cancers early is increasing as precision medicine targets diseases, or stages of disease, at increasingly earlier stages.

This paper makes three key contributions. First, this paper builds on a small and growing literature on the economics of precision medicine (Berndt et al., 2019; Conner et al., 2022; Hult, 2018; Pulk et al., 2018). Similar to a nascent literature on the effects of machine learning, AI, and algorithms on physician decision-making (Kleinberg et al., 2018; Mullainathan and Obermeyer, 2022, Agarwal et al., 2023), the findings of this paper suggest the potential for large efficiency gains from the use of algorithms to guide physician decision-making, specifically driven by a reduction in overtreatment as a result of diagnostic inaccuracy.[8] The findings also highlight how the efficiency gains may vary considerably across providers.

Second, this paper contributes to the literature on the causes of racial disparities in health, and in particular the role of within- versus between-provider variation (Chandra et al., 2022; Alsan et al., 2019; Alsan and Wanamaker, 2018, Chandra and Staiger, 2010). I study these forces in the context of breast cancer, which is characterized by pressing racial disparities, and for which the existence of granular cancer registry data allows for a better understanding of the root causes of disparities.

Third, this paper provides evidence on the performance of the 21-gene recurrence in the real-world setting, using quasi-experimental variation in access to testing to quantify the (heterogenous) impact of the test on treatments. As such it complements the evidence from clinical trials, which

[8] Although not the emphasis of the paper, heterogeneity in the impacts of technology adoption by provider characteristics, including prior-to-adoption treatment intensities, highlight the potential role of genetic testing to, through the information that it brings, reduce the widely documented variation in healthcare across geographies and providers (Agha et al., 2022) and to affect allocative inefficiency (Chandra and Staiger, 2020).

tend to carry the highest form of internal validity but which often have limited external validity given selection into participation, with minorities and black patients often underrepresented (Nazha et al., 2019; Alsan et al., 2022; Alsan et al., 2023; Unger et al., 2016). In particular, the largest randomized clinical trial of the 21-gene recurrence score, the Trial Assigning Individualized Options for Treatment (TAILORx), randomized over 10,200 women with early-stage breast cancer across more than 1,000 sites in the United States, Australia, Canada, Ireland, New Zealand, and Peru (National Cancer Institute, 2018). Results from the trial suggested that standard of care would lead to overtreating 25 percent of patients with a low risk of recurrence, while undertreating 43 percent of patients with high risk (Sparano et al., 2015; Sparano et al., 2018). The findings from this study also complement medical studies documenting trends in the use of testing, and the association between testing and chemotherapy use in the real-world setting.[9] In this regard, the contribution of this study is to provide causal estimates of the effects of increased access to the 21-gene recurrence score on chemotherapy use, complementary treatments, and metastasis and mortality in a large nationally representative population, and to quantify heterogeneous treatment effects according to both patient and provider (treatment) characteristics.

This paper is organized as follows. Section 2 provides background on breast cancer treatments and genomic testing. Section 3 describes the data and provides descriptive statistics. Section 4 describes the empirical strategy and the impacts of increased access to genomic testing. Section 5 describes the implications of technology diffusion on racial disparities, and Section 6 concludes.

[9]More specifically, a large body of prior medical literature has shown that test use is associated with an overall reduction in chemotherapy use, although results have been mixed, partly reflecting different patient populations and study periods (Schaafsma et al., 2021; Dinan et al., 2015b; Su et al., 2016; Carlson and Roth, 2013; Ademuyiwa et al., 2011; Losk et al., 2021; Choi et al., 2020; Eiermann et al., 2013; Geffen et al., 2011; Paik et al., 2006; Bhutiani et al., 2018; Marchionni et al., 2007). At least in the shorter-run, no evidence of increased mortality has been documented (Roberts et al., 2017; Petkov et al., 2016). Most relevant to this study is Dinan et al. (2020) which uses an approach to address selection bias.

2 Setting

Breast cancer is the second most common cancer in women in the United states, representing about 1 in 3 of all new female cancers each year (American Cancer Society, 2023a). It is also the second leading cause of cancer death in women. According to the American Cancer Society's 2023 estimates, there will be 297,790 new cases of invasive breast cancer diagnosed in women, of which 43,700 will result in death. On the upside, the probability of surviving breast cancer has increased considerably in the past decades. Estimates from the Surveillance, Epidemiology, and End Results (SEER) database for cancers diagnosed between 2012-2018 suggest an overall 5-year relative survival rate of 91 percent, ranging from 30 percent to 99 percent depending on the spread of the cancer (American Cancer Society, 2023b). Breast cancer is a disease affecting women across the age distribution with a median age at diagnosis of 62 years.

2.1 Breast cancer treatment

Breast cancer is often discovered after an individual experiences symptoms (e.g. discovering a lump in the breast), or through an abnormal finding during a screening mammogram. To confirm that the abnormal finding is a breast cancer, diagnosis is made following a (surgical) biopsy. If a patient is found to have breast cancer, several tests are often performed to determine the type of the cancer. There are different types of breast cancer, were "type" refers to the protein/hormone and gene expression of the cancer cell. For instance, many cancers are characterized by cancer cells that have hormone receptors (also known ass hormone receptor positive cancers) and some cancers have the HER2 gene (also known as HER2+ cancers). The treatment a patient receives, in turn, if any, depends on the type of the breast cancer.

Most women with breast cancer will have some type of surgery to remove the tumor. This may then be followed by treatment with "systemic therapies" or drugs. Common options are chemotherapy, hormone therapy, targeted drug therapy, or immunotherapy. The overall treatment decision is generally guided by the type of the cancer and the stage of the cancer. So for instance, a patient with breast cancer and cells that have hormone receptors, would be treated with hormone therapy, possibly in addition to other therapies, and a patient with HER2+ cancer would be treated with targeted drug therapies such as Trastuzumab (brand name: Herceptin).

Different systemic therapies carry different risks and benefits. While potentially very effective in treating cancer, chemotherapy is notorious for its dreaded side effects, which include hair loss, nausea, fatigue, as well as potential long-term damages to the heart and nerves. To avoid or treat these side effects, patients may receive other treatments and drugs, such as anti-emetic drugs to combat nausea. By contrast, hormone therapy does not carry the same side effects profile.

2.2 Genomic testing

In a subset of breast cancer patients, genomic testing and the 21-gene recurrence score assay, can help determine which patients would benefit from chemotherapy treatment, and which patients could safely forgo it. In lay terms, this is the subset of patients who respond to hormone therapy, have HER2 negative cancer, and who have early-stage invasive breast cancers.[10] In this set of patients, hormone therapy may suffice.

The test was developed in 2004 by a private commercial lab located in Redwood City, California.[11] It assesses the expression of 21 genes in a tumor sample that is removed from the patient during surgery or biopsy. The expression of these genes, 16 which are cancer-related and 5 which are reference genes[12], are informative of 1) the likelihood of cancer recurrence, and 2) the likelihood that the patient will respond to chemotherapy. The test uses this information and an algorithm to produce a single score, ranging from 0 to 100, also known as the "recurrence score". The score reflects the risk of the breast cancer coming back (recurring) in the distant future if the patient is treated with hormone therapy alone and how likely the patient is to benefit from getting chemo after surgery. Individuals with low scores, can "safely" forgo chemotherapy, while individuals with high scores are likely to benefit from chemotherapy.

The typical treatment pathway may look like the following. 1) providers/patients discover a lump, 2) diagnostic workup is made to diagnose the cancer and to determine its characteristics

[10] In clinical terms, today, these are patients with ER/PR positive cancers, HER2- cancers, stages I-IIIa. Upon the inclusion of the technology in the NCCN guideline in 2008, the test was strongly recommended for node-negative patients with hormone receptor-positive (i.e. patients with cancer cells that have hormone receptors and who therefore may respond to hormonal therapies), HER2-negative tumors (i.e. patients with cancers cells that have HER2 receptors and may therefore respond to HER2 targeted treatments like Trastuzumab) that are 0.6-1.0 cm and moderately/poorly differentiated or with unfavorable features, or >1cm.

[11] Although several other tests are available on the market today, the use of other similar tests is negligible in the Medicare covered population.

[12] The references genes are: Beta-actin, GAPDH, RPLPO, GUS, and TFRC. The cancer-related genes are HER2-related(GRB7 and HER2), Estrogen-related (ER, PGR, Bcl2, SCUBE2), Invasion-related (Stromelysin 3, Cathepsin L2), and Proliferation-related (Ki-67, STK15, Survivin, Cyclin B1, MYBL2).

(HER2-, hormone+, early stage) and the 21-gene recurrence score is potentially ordered, and 3) a decision is made about the course of treatment and in particular, if chemotherapy should be used in addition to hormone therapy:

Simplified pathway to genomic testing and chemotherapy

1. Abnormal finding
2. Diagnostic workup to determine type and stage of cancer
3. Genomic testing to determine the benefit from chemo and the risk of recurrence
4. Begin hormone therapy and potentially chemotherapy to treat the cancer and reduce the risk of recurrence

The major clinical guidelines for oncology in the US, the American Society of Clinical Oncology (ASCO) and National Comprehensive Cancer Network (NCCN) guidelines, began recommending the use of the technology in 2007 (Harris et al., 2007), and January 2008, respectively.[13] The guidelines include score cutoffs to determine patients at low, intermediate, and high risk of recurrence. These cutoffs have changed over time as the evidence base has evolved. In the first release of the NCCN guidelines in 2008, patients were deemed to be "low risk" if they had scores below 18.[14]

To test a patient, a provider orders a specimen kit from the manufacturing laboratory, and submits a sample obtained during surgery or biopsy to the lab. The lab performs the analysis using the technology, and submits a report to the physician within two weeks. See Figure A.1 for a sample report and Figure A.2 for a detailed visual of the steps involved.

2.3 Medicare coverage policies relevant to cancer

Medicare is the largest US public health insurance program covering individuals aged 65 and older, those who are disabled, and those with end-stage renal disease. Different parts of Medicare cover

[13]How were providers and patients making chemotherapy decisions prior to the inclusion of the technology in the guidelines? From the 2007 version of the NCCN guidelines: "The decision to add chemotherapy to hormonal therapy should be individualized, especially in those with a favorable prognosis and in women age 60 y where the incremental benefit of chemotherapy may be smaller. Available data suggest sequential or concurrent hormonal therapy with RT is acceptable."

[14]Moreover, "intermediate" was defined as a score between 18 and 30, and "high" was defined as a score greater than or equal to 31. By 2020, the cutoffs were contingent on the node status of the cancer. The cutoffs were the same for node positive patients. For node negative patients they were 26, 26-30 and greater to or equal to 31. The greatest change in the recommended use of the test occurred after the release of new findings from the ongoing clinical

different types of healthcare services. Medicare Part A primarily covers inpatient hospital stays, Part B primarily covers physician services, outpatient care, as well as medical devices, and Part D covers prescription drugs. Part C refers to the Medicare Advantage (MA) program, representing private health plans that Medicare has contracted with. Most elderly patients in the US are enrolled in "traditional" Medicare; typically these are individuals with Part A and Part B coverage, and to an increasing extent Part D coverage since 2006, although MA enrollment has increased rapidly in the last decade.[15]

Medicare started covering the technology in 2006 under the Part B schedule.[16] Although most Part B services are subject to a deductible and 20 percent coinsurance, provided on having a breast cancer diagnosis, a tested Medicare patient faces no co-insurance, i.e. the test comes at no cost to the patient. Medicare generally reimburses the lab for the cost of the test under the Clinical Laboratory Fee Schedule (CLFS). In 2018, this rate was set at $\$3,873$. In some instances, and in particular, when the test is performed as part of an inpatient stay our as part of certain outpatient stays, the laboratory receives reimbursement from the hospital, and the hospital bills Medicare. Physicians are required to order the test, but face no direct cost and receive no reimbursement for doing so.

Chemotherapy drugs are primarily covered under the Part B Schedule,[17] which means patients face a 20 percent coinsurance. Given that there is no maximum out-of-pocket (OOP) for services on the Part B schedule, Medicare patients can be particularly vulnerable to the costs of cancer treatments, potentially facing OOP costs that are between 23.7 percent of household income (Narang and Nicholas, 2017). Most other self-administered drugs are covered under Part D. This includes most hormone therapy drugs. Anti-emetic medications taken to combat nausea during chemotherapy treatment are covered by both Part B and Part D, depending on the timing of the prescription in relation to the chemotherapy treatment. For drugs that are on the Part B schedule, providers purchase them from wholesalers and get reimbursement by Medicare.

trial associated with the technology in 2022. As a result, the intermediate risk-group was removed for several patient groups, including postmenopausal women, and the cutoffs were set at, less than 26 or greater than 26.

[15] More specifically, MA enrollment increased from roughly 16 percent of all Medicare beneficiaries in 2006 to 34 percent in 2018 (Kaiser Family Foundation, 2019).

[16] In practice, NHIC - a Medicare contractor - issued a Local Coverage Determination (LCD) in 2006, but because the laboratory manufacturing the test (at that point, Genomic Health) is located at a single site (Redwood city, California), the LCD effectively became a national policy.

[17] Some chemotherapy drugs are covered under Part D. However, the use of these drugs is negligible in the setting of this study.

3 Data and Descriptive Statistics

The primary source of data used to show the impact of genomic testing diffusion is administrative Medicare claims data for a 20 percent sample of the Medicare population in the years 2006-2018. For each individual, I observe at the daily level, the diagnosis and treatments individuals receive, and the doctors who treat them. The Medicare claims data is organized into different files and the analysis relies on the following files: 1) the master beneficiary summary File (MBSF) which tracks beneficiary characteristics such as the age of the beneficiary and the zip code of residence, 2) the carrier file which contains claims submitted by non-institutional providers such as physicians and clinical laboratories, 3) the outpatient file which contains claims submitted by hospitals for non-inpatient care, 4) the chronic conditions file which contains information about the history of major chronic conditions of patients, including the first time a breast cancer diagnosis was established, 5) the MEDPAR file which contains information about inpatient stays, and 6) the Part D event file which contains information about prescription drugs.

3.1 Sample construction

Sample of patients at-risk. To identify the sample of patients potentially eligible for the technology, the carrier and outpatient files are used to identify all women with a claim for a breast cancer related surgery or biopsy and a confirmed breast cancer diagnosis according to the chronic conditions file between Jan 1, 2007 and Dec 31, 2017. Next, the following set of exclusions are made. First, individuals are excluded if they were enrolled in HMO plans, or were not continuously enrolled in Medicare Parts A and B in the year prior to, and the year of, surgery, unless the patient died within the year. This restriction is made to be able to follow treatment decisions in the year following surgery and to measure comorbidities in the year prior to surgery. Second, individuals are excluded if they had a prior history of breast, colorectal, lung, and endometrial cancer, as the testing and chemotherapy decision facing a patient with a recurrent cancer is different from that of a newly diagnosed patient. Third, patients are excluded if they take drugs indicating they are HER2 positive, and hence not indicated for the test. Moreover, individuals are excluded if they are younger than 40 years or older than 80 years at the time point of surgery. This restriction is made to limit the analysis to patients who are not too old to be considered for the technology/chemotherapy. This

sample of N=107,252 is the at-risk population. This population is a superset of the "true" at-risk population. That is, some patients in this risk-set are not necessarily eligible for the technology, in particular patients with advanced stages of cancer. This does not impact the interpretation of the proceeding analysis, it does however preclude inference about the extent to which the technology is over- or underused.

Matching patients to providers. At-risk patients are matched to oncologists by identifying any oncologist[18] seen by the patient for an office visit within [-90, 180] days of the breast cancer surgery. The sample is also restricted to patients who saw providers with at least 8 patients overall (this corresponds to the mean number of patients per provider), excluding the index patient (i.e., the first patient the provider tests). A flow chart of the sample construction process is found in Figure 1. The final sample for the event study analysis consists of N=53,315 patients and N=4,228 providers.

3.2 Measurement

Treatments and outcomes. For each patient in the analysis sample, the Medicare files are used to determine if the patient was tested, the treatments the patient received, mortality and proxies for recurrence. All outcomes are measured at various time points relative to surgery. Testing is identified using the Carrier file.[19] Since the Carrier file includes files submitted by commercial laboratories, all patients who were tested can be identified by finding all claims submitted by Genomic Health (CLIA lab number 05D1018272) to Medicare.[20] It is also possible that a patient is tested as part

[18] "Oncologists" are identified as physicians with a CMS speciality code in hematology/oncology (83), medical oncology (90), or surgical oncology (91). Radiation oncology (92) and gynecologist/oncologist (98) are not included as these providers are unlikely to order the test. Providers from other specialties may use the test as well, but the analysis is restricted to oncologists since this subset is the most relevant provider population to adopt the technology

[19] The early arrival of the 21-gene assay allows for an analysis of both the short-term and long-term implications of technological progress. This makes this technology a particularly important one to study and it also makes the study sufficiently powered. Moreover, coding for laboratory tests predates the entry of precision medicine. More specifically, laboratory tests were historically billed using CPT codes that reflected the individual steps or components of a molecular service, such as "DNA extraction" (also known as "stacking codes"). This made it difficult for payers to know what tests they were paying for. Amid increasing pressure to reform the system of coding for molecular pathology tests - the AMA implemented several changes, of which the major reform was the replacement of the process-oriented CPT codes to gene-specifc CPT codes starting in 2012. As such it is often not possible to identify the receipt of a particular genomic/genetic test in most sources of administrative claims data in the United States. By contrast the 21-gene recurrence assay is identifiable in claims data over time. The reason for this is that the 21-recurrence assay was manufactured by a single lab - identifiable in the claims data - and for which the 21-gene assay was its main product.

[20] Later on in the sample period Genomic Health also launched a separate test for prostate cancer. To avoid including these tests, an individual's testing date is defined as the first date at which a patient had a claim submitted by Genomic Health for a covered breast cancer diagnosis code.

of an inpatient stay or a hospital outpatient visit. In the latter case, the test is generally bundled with other services and falls under the Hospital Outpatient Prospective Payment System. The hospital bills Medicare, and the laboratory collects payment from the hospital. Importantly, those tests would not be identifiable in the data. However, according to the company's annual report from 2011, such patients represent less than 1 percent of the company's total breast cancer testing population.[21] Nevertheless, measurement error in test receipt may lead to an under count of the true testing rate. To the extent that this is true, this would lead to an attenuation bias as some of the patients in the control group may be treated. Moreover, because the identification strategy leverages within-provider variation, this concern is limited unless providers use different billing rules for different patients.

The main treatment of interest is chemotherapy, as this is the treatment directly impacted by the use of the test. I also consider treatments for the management of nausea, which is a common side effect of chemotherapy, and treatment of depression, which individuals may be at a heightened risk of as a result of chemotherapy. To identify the treatments patients receive, including chemotherapy, anti-emetic medications, and anti-depressants, the carrier, outpatient, MEDPAR, and Part D files are used.

The main measures of patient health are mortality and the recurrence of the cancer. All-cause mortality is measured using the master beneficiary summary file. As a proxy for the spread of cancer, the carrier, outpatient, and MEDPAR files are used to identify claims with diagnosis codes indicating a secondary cancer or metastasis. I refer to this as a *proxy* for recurrence, as coding for metastasis may be measured with noise.

For a complete list of codes used, see Appendix A.2. Because there may be measurement error in the coding of medical procedures, the proceeding analysis is also performed using alternative definitions of breast cancer surgery and chemotherapy used in prior medical literature.[22] The results are not sensitive to alternative definitions and available upon request.

Patient characteristics. Patient comorbidities are measured in the year prior to the surgery using the chronic conditions files. The master summary beneficiary file is used to identify a patient's zip code of residence, age, race, original reason for Medicare enrollment, and more specifically whether or not the patient was originally eligible due to disability or old-age, where the former

[21] Source: https://www.sec.gov/Archives/edgar/data/1131324/000095012311024832/f58029e10vk.htm

[22] More specifically, these include Dinan et al. (2015a); Zipkin et al. (2021); Dinan et al. (2015b); Su et al. (2016)

represents a much more vulnerable population, a patient's dual status or enrollment in Medicaid in addition to Medicare, prescription drug or Part D coverage, and eligibility for the Part D Low income subsidy, conditional on having Part D coverage.[23] For each individual, the metropolitan status of an individual's county of residence is determined according to the Rural-Urban Continuum Codes in 2013, which define metropolitan counties as counties in metro areas.[24]

To characterize the socioeconomic environment, the National Neighborhood Data Archive (NaNDA) is used (Melendez et al., 2020). The NaNDA contains data on zip code level neighborhood deprivation and affluence measures, which are indices based on zip-code level statistics from the American Community Surveys.[25] More specifically, the neighborhood socioeconomic disadvantage is originally constructed using information from the American Community Survey (2008-2012) as an average of five census indicators (proportion non-Hispanic Black, proportion of female headed families with children, proportion of households with public assistance income or food stamps; proportion of families with income below the federal poverty level; proportion of population age 16+ unemployed) and it ranges from 0 to 1.0. The neighborhood affluence is an average of three census indicators (proportion of households with income greater than $75K, proportion of population age 16+ employed in professional or managerial occupations; proportion of adults with Bachelor's Degree or higher) ranging from 0 to 1.0. Using this data, patient zip codes are characterized according to their 2008-2012 1) neighborhood disadvantage index, 2) neighborhood affluence index, 3) proportion of people with income past 12 months below poverty level, and 4) proportion of households with public assistance income. Zip codes are then classified into deciles of each of the above measures.

Provider technology adoption. A provider's adoption date is defined as the first date the provider used the technology for any breast cancer patient in the Medicare population. Since

[23]More specifically, this includes all beneficiaries who were 1) enrolled in Parts A and/or B, and Part D; deemed eligible for LIS with 100% premium subsidy and no copayment, 2) enrolled in Parts A and/or B, and Part D; deemed eligible for LIS with 100% premium subsidy and low copayment, or 3) enrolled in Parts A and/or B, and Part D; deemed eligible for LIS with 100% premium subsidy and high copayment

[24]More specifically, metropolitan counties are defined as counties in 1) Counties in metro areas of 1 million population or more, 2) Counties in metro areas of 250,000 to 1 million population, or 3) Counties in metro areas of fewer than 250,000 population. Non-metropolitan counties are counties with 4) Urban population of 20,000 or more, adjacent to a metro area, 5) Urban population of 20,000 or more, not adjacent to a metro area, 6) Urban population of 2,500 to 19,999, adjacent to a metro area, 7) Urban population of 2,500 to 19,999, not adjacent to a metro area, 8) Completely rural or less than 2,500 urban population, adjacent to a metro area, or 9) Completely rural or less than 2,500 urban population, not adjacent to a metro area according to the 2013 Rural-Urban Continuum Codes (RUCC).

[25]The NaNDA contains measures at the ZCTA level. A crosswalk from the USDS mapper is used to obtain the measures at the 5-digit zip level. Source: https://udsmapper.org/zip-code-to-zcta-crosswalk/

providers may have used the technology in a non-Medicare patient, there will be measurement error in the adoption date, and more specifically, the adoption date is likely to be biased upwards for all providers.

Provider characteristics. The Medicare Data on Provider Practice and Specialty file is used to identify a provider's age, gender, and practice as measured by the Tax Identification Number or (TIN). The Carrier file is used to identify the extent to which the provider is working at a practice that is financially integrated with a hospital. Following prior work (Neprash et al., 2015), providers are classified as "financially integrated" with a hospital, if the majority of their claims (with a non-zero allowable charge) submitted for any service in a place of service corresponding to either 1) inpatient hospital, 2) outpatient hospital, or 3) office, was associated with a place of service corresponding to an outpatient hospital. A provider is otherwise classified as "non-financially integrated". Providers are also characterized by their chemotherapy treatment intensity prior to technology adoption as follows. First, for the subset of providers who ever adopted the technology, 1) I restrict the sample to those who saw at least five patients prior to adoption, 2) define the treatment intensity as the share of patients receiving chemotherapy before technology adoption, and 3) rank providers based on this share and classify them into above and below median intensity providers.

3.3 Descriptive statistics

This section presents aggregate time series of technology diffusion in the at-risk population between 2007-2017 and summary statistics for the analysis sample.

3.3.1 Technology diffusion

Figure 2 shows the share of patients tested within three months of their breast cancer surgery over time in the at-risk sample. From the figure it can be seen that technology adoption increased from roughly 8 percent in 2007 to over 20 percent in 2017.[26] Over this time period, the share of patients treated with chemotherapy within one year of surgery also declined, potentially reflecting the impact of the technology. Conditional on being tested, almost 20 percent of patients were treated with chemotherapy at the beginning of the time period (Figure 3, panel a). Over time, there was a

[26]Not all patients in the sample will be indicated for the test, hence it is not possible to infer under-adoption.

relatively faster decline in chemotherapy use among tested patients, making tested patients overall less likely to be treated with chemotherapy by 2017. Tested patients are also substantially less likely to die within five years, compared to non-tested patients, consistent with the technology being more relevant for patients with earlier stage disease (Figure 3, panel b). Overall, these descriptive patterns illustrate that the technology has a big footprint - one in five breast cancer patients in the sample are tested by 2017, with tested patients being increasingly less likely to be treated with chemotherapy over time.

To what extent is adoption evenly distributed across space, and in particular across more vs less disadvantaged areas? Figure 4 suggests an uneven distribution. This figure shows the predicted share of patients tested by different measures of zip code level socioeconomic characteristics.[27] For instance, individuals living in zip codes in the bottom decile of the neighborhood affluence index have an adoption rate of roughly 15 percent while individuals living in the top decile have an adoption rate of roughy 19 percent, representing a difference of almost 27 percent in uptake.

To what extent was technology diffusion even across different patient groups, and race in particular? Figure 5 illustrates large differences in the share of patients getting tested by race and a proxy for patient income, namely, enrollment in Medicaid. In 2017, 26 percent of white patients were getting tested, while the corresponding share for Black patients was 16 percent (Figure 5, panel a). Compared to low-income Medicare patients, i.e., patients who are also eligible for Medicaid, relatively high-income Medicare patients are more likely to be tested (Figure 5, panel b). Figure A.3 illustrates how similar gaps are observed for another measure of income - namely eligibility for the Part D low income subsidy. This figure also illustrates that diffusion was evenly distributed across metropolitan and non-metropolitan counties.

To gauge to what extent the racial gap in testing is driven by differences in income, Figure 5 panels (c) and (d) condition on a patient's Medicaid status. From these panels it can be seen that the racial gap exists independent of Medicaid status. Perhaps surprisingly, it appears to be larger among relatively higher-income patients. Overall, Figure 5 suggests an uneven diffusion of the technology by a patient's race and income, independently of each other. To gauge the extent to which this pattern is a function of were individuals live, and in light of the gradients observed in Figure 4, Figure A.4 depicts these gradients by race. From the figure it can be seen that Black

[27] More specifically, the predictions are based off of regressions of testing on the decile of a given measure of zip-code level SES, controlling for age at surgery indicators, comorbidity indicators, and metastasis within 3 months indicator.

patients are less likely to be tested than white patients, regardless of where they live. This suggests the racial gap in testing is not solely explained by differences in where people live.

3.3.2 Sample statistics

The empirical strategy leverages variation in when a patient undergoes breast cancer surgery relative to when the provider adopts the technology. This design hinges on sufficient variation in the timing of adoption by providers. Figure 6 illustrates considerable variation in the timing of adoption. It increases rapidly following Medicare's decision to cover the technology in 2006 and reaches a peak in 2008, coinciding with the release of a major clinical guideline recommending the use of the technology in clinical practice.

Summary statistics of the analysis sample are displayed in Table 1. The median age at surgery is approximately 70 years, the majority of patients are white (87 percent), and 14 percent have Medicaid coverage. Almost 18 percent were tested and 23 percent were treated with chemotherapy. The most common chemotherapy drug used was Cyclophosphamide. Table 2 compares the characteristics and outcomes of patients by the adoption status of their oncologist. The first column display characteristics of patients who saw providers who never adopted the technology between 2006-2018, the second column displays characteristics of patients who underwent surgery before the provider adopted the technology, the third column displays characteristics of patients who underwent surgery after the provider adopted the technology, and finally, the fourth column shows characteristics of patients who saw providers who had adopted the technology in 2006. From the table it can be seen that patient characteristics before and after adoption are in general similar, although the following sections will evaluate this claim more formally. The empirical design does not hinge on balance in levels, or the absence of selection on unobservables, however, the empirical analysis will control for baseline differences in patient characteristics.

4 Impacts of Increased Access to Genomic Testing

In this section, I show how an oncologist's decision to adopt genomic testing impacts a breast cancer patient's probability of undergoing testing, receiving certain treatments, and intermediate-run mortality. To do so, I leverage variation in the timing of technology adoption across providers relative to when a patient undergoes breast cancer surgery similar to previous literature looking

at the effect of physician guideline awareness (Abaluck et al., 2020). More specifically, I estimate event-study models that compare outcomes for patients who have their breast cancer surgery after their oncologist adopted the technology to patients who had it before, relative to the overall time trend of the outcome which is informed by all breast-cancer treating oncologists, including those who have not adopted the technology by the end of the time period:

$$Y_i = \sum_{r=-3, r\neq -1}^{r=5} \mathbb{1}(r(i) = r)\beta_r + \gamma_{d(i)} + \eta_{t(i)} + \delta X' + \epsilon_i \tag{1}$$

where $Y_i \in \{0, 1\}$ is the outcome of interest for patient i (e.g., chemotherapy treatment following surgery), $\mathbb{1}(\mathrm{r(i)} = \mathrm{r})$ is a function that returns the year of patient $i's$ surgery relative to the technology adoption date of the oncologist (i.e., a patient's surgery year − a provider's adoption year). $\gamma_{d(i)}$ are provider fixed effects and $\eta_{t(i)}$ are year of surgery fixed effects. X' includes a range of patient and provider controls measured at the time point of surgery, including patient age, comorbidities, disability status, and insurance coverage characteristics (covered by Medicaid, covered by Medicare Part D, recipient of the Low Income Medicare Part D subsidy).[28] These patient characteristics may be correlated with the likelihood that a patient receives chemotherapy, and as evidenced by Table 2, may also be correlated with whether or not the patient sees an adopting provider.[29] Controls also include indicators for physician age at surgery to account for age-related changes in provider practice patterns; indicators for the health referral region associated with the zip code of patient residence, as well as an indicator for the metropolitan status of the county, to account for geographic differences in treatment intensities.

The main coefficient of interest is β_r which represents the marginal (percentage point) change in Y_i for a patient that had her surgery r years after her oncologist had adopted the technology, relative to another patient who had her surgery one year before the same oncologist adopted the technology, adjusting for the underlying time trend in the outcome. Given that breast cancer surgery is measured with noise, and to avoid undercounting testing and treatment among individuals, testing is measured within 3 months of surgery, although the vast majority of individual who are tested have

[28] More specifically, comorbidities are controlled for by including in the regression a set of indicator variables equal to 1 if the patient had any of the following chronic conditions in the year prior the the surgery: Alzheimers, AMI, chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure, and stroke, as well as indicators for the total number of these comorbidities present before surgery.

[29] More specifically, the older the patient, and the greater the number of comorbidities, the less likely is it that the patient will benefit from being treated with chemotherapy. Moreover, given the high cost of chemotherapy, insurance status may be correlated with undergoing chemotherapy.

a testing claim within the first of month of surgery. Similarly, chemotherapy is measured within six months of surgery. The results are however, not sensitive to alternative time periods.

I also estimate the associated difference-in-differences model, to obtain a summary measure of the impact of technology adoption (β):

$$Y_i = \gamma_{d(i)} + \eta_{t(i)} + \beta \text{Adopted}_{d(i)} + \delta X' + \varepsilon_i \tag{2}$$

where again $\gamma_{d(i)}$ are provider fixed effects and $\eta_{t(i)}$ are year of surgery fixed effects, and $\text{Adopted}_{d(i)}$ is an indicator equal to 1 if the oncologist that the patient saw in relation to the breast cancer surgery had adopted the technology prior to that point.

Two key assumptions are critical for a causal interpretation in this setting. The first is that the timing of adoption is uncorrelated with time-varying determinants of patient outcomes, and in particular the likelihood of receiving chemotherapy. The second is that technology adoption did not coincide with the adoption of other de-escalation or chemo-reducing treatment styles or technologies.

To gauge the validity of the first assumption, I predict the likelihood that a patient receives chemotherapy within six months of their surgery, based on a patient's age, total number of comorbidities, indicators for the presence of comorbidities previously described, disability history, an indicator for having undergone a screening mammogram in the year prior to surgery, and an indicator for having metastatic cancer within three months of surgery. These predicted values are plotted against the timing of provider adoption in Figure 7. This figure illustrates a smoothly evolving predicted probability of receiving chemotherapy in support of the identifying assumption, with some caveats. More specifically, although most of these characteristics are statistically significant, there are likely many other factors that explain the likelihood of a chemotherapy receipt, as reflected by a relatively low R-squared from the prediction regression. More discussion is provided in the robustness section. Moreover, the absence of pre-trends in the proceeding event studies (e.g., Figure 9) provides further support for the identifying assumption.

Although the previous evidence lends support to the assumption that the timing of technology adoption is uncorrelated with time-varying determinants of patient outcomes, I impose more structure to the previously estimated event studies to address remaining concerns about selection, as well as recent debates about the interpretation of staggered difference-in-difference designs (Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak and Jaravel, 2018; Callaway and Sant'Anna, 2021;

De Chaisemartin and d'Haultfoeuille, 2022). More specifically, for the previously defined sample of patients and providers, for each cohort of patients, defined by their surgery year, patients who were seen by *at least* one oncologist who had adopted the technology in that year (before the surgery date of the patient), or the year preceding, are compared to patients with the same surgery year, but who met at least one oncologist who adopted the technology in that year (but after the surgery date of that patient) or in the following year. This identification strategy resembles that of Fadlon and Nielsen (2019) who estimate the causal impacts of health shocks to individuals on the health behaviors of their family members, by using as counterfactuals household who experience a shock a few years later.

Patients are followed in the 6 months prior to, and 12 months following the breast cancer surgery. More formally, I estimate the following patient-level (stacked) event-studies:

$$Y_{itc} = \gamma_t + \delta_c + \sum_{r=-6, r\neq=-1}^{12} \delta_r \times I_r + \sum_{r=-6, r\neq=-1}^{12} \beta_r \times I_r \times \text{Treat}_i + \eta X_i' + \varepsilon_{itc} \tag{3}$$

where Y_{itc} is an indicator variable for patient i in surgery cohort c being tested, or receiving chemotherapy in year-month t, γ_t are year and month of surgery fixed effects, and I_r is an indicator for month relative to year-month of surgery. δ_c are surgery year fixed effects which ensure the comparison of patients within the same surgery year cohort. X_i' are patient characteristics previously described. The main coefficient of interest is β_r which measures the marginal probability that patient i is e.g., tested in year-month t of a given surgery year, if she saw a provider who had adopted the technology before the surgery date or the year prior, relative to other patients having their surgery in the same year, but for whom the oncologist would adopt the technology later that year or the next year. The sample is further restricted to providers who adopted the technology between 2006-2009 to limit the comparisons to a relatively homogenous set of early adopters.

The identifying assumption of this version of the event study model is a relatively strong assumption that the likelihood of seeing at least one adopting provider is not correlated with observed and unobserved patient characteristics that predict chemotherapy receipt. If for instance, sicker patients in greater need of chemo were more likely to see at least one adopting provider, the estimated impact of seeing at least one adopting provider would be biased downwards, and conversely for healthier patients. To gauge this assumption Table 3 compares the characteristics of patients who saw early vs later adopters. Overall, patients who saw at least one adopting provider are similar

on most observables to patients who saw an oncologist who had not yet adopted the technology. Patients who saw an early adopter are not systematically sicker or healthier as measured by their comorbidity history: the former are more likely to have a history of diabetes or stroke, but less likely to have had COPD. One important exception is the metropolitan status of the patient's county of residence; patient's who see an early adopter are more likely to reside in metropolitan counties, although the magnitude of the difference is economically small. The event study models control for these differences, although it is not possible to rule out that other characteristics correlated with metropolitan status are different across the two groups of patients.

4.1 Chemotherapy

Figure 8 provides visual evidence of the "bite" of genomic testing adoption in the raw data. Patients with a breast cancer surgery one year after an oncologist has adopted the technology, are almost two times more likely to undergo genomic testing (0.21/0.08), and 15 percent less likely to receive chemotherapy (1-0.22/0.26). Table 4 illustrates the results from estimating this using the difference-in-differences model specified in Equation (2) - patient's who see an oncologist who have adopted the technology are roughly 7-11 percent ($2-3$ ppt) less likely to receive chemotherapy within 6 months of their surgery.

The results from estimating the event study models in Equation (1) corroborate these findings. Figure 9 suggests that patients who had breast cancer surgery three years after the oncologist had adopted the technology were almost 11 percentage points more likely to be tested than a patient who saw the same oncologist a year prior to technology adoption (panel a).[30] Once, a provider adopts the technology, there is a level-shift in the use of the technology, suggesting awareness of the technology rather than experience and learning are governing the adoption process. Moreover, patients are almost 5 percentage points less likely to be treated with chemotherapy within a year of the surgery (panel b). This represents an almost 15 percent (5/32) decline in chemotherapy use following technology adoption. The lack of pre-trends, and the clear level-shift in chemotherapy use at the time point of technology adoption, supports the notion that the change in chemotherapy use is a function of technology adoption. Figure A.9 documents that the overall reduction in chemotherapy use is driven by a reduction in specific chemotherapy drugs and in particular cyclophosphamide,

[30]Note, a patient who sees a provider who has not yet adopted the technology can get tested by another provider.

doxorubicin, and paclitaxel.

Results from estimating Equation (3) convey similar results (Figure 10). Patients who saw at least one early adopter at the time of their surgery are more likely to be tested following surgery (at most 5 percentage points more likely at one month after surgery) and between 1-2 percentage points less likely to be treated with chemotherapy in the six months following surgery (average chemo treatment rate is 26 percent in the sample).

4.2 Side effects

I next gauge the possible health spillover effects of technology adoption. Since chemotherapy is a physically and mentally costly treatment to undergo, Figure 11 displays results from estimating Equation (1) for plausibly related health effects that patients may avoid if they avoid chemotherapy. Indeed, patients are less likely to receive anti-nausea medications (panel a) - a medication that patients undergoing chemotherapy often take. By contrast, I do not find any impact on antidepressant use (panel b), here used to proxy the mental health effects of undergoing chemotherapy. It is important no note that nausea and depression represent only two margins of health that may be impacted by chemotherapy treatment, and the absence thereof. The true health spillovers of forgoing chemotherapy are likely much higher, and not necessarily measurable.

4.3 Patient mortality and proxies for recurrence

The sharp reduction in the likelihood of receiving chemotherapy for patients seeing an adopting provider raises the question of whether these treatments were unnecessary. On the one hand, chemotherapy can be physically, mentally, and financially costly in the short run. On the other hand, it carries the benefit of reducing the risk of the cancer recurring. Truly unnecessary treatments are treatments that don't increase the long-run likelihood from dying from cancer. Figure 12, displays the overall probability of dying within 1 and 5 years of the breast cancer surgery as well as the likelihood of a cancer metastasis. While there is no effect on short-run mortality from seeing an adopting provider, patients are if anything *less* likely to die within 5 years of the surgery. This is potentially consistent with the added long-run morbidity from undergoing chemotherapy. It may also be consistent with an overall better targeting of chemo to patients, such that previously undertreated patients receive treatment.

4.4 Spending

The spending consequences of technology adoption are partially gauged in Figure A.7. The increase in testing and the decrease in treatment is associated with an average increase of $500 spending on testing per patient, and a 20 percent reduction on Part B chemotherapy spending, in the overall population at relative year three. This paints a partial picture of chemotherapy spending, since a large portion of chemotherapy treatments are also administered in the hospital outpatient setting where payments may be bundled. Furthermore, the averages mask substantial heterogeneity across patient and chemotherapy treatment regimes and reduced spending associated with the avoidance of chemotherapy side effects (such as nausea).

4.5 Diagnostic accuracy

I next gauge the efficiency and productivity implications of the arrival of genomic testing. Recall the clinical pathway to chemotherapy. The medical decision-making process is characterized by a two-step process in which providers first determine the extent to which the patient would benefit from chemotherapy - i.e. gauge a patient's risk (of recurrence) type - and next, decide on the course of treatment. In a world without precision medicine, a patient's risk-type is observed with noise. With noise, providers make diagnostic errors. Hence, the value of the technology lies in improving the classification problem facing the provider.

Setup. To gauge this value I adopt the framework in Chan et al. (2022). Consider a simple classification model in which oncologists j classify patients i according to their latent risk. More formally, assume patient's can have one of two risk-types: $s_i \in \{\text{Low}, \text{High}\}$, but provider's only observe a noisy signal ($\tilde{s}_i$) of a patient's actual risk-type.[31] Noise results in diagnostic errors (Table 5): some low-risk patients are classified as high-risk (type I errors) - while other high-risk patients are classified as low-risk (type II errors). Providers follow a simple treatment decision rule in which they never treat an observed low-risk patient, and always treat an observed high-risk patient: $d_{ij} = 1$ if $\tilde{s}_i =$ High, $d_{ij} = 0$ if $\tilde{s}_i =$ Low , where d_{ij} denotes provider j treating patient i.

Mapping to the data. It is not possible to observe the risk-type that providers observe, nor is it possible to observe the actual risk type of a patient. However, if an *untreated* patient

[31] Assume providers observe the same noisy signal of a patient's true risk type. In practice, it may be that there is variation in preferences or skill rendering the signal less noisy to some providers. In fact, the heteroegenity analysis is suggestive of that. For now, this is abstracted from.

experiences a recurrence later down the line, this is suggestive of the patient's true type being high-risk. Similarly, if an *untreated* patient does not experience a recurrence later down the line, this is suggestive of the patient's true type being low-risk. For *treated* patients, it is not possible to infer risk-types, as recurrence is a function of both latent risk and treatment.

If the technology works as intended, we would expect to see an increase in the share of patients not getting treated with chemo and not experiencing a recurrence. Denote this as a proxy for the true negative rate $\hat{\text{TN}}_j \equiv \Pr(d_{ij} = 0, \hat{s}_i = 0)$, where $\hat{s}_i$ is the 5-year recurrence rate. Similarly, denote the proxy for the false negative rate as $\hat{\text{FN}}_j \equiv \Pr(d_{ij} = 0, \hat{s}_i = 1)$. There is an overall increase in efficiency if the true negative rate increases without a meaningful change in the false negative rate following technology adoption. Under the assumption that the actual risk distribution does not change before and after technology adoption, the difference-in-difference estimator yields an estimate of the *change* in the probability of a true negative and false negative as a result of technology adoption. Part of this effect is driven by selection into treatment, part of it is driven by the treatment effect conditional on treatment. Currently, the analysis does not allow for a separation between the two.

Estimates. Figure 13 illustrates the results from estimating Equation (1) using the true negative and false negative rate as the outcome variable. From the figure it can be seen that technology adoption is associated with an approximate 5 percentage point increase in the probability of a true negative (i.e. no chemotherapy within 6 months, and no recurrence within 5 years). Moreover, technology adoption is not associated with any impact on the probability of a false negative (i.e. no chemotherapy within 6 months and recurrence within 5 years). Hence, the estimates suggest that the performance of the classification problem improves following adoption. This represents the efficiency gain from genomic testing adoption.

4.6 Heterogeneity

Overall, the main results suggest technology adoption was associated with a reduction in chemotherapy use and an improvement in medical decision making as measured by proxies for the true and false negative rates. I next, consider whether these impacts are distributed evenly across providers and patients. Figure 14 shows heterogeneity in the results by different provider characteristics. Most notably, while patients are equally likely to be tested after technology adoption across providers who

prior to adoption were high vs low users of chemotherapy, patients who saw providers who were the most treatment-intensive providers prior to adoption are the ones to experience the largest percentage reduction in chemotherapy use. These findings suggest the technology is reducing the variation in treatment intensity across providers.

Figure 15 shows heterogeneity in the results for different patient subpopulations. From the figure, it can for instance be seen that white patients and patients of higher SES are relatively more likely to be tested, compared to black patients and patients of lower SES. To further gauge the racial gap in testing, Table A.2 estimates the racial gap in testing directly, in a sample of patients who saw providers who had adopted the technology at the time point of surgery. The results suggest black patients are almost 7 percentage points, or almost 30 percent, less likely to be tested, controlling for a host of patient characteristics, when they see the same provider. Overall, the results suggest white patients and patients of higher SES are more likely to benefit from the technology.

4.7 Robustness

Patient sorting. One potential concern with the empirical design is that patients respond to the adoption decision of providers. If patient sorting to adopting providers is correlated with the likelihood of the patient needing chemotherapy, the estimated impact on chemotherapy of seeing an adopting provider is partly due to the technology, and partly due to changing patient characteristics. Smoothly evolving patient characteristics, speak against patient sorting, although sorting on unobservable patient characteristics, it not verifiable. To gauge patient sorting, the previous event study is estimated and presented in Figure A.10. I don't find evidence consistent with patient sorting to oncologists based on adoption.

Placebo checks. Another concern is that the adoption of the technology was concurrent with other events that might have impacted the use of chemotherapy. Although it is not possible to completely rule out the possibility of other concurrent changes, I estimate whether providers are more likely to use a set of other technologies and services that are commonly used among breast cancer patients and that could affect chemotherapy use, after adoption, including the use of BRCA genetic testing and immunohistochemistry testing. I do not find support for this (Figure A.11).

Control vs treated indications. Finally, I leverage variation in provider adoption dates in addi-

tion to variation in a patients appropriateness for testing as an alternative identification strategy. More specifically, since the technology is primarily indicated for patients with HER2 negative cancers, patients with HER2 positive cancers can be used as a control group.[32] Both HER2 negative and HER2 positive patients may undergo chemotherapy in conjunction with hormone therapy. Intuitively, the empirical design compares the probability that a patient without a HER2 positive cancer receives chemotherapy after her provider has adopted the technology, compared to before, relative to a patient with a HER2 positive cancer. The corresponding event studies are given by:

$$Y_i = \sum_{r=-3, t\neq -1}^{r=4} \mathbb{1}(\text{r(i)} = \text{r})\mathbb{1}(\text{Treated}_i)\beta_m + \mathbb{1}(\text{Treated}_i)\tau + \gamma_{d(i)} + \eta_{t(i)} + \delta X' + \epsilon_i \tag{4}$$

where Y_i is the outcome variables for individual i (e.g. and indicator equal to one if patient i gets chemotherapy within 6 months of the surgery), $\mathbb{1}(\text{r(i)} = \text{r})$ is a function that returns the year of $i's$ surgery relative to the technology adoption date of the oncologist, and $\mathbb{1}(\text{Treated}_i)$ is an indicator equal to one if the patient is flagged as having a HER2 negative cancer and hence would be appropriate for the technology. $\gamma_{d(i)}$ are provider fixed effects and $\eta_{t(i)}$ are year of surgery fixed effect. X' include time-invariant patient characteristics and time-varying provider characteristics previously defined.[33] The main coefficient of interest is β_m which measures the increased/decreased probability of e.g., technology and chemotherapy receipt for patient i who had a HER2 negative cancer and who saw provider j, t years after provider j first started using the technology, relative to a patient with a HER2 positive cancer. The results in Figure A.12 support the overall results.

[32] The claims data do not allow for me to identify the HER2 status of a breast cancer patient, however, because the hormone drug Trastuzumab (brand name: Herceptin) is indicated for patients with HER2 positive cancers, I use the prescription for Trastuzumab within one year of the cancer surgery as a signal that the patient is HER2 positive.

[33] More specifically, they include Medicaid status, disability status, any Part D coverage, eligibility for the Part D Low Income Subsidy, indicators for age at surgery, and indicators for any prior history of Alzheimers, AMI, Cancers (lung, colorectal, endometrial), chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure, and stroke, indicators for the total number of comorbidities present before surgery, an indicator for a screening mammogram in the prior 180 days, indicators for HRR of residence, and an indicator for whether or not the county of residence is metropolitan. The time-varying provider characteristics include indicators for the provider's age at the time point of patient surgery.

5 Implications for Racial Disparities

What explains the within-provider racial gap in testing? In particular, is the gap in testing reflective of racial differences in medical appropriateness? For instance, black patients may be less likely to be tested due to unobserved (to the econometrician) patient characteristics that make them less likely to benefit from the technology. As an example, if black patients are more likely to have advanced stages of cancer that would require chemotherapy than white patients, testing will be less beneficial in black patients. To gauge the extent to which the gap in testing is a function of differences in appropriateness, as opposed to differences in provider testing decisions, I leverage rich cancer registry data.

5.1 SEER-Medicare linked data

The Surveillance, Epidemiology and End Results (SEER) program is a program that the National Cancer Institute (NCI) uses to support cancer surveillance activities. Established in 1973, the SEER program collects data from population-based cancer registries. The number of registries participating in the program has grown over time; in 1973 the program covered less than 10 percent of the US population, and by 2022 the program consisted of 18 registries representing 48 percent of the US population. The SEER-Medicare linked data represents the linkage of SEER data to a 100 percent sample of Medicare claims data for certain cancer types, including breast cancer. For this subset of patients, in addition to all the information available in the Medicare claims data, the SEER data file includes detailed information about the cancer. More specifically, this data file includes one record per tumor diagnosed, and each record includes information such as the stage, histology, and site of the cancer.

5.2 Sample construction

As in the main analysis, the goal is to construct a dataset where each row represents a patient-provider match. Due to changes in the way cancer characteristics such as staging is recorded, the sample is restricted to cancer diagnosis during 2010-2015.[34]. The sample is constructed as follows.

[34]More specifically, the sample is limited to 1) a time period during which the so called Collaborative Stage (CS) was in place (2004-2015), which facilitates the uniform tracking of cancer characteristics such as staging over time, and 2) a time period during which the HER2 status of a patient's tumor was recorded (2010-)

First, the earliest month and year of diagnosis is identified for all patients with breast cancer between 2010-2015 who did not die within 12 months of the cancer diagnosis, were at most 80 years old at the time point of diagnosis, and for whom the primary payer/insurance carrier at the time of diagnosis was Medicare.[35] This results in a sample of N=71,832 patients.

Second, all breast cancer patients are matched to oncologists by identifying any oncologist[36] seen by the patient for an evaluation and management visit, identified as a carrier claim with an associated procedure code that starts with "992" within [-3, 6] months of the breast cancer diagnosis year and month. Of the 71,832 patients identified as the risk set, 51,188 patients were matched to at least one oncologist in this way, corresponding to N=4,500 providers. Third, the sample is further restricted to providers who saw at least 10 patients overall and at least one black patient (N=37,111 patients and N=1,268 providers), excluding the index patient(s) (N=36,953 and N=1,268 providers). Fourth, the sample is restricted to patient-provider encounters that occur after the provider has adopted the technology (N=31,319 patients, N=1,029 providers). In the sample, black patients tend to have more advanced stages of cancer, are less likely to have hormone positive cancers and HER2-negative cancers, and more likely to have larger tumors. This is suggestive of the technology being less relevant for black patients than white patients overall.

5.3 Decomposition results

Next, the probability of being tested within 3 months of a breast cancer diagnosis is estimated in the previously defined sample using the following regression model:

$$Y_i = \beta \text{Black}_i + \gamma_{d(i)} + \delta X_i' + \epsilon_i \tag{5}$$

where Y_i is the probability of being tested within 3 months of the breast cancer diagnosis month, $\gamma_{d(i)}$ are provider fixed effects, and X_i' are patient-level characteristics measured at the time point of diagnosis (e.g., age at diagnosis). The racial gap in testing (i.e., β) is then estimated in a sample of provider-patient pairs, were the provider has already adopted the technology at the time point of a patient's diagnosis.

[35] More specifically, the set of possible payers are "Medicare", "Medicare with private supplement", and "Medicare with Medicaid eligibility"

[36] "Oncologists" are as previously identified as physicians with a CMS speciality code in hematology/oncology (83), medical oncology (90), or surgical oncology (91).

To gauge the extent to which the within-provider racial gap is due to differences in medical appropriateness between Black and white patients, aspects of medical appropriateness are successively controlled for in Table 6. From the table it can be seen that controlling for staging reduces the racial gap in testing by 12 percent, while controlling for whether or not the cancer is hormone positive, reduces the gap by 23 percent. While a large fraction of the gap is explained by differences in medical appropriateness (35 percent), a large fraction of the gap remains unexplained after having controlled for these particular aspects of medical appropriateness. It is possible that other aspects of medical appropriateness, not captured here, explain differences in testing across black and white patients, although the ones selected here are the most relevant medical ones in deciding whether or not to test a patient.[37]

5.4 Policy implications

The previous analysis, highlights how different forces govern the extent to which different population groups eventually gain from the arrival of a new technology. In particular, a disparity in the gains from innovation across two groups emerges and amplifies when the technology 1) is more appropriate in one group because it targets a disease more prevalent in one group ("differential appropriatenes"), 2) conditional on appropriateness is accessed to a greater extent by one group ("differential access or allocation"), 3) conditional on appropriateness and access, is used more intensively in one group ("differential testing or discrimination"), and conditional on all of the above, 4) is of greater value in one group "differential treatment effect"). When this is true, and groups are defined along the lines of socioeconomic status or race, the arrival of a new technology gives rise to, or worsens, an existing health disparity. Appendix A.7 formalizes this idea.

Abstracting from differences in treatment effects, and focusing on the determinants of testing, I do a simple back-of-the-envelope calculation of the role of differences in access, appropriateness, and testing. More specifically, using the previously defined sample for the SEER data, I calculate 1) the share of Black and white patients who have access to an adopting provider, 2) conditional access, the share of Black and white patients who are medically appropriate using the characteristics from Table 6, and 3) conditional on access and appropriateness, the share of Black and white patients who are tested. Appendix A.7 describes how the product of these probabilities constitutes the

[37]The R-squared from a regression of testing on the selected medical appropriateness measures in the sample of white patients is approximately 20 percent.

estimated conditional probability of getting tested for a Black and white patient, and how a log-transformation allows for backing out the relative role of each factor. Table 7 shows the results from these calculations, and it highlights the role of differential appropriateness and testing as driving the overall gap in testing, as opposed to differences in access. It is important to note that these calculations are performed in a sample of patients that were matched to an oncologist. To the extent that there are racial differences in access to any oncologist, this could magnify the role of access.

6 Discussion and Conclusion

The last two decades have seen a rapid rate of entry of genetic and genomic technologies designed to personalize medicine. This paper evaluated the efficiency and equity consequences of the diffusion of genomic testing in the context of breast cancer in the Medicare population. The findings suggest substantial efficiency gains. More specifically, patients who were diagnosed with breast cancer after their oncologist had adopted the technology, were less likely to receive chemotherapy, at no intermediate-term increased mortality or recurrence risk. Patients were also as a result less likely to experience chemotherapy related side-effect. These effects reflect only a portion of the true value of forgoing chemotherapy, which to the patient aside from health costs also include the financial burden of chemotherapy treatments and productivity loss for those still in the workforce. From a societal perspective, there are substantial gains from reduced healthcare spending on chemotherapy, the management of its side effect, and the freeing up of healthcare resources deployed to chemotherapy treatment.

However, the gains from innovation appear to have been concentrated to certain patient populations, with Black patients less likely to be tested, primarily for reasons other than costs and access. Existing disparities in staging contribute to the technology being less relevant to the average Black patient. To the extent that disparities in screening correlate with the increased likelihood of Black patients presenting with later stage disease (Smith-Bindman et al., 2006), addressing the causes of these patterns may render a substantial fraction of Black patients eligible for the technology. However, controlling for staging and other medical characteristics, Black patients are still less likely to be tested.

As such, this paper contributes to our understanding of the role of medical advancements in precision medicine on the healthcare system. While such innovation can generate a lot of effi-

ciency gains to the healthcare system, by for instance improving diagnostic accuracy, it may also generate or exacerbate health disparities. Addressing these disparities may require a more nuanced understanding of its root causes, that include but are not limited to differences in affordability or healthcare access, but that also include a better understanding of potential racial differences in the ways providers are treating patients as well as existing disparities in medical care such as screenings.

As a case in point, although today Black women with breast cancer have a 40 percent higher death rate than white women, this racial divergence is a relatively recent phenomenon emerging in the 1980s. The divergence has in part been attributed to medical advancements including the arrival of mammography and hormone therapy, which due to access and differences in medical appropriateness, tended to benefit white patients more Jatoi et al. (2022).

As precision medicine and oncology to an increasing extent targets diseases that occur in earlier stages, as opposed to end-of-life, and population health improves not only as a result of reductions in mortality but also morbidity, the case for reducing existing racial disparities in preventive medicine and screening is becoming increasingly important. In the absence of interventions that address these disparities, current and future technologies that target early stages of disease, such as the much anticipated "liquid biopsies", may end up disproportionately benefiting certain groups in society more. In the context of precision technologies that *spare* patients from treatments, the effects can be two-fold and regressive - patients not only fail to realize the health benefits stemming from the technology, they also fail to realize the financial savings from forgoing costly treatments.

To conclude, as new precision technologies continue to develop and diffuse through the healthcare, policies that ensure the equitable diffusion of these technologies are critical in ensuring that the gains from innovation are realized across patient groups, regardless of socioeconomic status and race.

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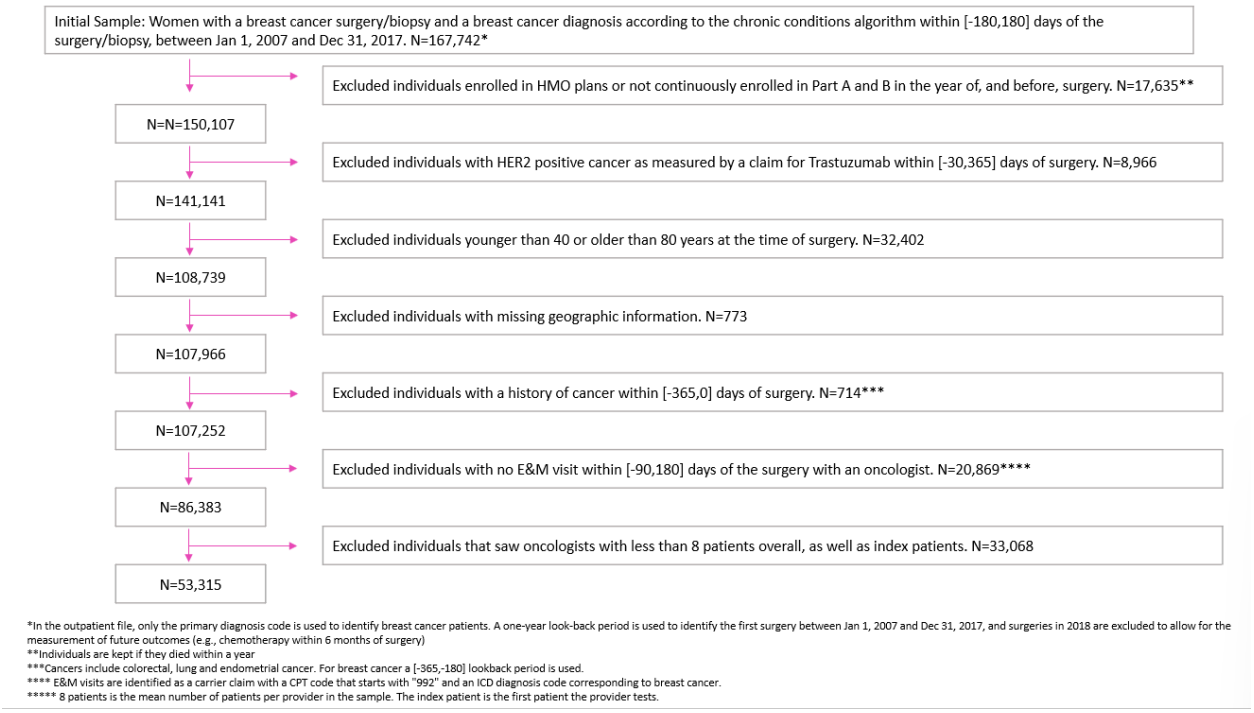
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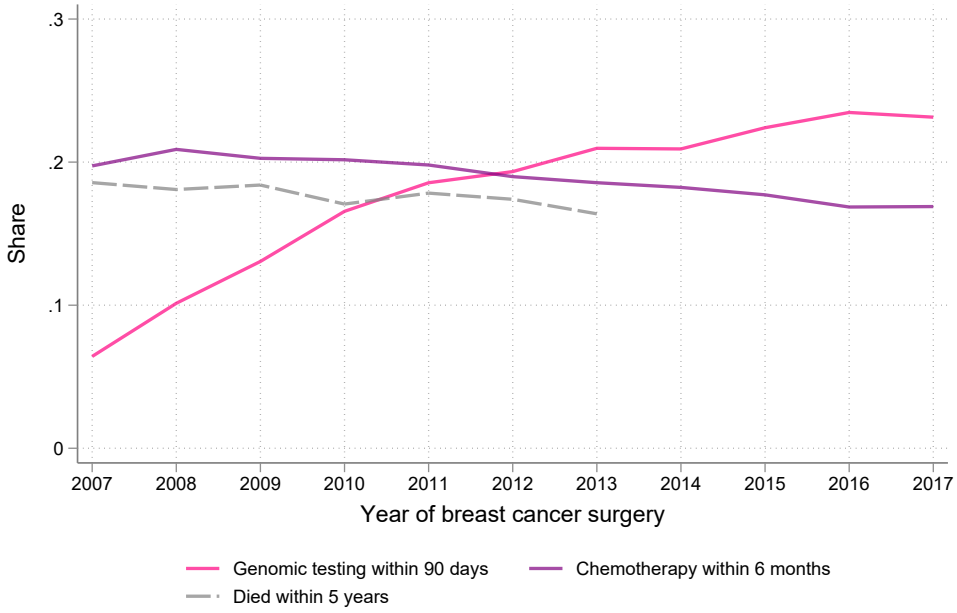
7 List of exhibits

Figure 1: Sample construction



Note. Flow chart of the sample construction.

Figure 2: Technology diffusion and trends in treatment and mortality

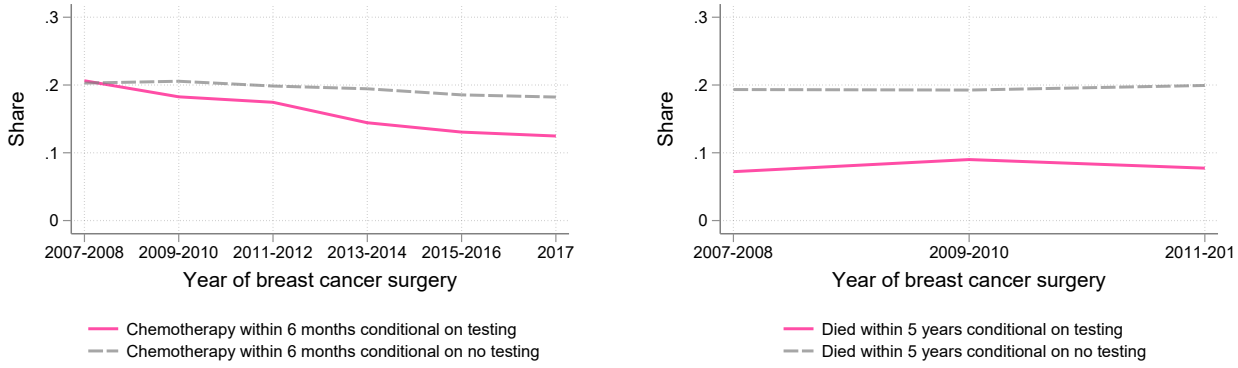


Note. N=107,252 patients.

Figure 3: Treatment and mortality conditional on testing

(a) Chemotherapy

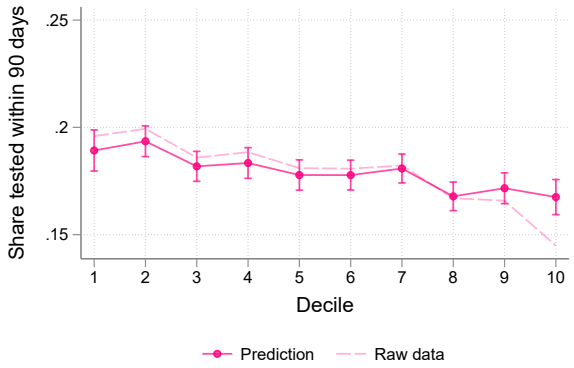
(b) Mortality



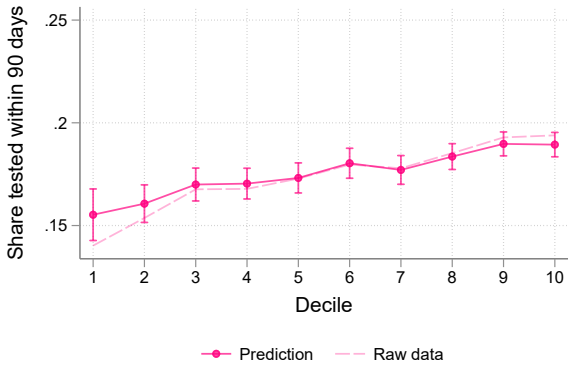
Note. Panel (a): N=107,252 patients. Panel (b): N=66,492 (restricted to surgeries before 2013).

Figure 4: Socioeconomic gradients in genomic testing - 2007-2017

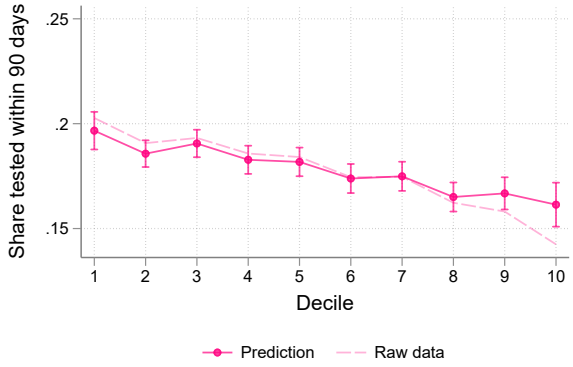
(a) Neighborhood disadvantage index



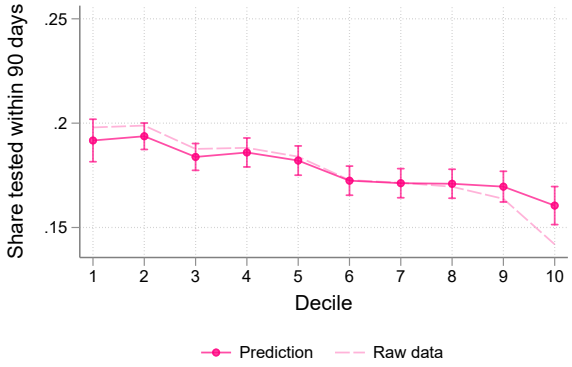
(b) Neighborhood affluence index



(c) Proportion people w/ income past 12 months below poverty level



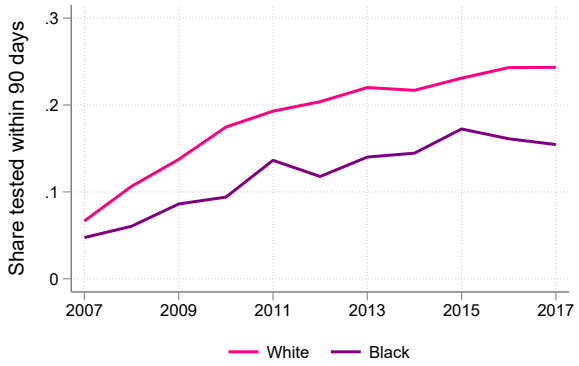
(d) Proportion of households with public assistance income



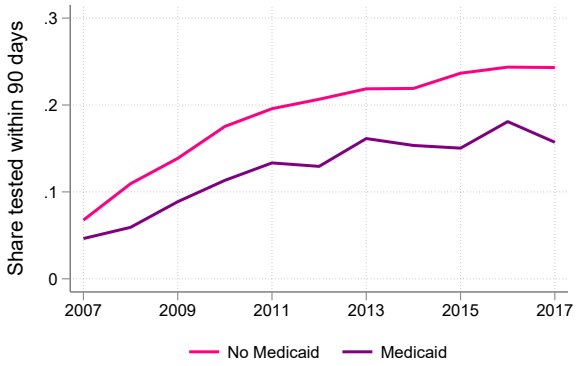
Note. N=107,252 patients. The raw data shows the average share of patients tested within 90 days of surgery in each decile of a given measure of socioeconomic status (e.g., the neighborhood disadvantage index). "Prediction" refers to the prediction from a regression that adjusts for age at surgery, comorbidity history, and a proxy for metastasis.

Figure 5: Diffusion of genomic testing by race and SES

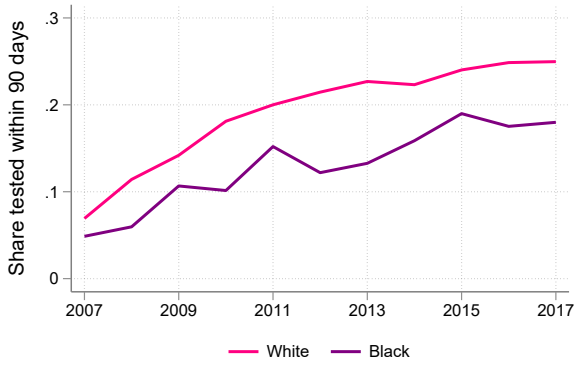
(a) Black vs white



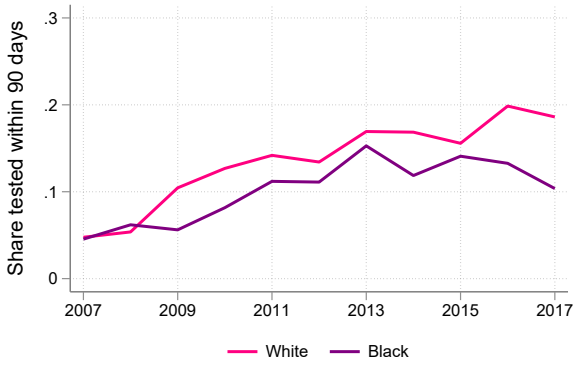
(b) Duals vs non-duals



(c) Black vs white among non-duals

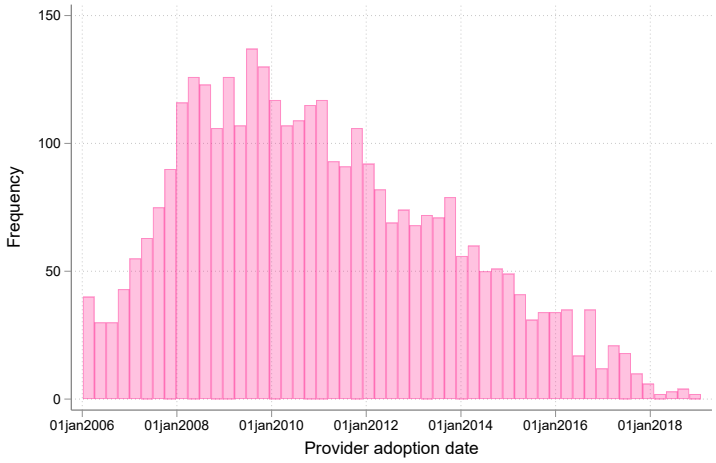


(d) Black vs white among duals



Note. The figure shows the share of patients tested within 90 days of surgery between 2007 and 2017 for different patient populations. Panel (a)-(b): N=102,725 patients (restricted to white and Black patients). Panel (c): N=87,930 patients (restricted to Black and white patients not on Medicaid). Panel (d): N=14,795 patients (restricted to Black and white patients on both Medicaid and Medicare).

Figure 6: Provider variation in the timing of technology adoption



Note. The figure shows the distribution of the time of adoption between 2006-2018) of oncologists in the analysis sample. N=3,430 adopting oncologists.

Table 1: Summary statistics

	Mean	SD
Patient demographics		
Age at surgery	70.56	6.36
White (%)	86.58	34.09
Black (%)	9.75	29.66
Hispanic (%)	0.76	8.69
Asian (%)	0.90	9.45
Other race (%)	1.55	12.34
Medicaid eligible (%)	14.08	34.78
Part D coverage (%)	61.88	48.57
Original enrollment SSDI (%)	17.14	37.69
Metropolitan county (%)	79.85	40.11
Patient comorbidities		
Acute Myocardial Infarction (%)	0.28	5.31
Alzheimer's or dementia (%)	1.16	10.70
Chronic obstructive pulmonary disease (%)	2.40	15.31
Heart failure (%)	2.11	14.36
Hypertension (%)	7.60	26.49
Diabetes (%)	3.53	18.46
Chronic kidney disease (%)	3.14	17.43
Stroke (%)	1.23	11.03
Number of comorbidities (count)	0.21	0.53
Predicted probability of chemotherapy	20.08	11.87
Metastatic (%)	11.73	32.18
Area demographics		
% Income below poverty	13.68	8.66
% Public assistance income	11.32	8.17
% Population black	11.40	17.88
Treatments		
Genomic testing within 3 months (%)	17.71	38.17
Chemotherapy within 6 months (%)	23.36	42.31
Carboplatin within 6 months (%)	1.14	10.60
Cyclophosphamide within 6 months (%)	20.60	40.45
Docetaxel within 6 months (%)	12.24	32.78
Doxorubicin within 6 months (%)	9.73	29.63
Epirubicin within 6 months (%)	0.60	7.71
Paclitaxel within 6 months (%)	7.90	26.97
Methotrexate within 6 months (%)	1.27	11.18
Patients (N)	53,315	53,315

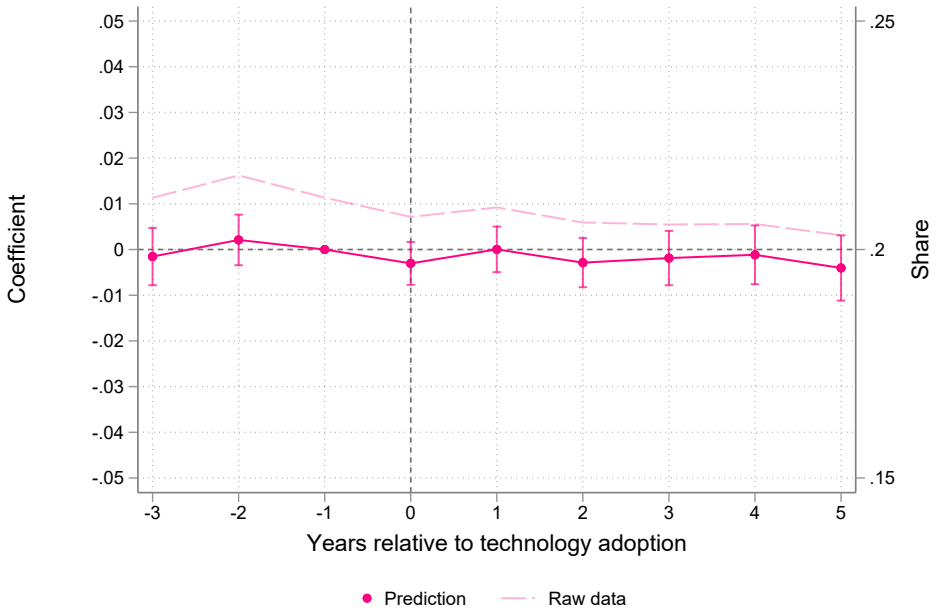
Note. N=53,315 patients (analysis sample).

Table 2: Patient characteristics by the technology adoption status of the oncologist

	Never-adopter	Before	After	Always-adopter
Patient demographics				
Age at surgery	70.43	70.46	70.40	70.67
White (%)	84.27	86.98	86.85	87.69
Black (%)	11.54	9.73	9.48	10.23
Hispanic (%)	0.98	0.73	0.68	0.42
Asian (%)	1.08	0.75	0.92	0.66
Other race (%)	1.58	1.50	1.55	0.80
Medicaid eligible (%)	15.48	14.53	13.17	13.67
Part D coverage (%)	62.28	57.45	64.10	54.64
Original enrollment SSDI (%)	17.84	18.10	17.02	14.80
Metropolitan county (%)	83.03	79.24	80.19	83.78
Area demographics				
% Income below poverty	13.53	13.91	13.46	14.08
% Public assistance income	11.27	11.47	11.10	11.45
% Population black	12.06	11.56	11.28	12.68
Patient comorbidities				
Acute Myocardial Infarction (%)	0.26	0.30	0.26	0.33
Alzheimer's or dementia (%)	1.45	1.12	1.04	1.04
Chronic obstructive pulmonary disease (%)	2.45	2.82	2.24	2.03
Heart failure (%)	1.96	2.30	2.01	2.69
Hypertension (%)	7.51	8.10	7.65	7.07
Diabetes (%)	3.48	3.58	3.43	4.29
Chronic kidney disease (%)	3.61	2.60	3.19	2.22
Stroke (%)	1.34	1.26	1.20	1.13
Number of comorbidities (count)	0.22	0.22	0.21	0.21
Predicted probability of chemotherapy	20.58	20.94	20.48	20.72
Metastatic (%)	12.99	13.74	12.39	14.10
Treatments				
Genomic testing within 3 months (%)	11.97	8.50	23.39	19.38
Chemotherapy within 6 months (%)	26.56	29.54	25.71	26.92
Carboplatin within 6 months (%)	1.47	1.14	1.29	0.80
Cyclophosphamide within 6 months (%)	23.22	25.97	22.87	23.95
Docetaxel within 6 months (%)	13.06	15.12	13.90	14.10
Doxorubicin within 6 months (%)	11.61	13.60	10.09	12.54
Epirubicin within 6 months (%)	0.66	0.95	0.60	0.85
Paclitaxel within 6 months (%)	9.57	10.41	8.81	8.91
Methotrexate within 6 months (%)	1.40	1.39	1.38	1.89
Patients (N)	11,858	14,873	34,210	2,121

Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider.

Figure 7: Technology adoption and predicted probability of chemotherapy treatment



Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The outcome variable is the "predicted probability" of receiving chemotherapy within 180 days of surgery, estimated in a regression that includes a patient's year of surgery, age, total number of comorbidities, indicators for the presence of comorbidities previously described, disability history, an indicator for having undergone a screening mammogram in the year prior to surgery, as well as an indicator for cancer metastasis. The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. Standard errors are clustered at the provider-level.

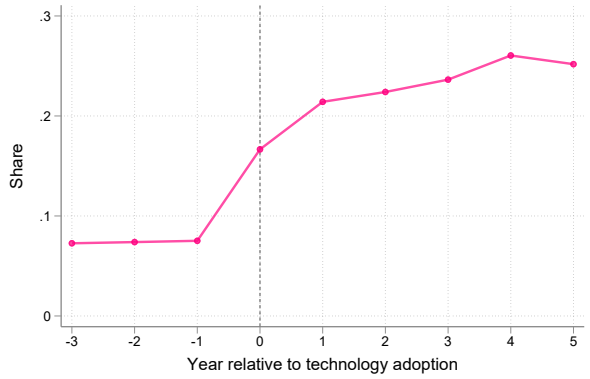
Table 3: Balance - Early vs Late Adopters

	Late adopter N=4,281		Early adopter N=4,793		
	Mean	SD	Mean	SD	Diff
Patient demographics					
Age (years)	70.82	6.57	70.62	6.45	-0.206
White	0.87	0.33	0.88	0.32	0.006
Black	0.10	0.29	0.09	0.29	-0.005
Hispanic	0.01	0.09	0.00	0.07	-0.003**
Asian	0.01	0.07	0.01	0.10	0.004**
Other race	0.02	0.13	0.01	0.11	-0.003
Dual eligible	0.14	0.35	0.13	0.34	-0.012*
Part D coverage	0.53	0.50	0.53	0.50	-0.003
Original enrollment SSDI	0.17	0.37	0.16	0.37	-0.004
Metropolitan county	0.78	0.41	0.80	0.40	0.019**
Patient comorbidities					
AMI	0.00	0.07	0.00	0.05	-0.002
Alzheimers	0.01	0.11	0.01	0.10	-0.002
COPD	0.03	0.17	0.02	0.15	-0.009***
Heart failure	0.02	0.15	0.03	0.16	0.003
Hypertension	0.08	0.27	0.07	0.26	-0.006
Diabetes	0.03	0.18	0.04	0.20	0.008**
Chronic kidney disease	0.03	0.16	0.02	0.15	-0.001
Stroke	0.01	0.11	0.02	0.13	0.006**
Number of comorbidities	0.22	0.52	0.22	0.53	-0.004
Predicted chemo	0.21	0.15	0.21	0.15	0.002
Metastatis	0.20	0.40	0.21	0.41	0.004
Area demographics					
%Income below poverty	0.14	0.09	0.14	0.09	-0.001
%Public assistance income	0.11	0.08	0.11	0.08	-0.002
%Population black	0.12	0.18	0.12	0.18	0.001
Treatments					
Genomic testing within 3 months	0.05	0.22	0.18	0.38	0.131***
Chemotherapy within 6 months	0.27	0.44	0.25	0.43	-0.017*
Carboplatin within 6 months	0.01	0.10	0.01	0.10	0.000
Cyclophosphamide within 6 months	0.24	0.43	0.23	0.42	-0.012
Docetaxel within 6 months	0.14	0.35	0.15	0.35	0.005
Doxorubicin within 6 months	0.13	0.33	0.10	0.30	-0.027***
Epirubicin within 6 months	0.01	0.11	0.01	0.10	-0.002
Paclitaxel within 6 months	0.09	0.28	0.07	0.26	-0.015***
Methotrexate within 6 months	0.01	0.11	0.01	0.12	0.002

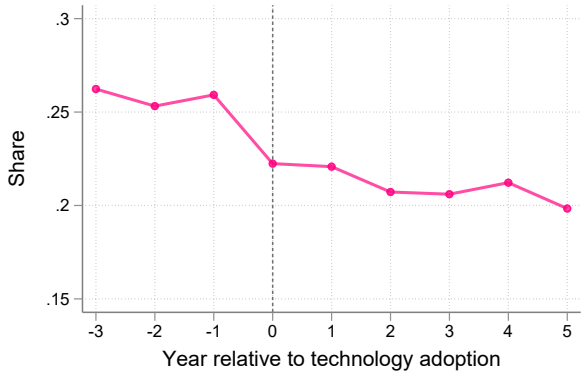
Note. An observations is a patient. N=9,074 patients with surgeries in 2007-2009. See text for further definition of a late and early adopter. *, **, ***, indicate significance at the 10%, 5% and 1% level.

Figure 8: Technology adoption and treatment decisions - raw data

(a) Genomic testing within 90 days



(b) Any chemotherapy within 180 days



Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The figure shows the average share of patients tested within 90 days (panel a) per provider and the average share of patients treated with chemotherapy within 180 days per provider (panel b), before and after technology adoption.

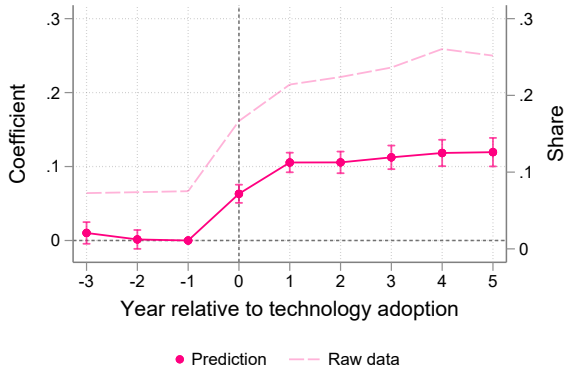
Table 4: Effect of technology adoption on chemotherapy use

	(1)	(2)	(3)	(4)	(5)
Adopted	-0.0256***	-0.0276***	-0.0256***	-0.0252***	-0.0254***
	(0.0064)	(0.0063)	(0.0062)	(0.0063)	(0.0063)
Mean of Y	0.268	0.268	0.268	0.268	0.268
N	63,058	63,058	63,058	63,058	63,058
Patient demographics		✓	✓	✓	✓
Patient comorbidities			✓	✓	✓
Physician controls				✓	✓
Regional controls					✓

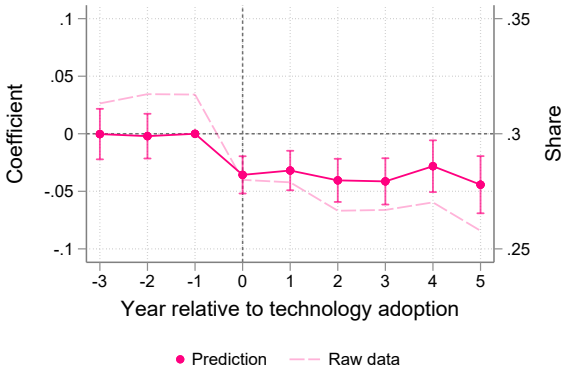
Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The table shows the results from estimating 2, with the outcome variable being chemotherapy within 6 months of breast cancer surgery. Patient demographics include: age at surgery, race, medicaid status, Medicare Part D coverage, and disability status. Patient comorbidities include indicators for a history of Alzheimer's or dementia, AMI, chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure, stroke, hypertension, the total number of comorbidities, and an indicator for metastatic cancer within 3 months of surgery. Physician controls include physisician age at surgery. Regional controls include metropolitan status of the patient's county of residence, and hospital referral region. Standard errors are clustered at the provider level. *, **, ***, indicate significance at the 10%, 5% and 1% level.

Figure 9: Effect of technology adoption on testing and chemotherapy use

(a) Genomic testing within 90 days



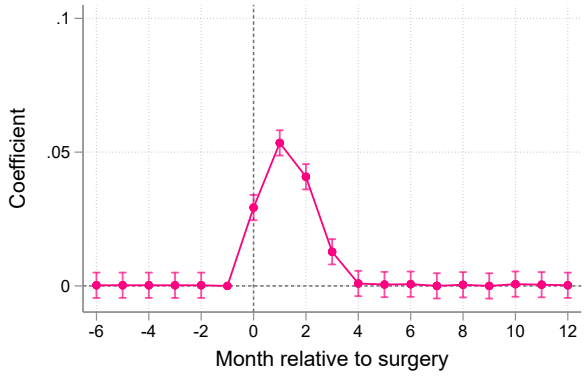
(b) Chemotherapy within 6 months



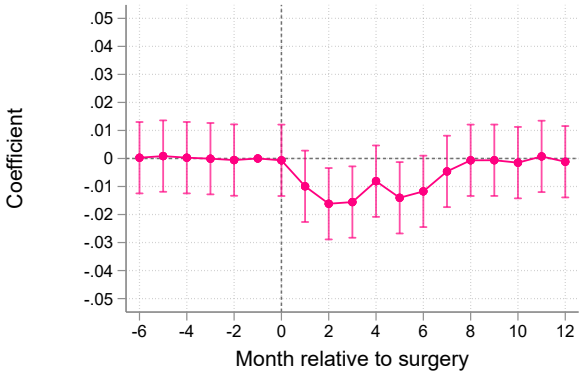
Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, any Part D coverage, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level.

Figure 10: Effect of seeing an early adopter, relative to a late adopter, on testing and chemotherapy use

(a) Genomic testing in month t



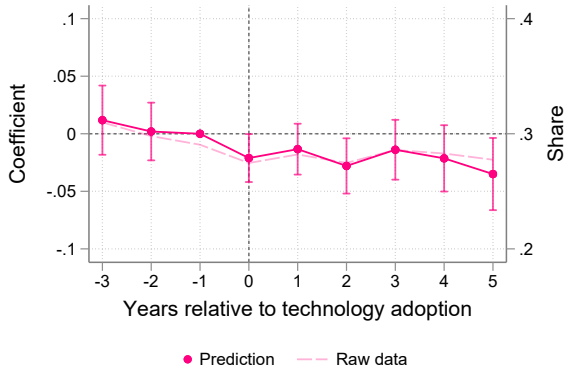
(b) Chemotherapy in month t



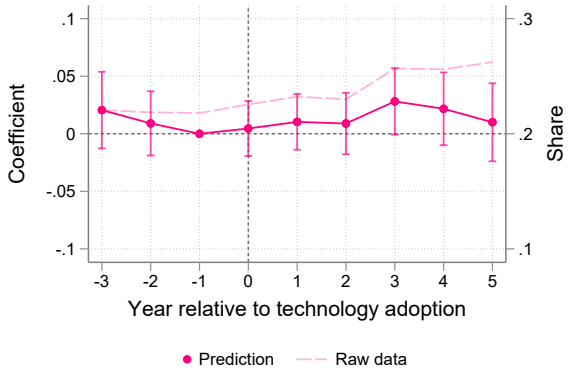
Note. N=9,074 patients with surgeries in 2007-2009. An observation is a patient. The figure depicts results from estimating Equation (3).

Figure 11: Effect of technology adoption on anti-emetic and anti-depressant prescriptions

(a) Anti-emetic prescription within 6 months

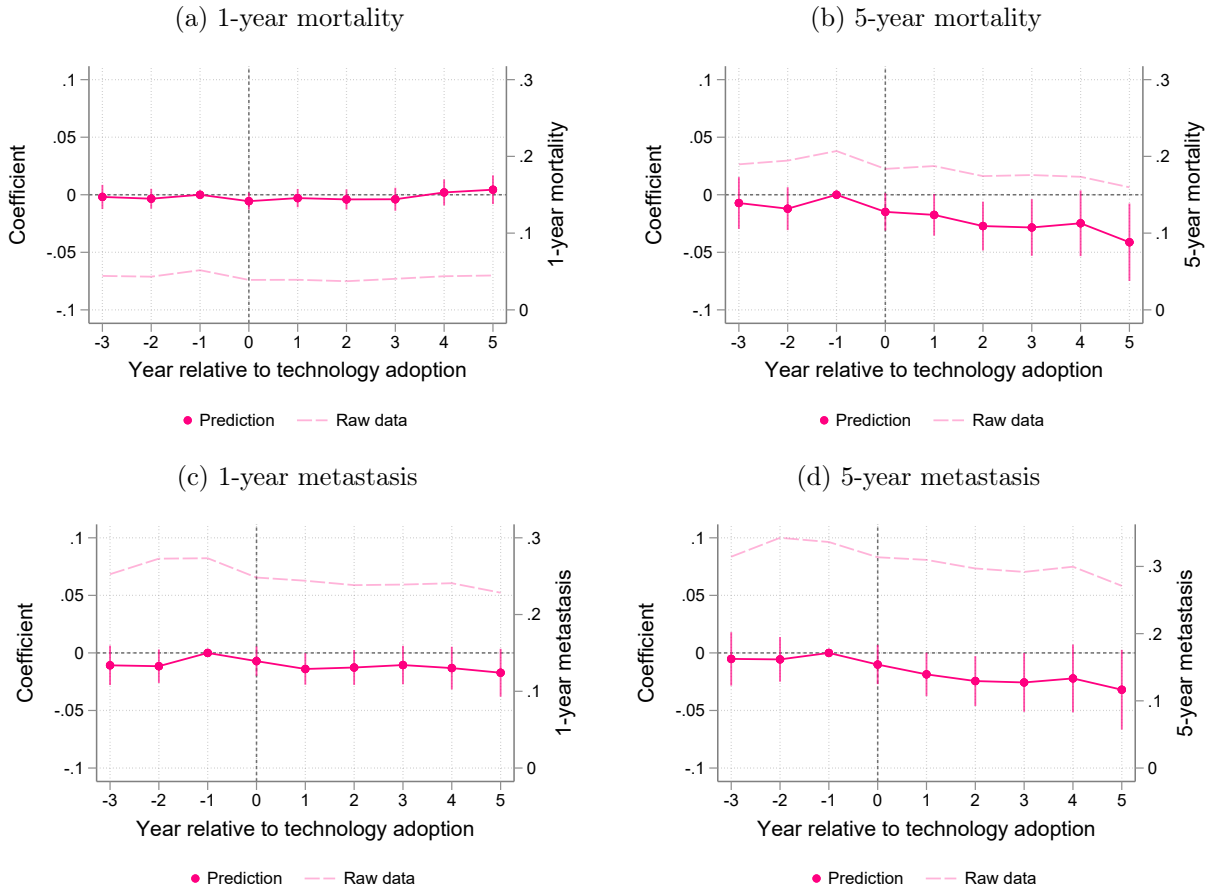


(b) Anti-depressant prescription within one year



Note. N=32,993 patients and N=4,225 providers (analysis sample restricted to patients with Part D coverage). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level.

Figure 12: Effect of technology adoption on mortality and metastasis



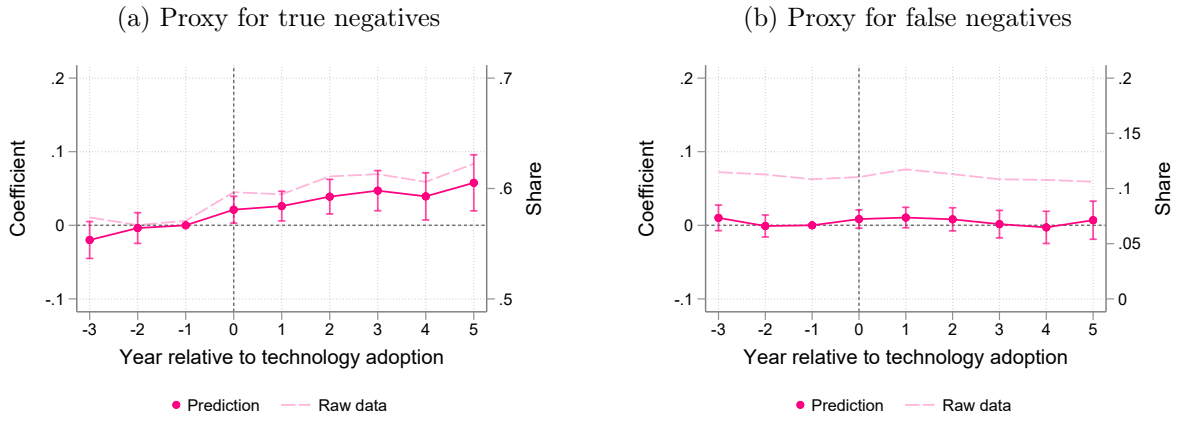
Note. Panel (a) and (c): N=53,315 patients and N=4,228 providers (analysis sample). Panel (b) and (d): N=36,326 patients and N=3,969 providers (analysis sample restricted to surgery before or in 2013 to allow for a 5-year follow-up period). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level.

Table 5: Classification matrix

Pred. Risk, $\tilde{s}_i$ \ Actual Risk, s_i	Low	High
Low	True negative	False negative
High	False positive	True positive

Note. The table presents the four mutually exclusive and exhaustive outcomes that arise when providers/patients engage in the classical classification problem of predicting patient risk (of recurrence) based on a noisy signal of a patient's actual risk (of recurrence).

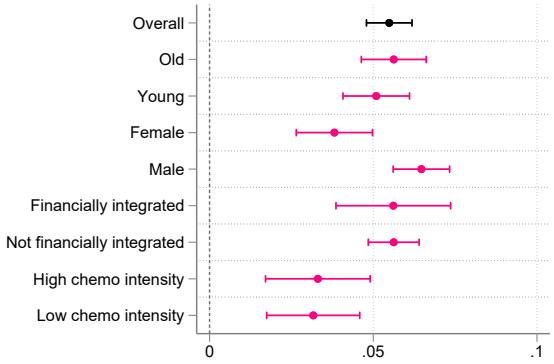
Figure 13: Effect of technology adoption on medical errors



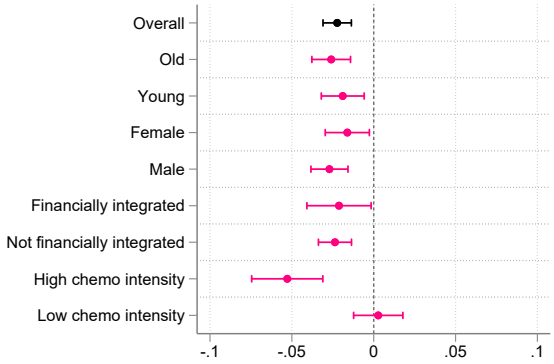
Note. N=36,326 patients and N=3,969 providers (analysis sample restricted to surgery before or in 2013 to allow for a 5-year follow-up period). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level.

Figure 14: Treatment effect heterogeneity by provider characteristics

(a) Genomic testing within 90 days



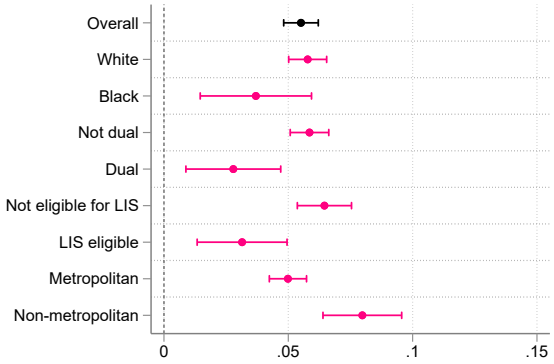
(b) Chemotherapy within 6 months



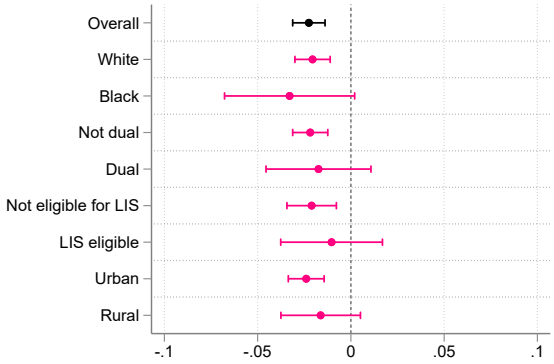
Note. Each panel displays the difference-in-difference coefficient for the transformed outcome variable (e.g. log(testing+1)), in the entire sample (denoted "overall") as well as in subsamples (e.g., white). The regressions include controls for proxies for patient SES including Medicaid status, disability status, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. For the "overall" sample: N=53,315 patients and N=4,228 providers (analysis sample). Standard errors are clustered at the provider level.

Figure 15: Treatment effect heterogeneity by patient characteristics

(a) Genomic testing within 90 days



(b) Chemotherapy within 6 months



Note. Each panel displays the difference-in-difference coefficient for the transformed outcome variable (e.g., log(testing+1)), in the entire sample (denoted "overall") as well as in subsamples (e.g. white). The regressions include controls for patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and physician age at the time point of surgery. For the "overall" sample: N=53,315 patients and N=4,228 providers (analysis sample). Standard errors are clustered at the provider level.

Table 6: Decomposing the within-provider racial gap

Panel A. Baseline	**Gap**	**SE**	**Change in Gap**
Unadjusted	0.091	0.007	
Age-adjusted	0.088	0.007	baseline
Panel B: Medical Appropriateness			
Early stage (I-IIIA)	0.078	0.006	12%
Hormone positive (ER/PR)	0.068	0.006	23%
HER2 negative	0.083	0.006	6%
Proxies for aggressiveness	0.071	0.006	20%
All medical appropriateness variables	0.057	0.006	35%
Panel C: Other			
Dual eligible	0.086	0.007	3%
County of residence	0.090	0.006	-1%
SEER registry	0.090	0.006	-2%
All other variables	0.087	0.006	1%
All variables	0.055	0.006	37%

Note. The table shows the results from estimating equation 5 in a sample of N=31,319 patients diagnosed with breast cancer between 2010-2015 and N=1,029 adopting providers. The average share of patients tested during this period was 0.22. The column "Gap" displays β from equation 5, "SE" displays the associated standard error, and "Change in Gap", displays the change in the estimated gap when controlling for the characteristics displayed in Panels B and C, relative to the baseline. The "baseline" corresponds to the racial gap when controlling for 1-year patient age indicators measured at the time point of diagnosis. In Panel B, each row represents the addition of one aspect of medical appropriateness to the regression, and similarly for Panel C. Standard errors are clustered at the provider-level.

Table 7: Raw probability of testing in SEER-Medicare linked data

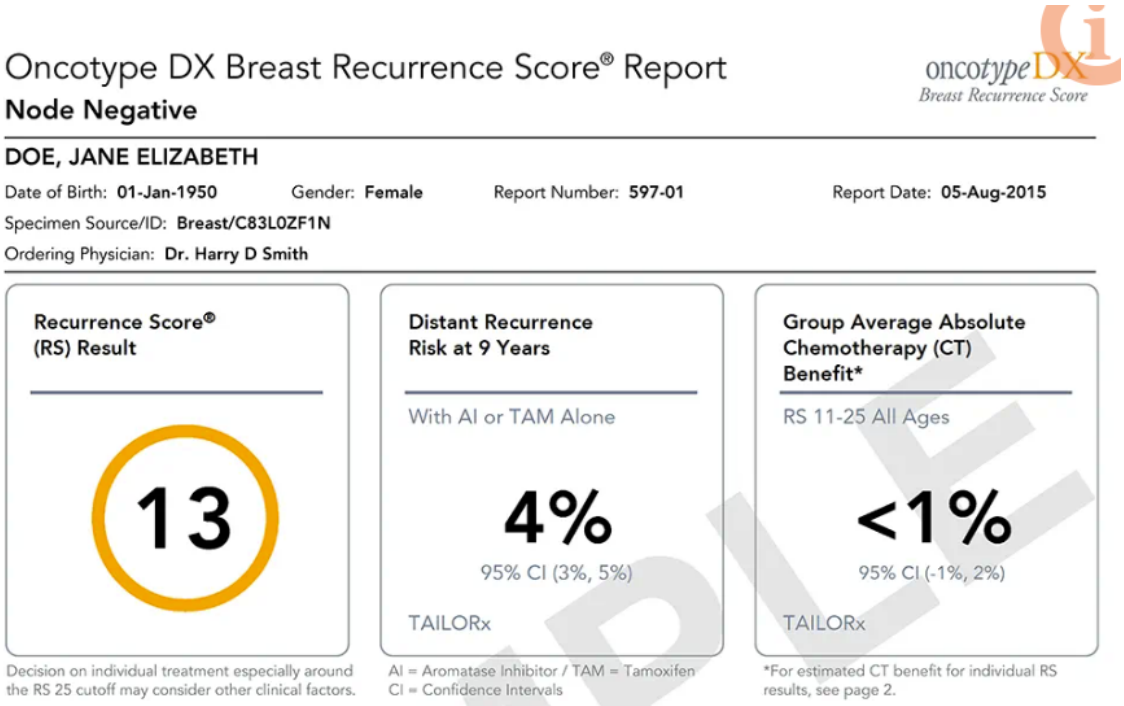
	White	Black	Gap	Log	Share of gap
Conditional probability of testing	0.12	0.07	0.57	-0.25	100%
P(Access)	0.57	0.56	0.98	-0.01	3%
P(Appropriateness|Access=1)	0.73	0.63	0.86	-0.06	26%
P(Testing|Access=1, Appropriateness==1)	0.30	0.20	0.67	-0.18	71%

Note. The table displays raw averages in the sample of N=31,319 patients diagnosed with breast cancer between 2010-2015 and N=1,029 adopting providers. 'P(Access)' denotes the share of patients who saw an adopting oncologist, 'P(Appropriateness|Access=1)' denotes the share of patients medically appropriate for the technology conditional on having access, 'P(Testing|Access=1, Appropriateness=1)' denotes the share of patients who were tested conditional on access and appropriateness. 'Conditional probability of testing' is the product of the previously described probabilities. 'Share of gap' denotes the share of the log of the conditional probability attributable to each of the rows in the table.

A Appendix

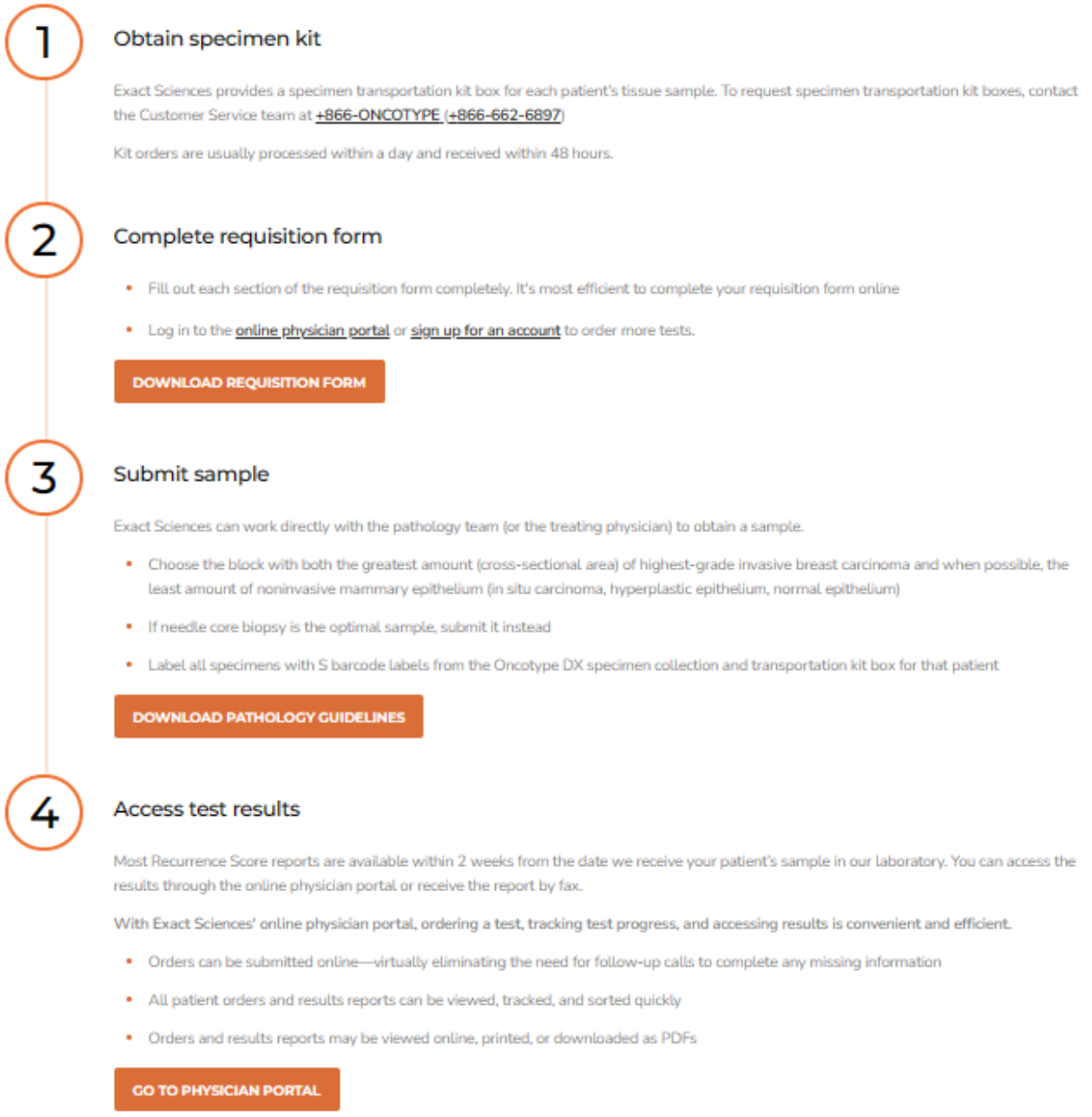
A.1 Institutional details

Figure A.1: Sample rest report



Source: https://www.oncotypeiq.com/en-ca/breast-cancer/healthcare-professionals/oncotype-dx-breast-recurrence-score/interpreting-the-results

Figure A.2: Steps in ordering a test



Source: https://precisiononcology.exactsciences.com/healthcare-providers/treatment-determination/breast-cancer/oncotype-dx-breast-recurrence-score/how-to-orderrrence-score/interpreting-the-results

A.2 Measurement

- **Breast cancer diagnosis.** Chronic conditions algorithm for breast cancer: at least 1 inpatient/SNF claim OR 2 HOP/Carrier claims with the following DX codes. ICD-10 codes: C50.011, C50.012, C50.019, C50.021, C50.022, C50.029, C50.111, C50.112, C50.119, C50.121, C50.122, C50.129, C50.211, C50.212, C50.219, C50.221, C50.222, C50.229, C50.311, C50.312, C50.319, C50.321, C50.322, C50.329, C50.411, C50.412, C50.419, C50.421, C50.422, C50.429, C50.511, C50.512, C50.519, C50.521, C50.522, C50.529, C50.611, C50.612, C50.619, C50.621, C50.622, C50.629, C50.811, C50.812, C50.819, C50.821, C50.822, C50.829, C50.911, C50.912, C50.919, C50.921, C50.922, C50.929, D05.00, D05.01, D05.02, D05.10, D05.11, D05.12, D05.80, D05.81, D05.82, D05.90, D05.91, D05.92, Z85.3 (any DX on the claim). ICD-9 codes: 174.0, 174.1, 174.2, 174.3, 174.4, 174.5, 174.6, 174.8, 174.9, 175.0, 175.9, 233.0, V10.3 (any DX on the claim).
- **Secondary cancer diagnosis.** 1962, 1965, 1966, 197, 1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 19881, 19882,19889, C772. C774, C775, C7801, C7802, C7800, C781, C782, C7830, C7839, C784, C785, C786, C787, C7880, C787, C7889, C7901, C7902, C7900, C7910, C7911, C7919, C792, C7931, C7940, C7932, C7949, C7951, C7952, C7961, C7962, C7963, C7960, C7971, C7972, C7970, C7981, C7982, C799, C7989
- **Breast cancer surgery**. Following prior medical literature, and for instance Zipkin et al. (2021). 10222, 15777, 19081, 19082, 19083, 19084, 19085, 19086, 19100, 19101, 19102, 19103, 19112, 19120, 19125, 19126, 19160, 19162, 19180, 19182, 19200, 19220, 19240, 19260, 19271, 19272, 19281, 19282, 19283, 19284, 19285, 19286, 19287, 19288, 19295, 19301, 19302, 19303, 19304, 19305, 19306, 19307, 19340, 19342, 19350, 19355, 19357, 19361, 19364, 19366, 19367, 19368, 19369, 19380, 38470, 38500, 38505, 38525, 38745, 38792, 38792, 76942, 77012, 77031, 77032, 78195, 78800, 78801, 88305, 88309.
- **Chemotherapy.** Source: SEER CanMED Database
- **Trastuzumab**. At least one HOP/Carrier claim with HCPCS code for trastuzumabL J9316, J9355, J9356, J9358, Q5112, Q5113, Q5114, Q5116, Q5117
- **Hormone therapy.** Any Part D claim with generic drugs: "tamoxifen citrate", "anaztrozole", "letrozole", exemstane"
- **Anti-emetic prescriptions.** At least one Part D claim with generic drug name: aprepitant, dolasetron mesylate, granisetron, granisetron hcl, granisetron hcl/pf, ondansetron, ondansetron hcl, ondansetron hcl/pf, ondansetron hcl/d5w/pf, ondansetron/sod cl/pf, palonosetron hcl, prochlorperazine, prochlorperazine maleate, prochlorperazine edisylate, promethazine, promethazine hcl, promethazine hcl/codeine, promethazine/dextromethorphan, promethazine/phenyleph/codeine, netupitant/palonosetron hcl, rolapitant hcl, rolapitant hydrochloride, lorazepam, metoclopramide hcl, dexamethasone, dexamethasone acetate, dexamethasone, micronized, dexamethasone sod phosphate, dexamethasone sodium phosphate, dexamethasone sod phosphate/pf, dexamethasone sodium phosp/pf, famotidine, famotidine/pf, famotidine/calcium carb/mag, famotidine in nacl, iso-osm/pf, famotidine I, famotidine/ca carb/mag hydrox, ranitidine hcl, ranitidine hcl in 1/2 ns, ranitidine hcl in 0.45 % sodium cl OR at least one Part B claim with HCPCS codes J8501, S0174, Q0180, J1260, Q0167, Q0168,

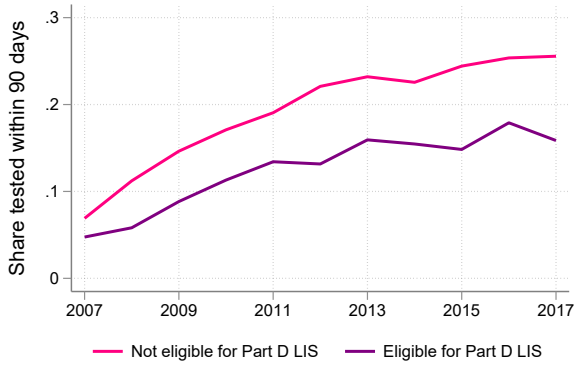
J1453, J1627, J1626, Q0166, S0091, J8650, J8655, Q9978, C9448, J2405, Q0179, Q0162, S0181, S0119, J2469, J8670, J1456, C9145. Source: SEER CanMED Database

- **Antidepressant prescriptions.** At least one Part D claim with generic drug name: duloxetine hcl, buspirone hcl, maprotiline hcl, selegiline, phenelzine sulfate, selegiline hcl, citalopram hybrobromide, olanzapine/fluoxetine hcl, nortriptyline hcl, bupropion hbr, vortioxetine hybrobromide, mirtazapine, trazodone hcl, paroxetine hcl, fluoxetine hcl, fluvoxamine maleate, clomipramine hcl, perphenazine/amitriptyline hcl, venlafaxine hcl, imipramine hcl, imipramine pamoate, desvenlafaxine succinate, volazodone hcl, protriptyline hcl, trimipramine maleate, escitalopram oxalate, levomilnacipran hcl, paroxetine mesylate, sertraline hcl, isocarboxazid, nefazodone hcl, amoxapine, desipramine hcl, vilazodone hydrochloride, tranylcypromine sulfate, levomilnacipran hydrochloride, buproprion hcl, desvenlafaxine, amitriptyline/chlordiazepoxide, amitriptyline hcl, doxepin hcl.
- **Immunohistochemistry.** At least one carrier claim with HCPCS code 88360, 88361, 88341, 88342
- **Screening mammogram.** At least one carrier claim with HCPCS code 76092, 77057, G0202, 77067

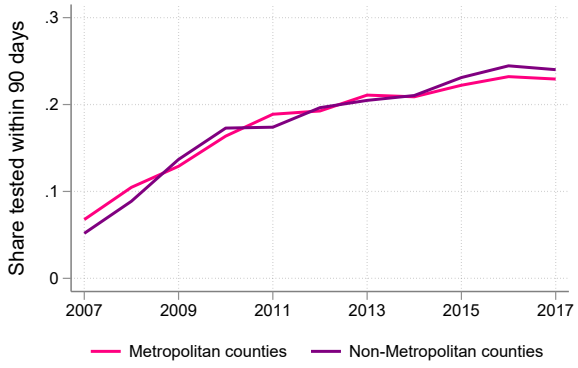
A.3 Descriptives of adoption and diffusion

Figure A.3: Diffusion of genomic testing by other markers of SES

(a) Eligible vs ineligible for Part D Low Income Subsidy



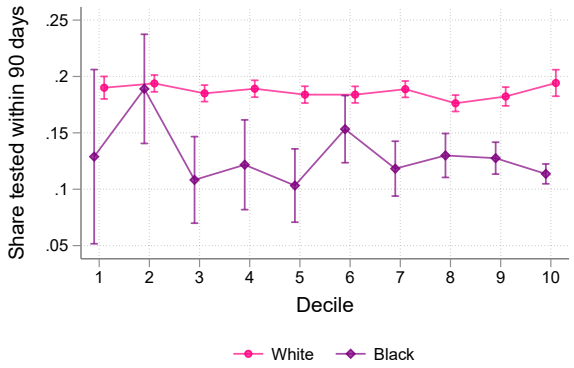
(b) Metropolitan vs non-metropolitan county of residence



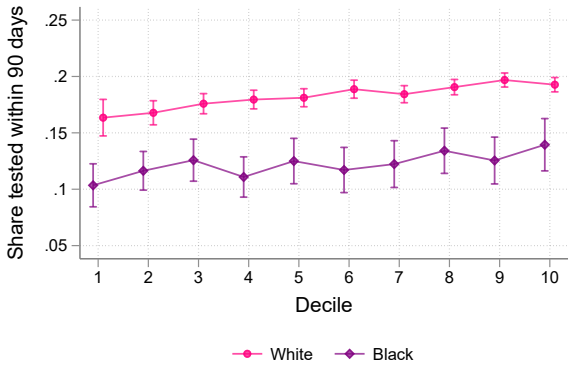
Note. Panel (a): N=67,698 patients (restricted to patients with Medicare Part D coverage), panel (b): N=107,252 patients. An individual is deemed eligible for Part D if the individual was deemed eligible for LIS with 100% premium subsidy and any copayment (i.e., no, low, or high).

Figure A.4: Socioeconomic gradients in genomic testing by race - 2007-2017

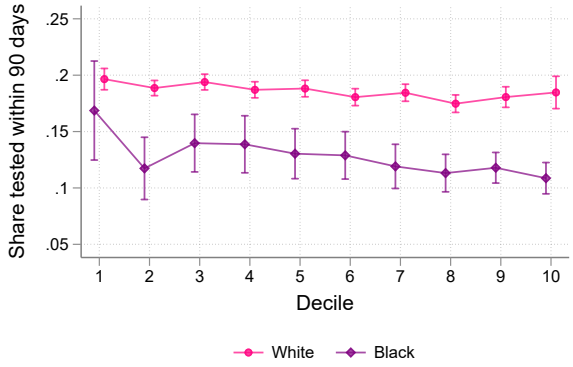
(a) Neighborhood disadvantage index



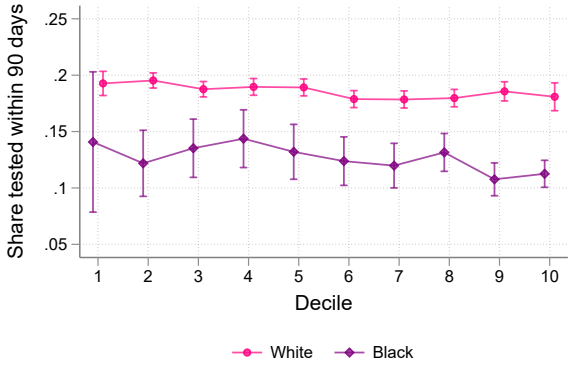
(b) Neighborhood affluence index



(c) Proportion people w/ income past 12 months below poverty level



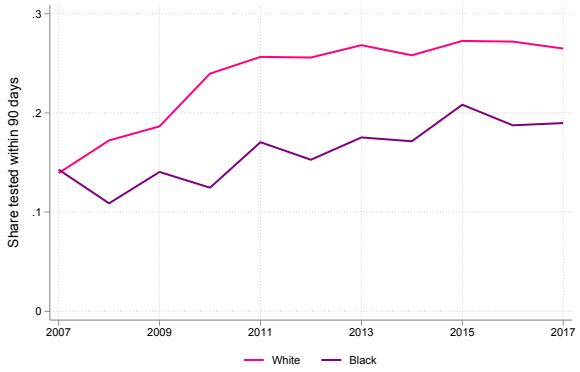
(d) Proportion of households with public assistance income



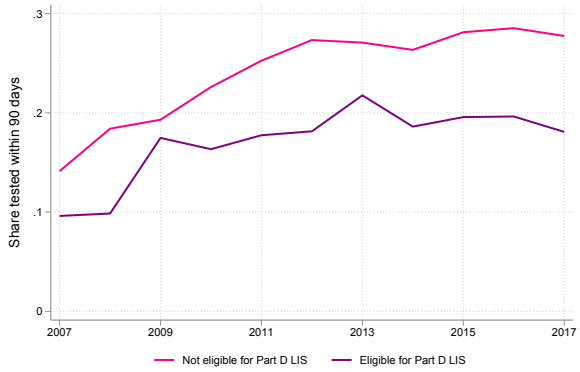
Note. N=102,725 patients. The figure shows the estimated share of patients tested within 90 days of surgery in each decile of a given measure of socioeconomic status (e.g., the neighborhood disadvantage index), controlling for age at surgery, comorbidity history, and a proxy for metastasis, separately for Black and white patients.

Figure A.5: Diffusion of genomic testing by race and SES conditional on seeing an adopting provider

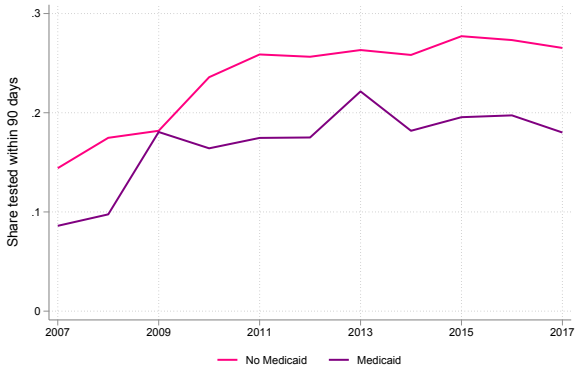
(a) Black vs White



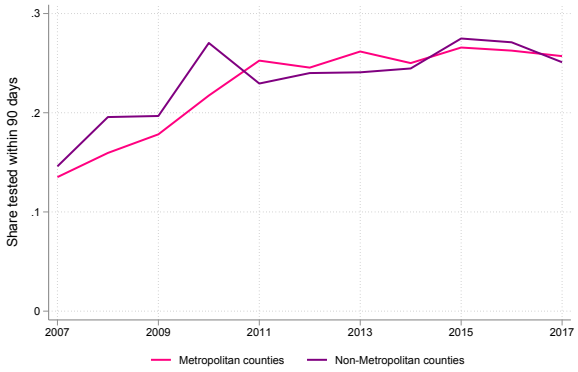
(b) Eligible vs ineligible for Part D Low Income Subsidy



(c) Duals vs non-duals



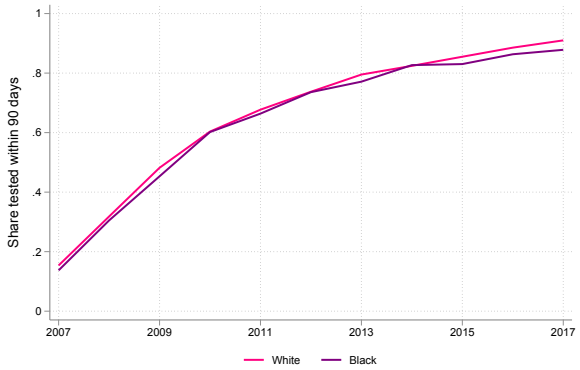
(d) Urban vs rural county of residence



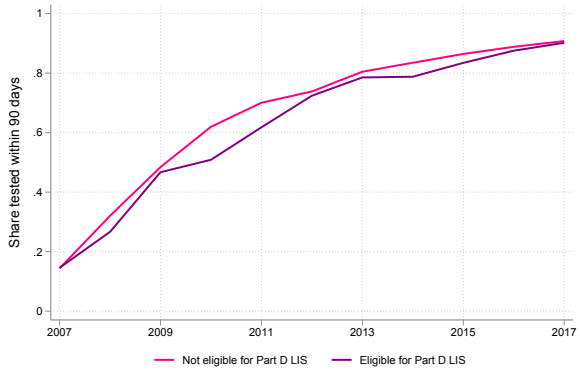
Note. The figure shows the raw share of patients tested conditional on seeing an adopting provider, separately by different patient characteristics (e.g., Black vs white).

Figure A.6: Share of patients seeing an adopting provider

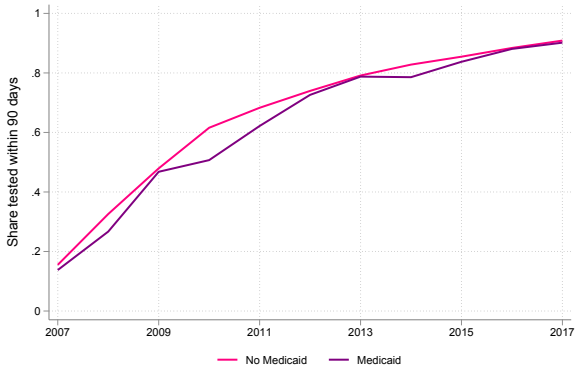
(a) Black vs White



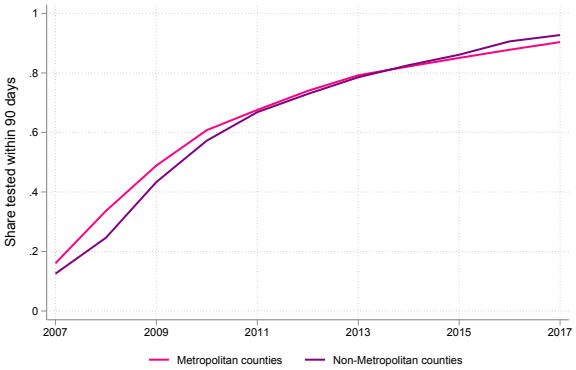
(b) Eligible vs ineligible for Part D Low Income Subsidy



(c) Duals vs non-duals



(d) Urban vs rural county of residence

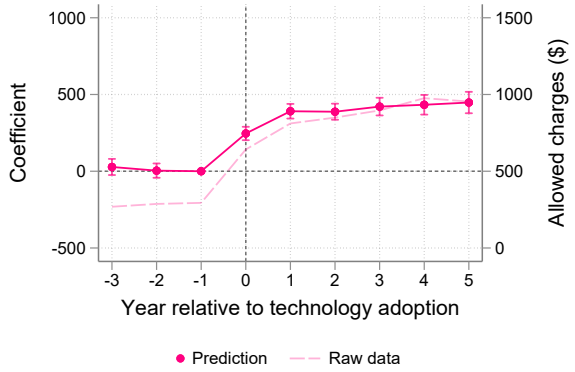


Note. The figure shows the raw share of patients seeing an adopting provider, separately by different patient characteristics (e.g., Black vs white).

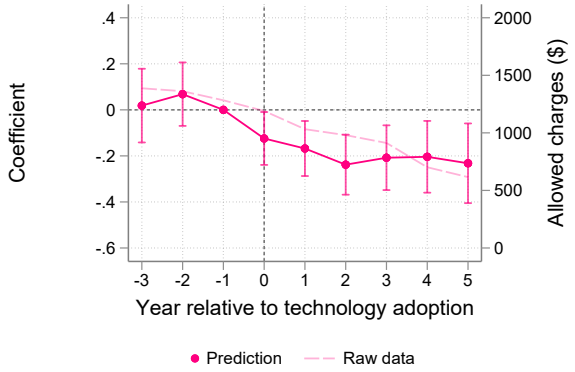
A.4 Additional results

Figure A.7: Effects of technology adoption on spending

(a) Part B technology spending per patient



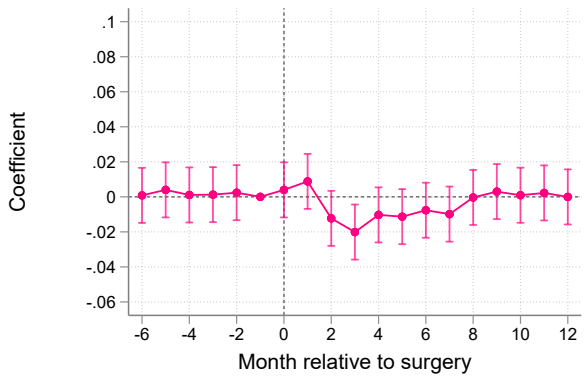
(b) Part B chemotherapy spending per patient



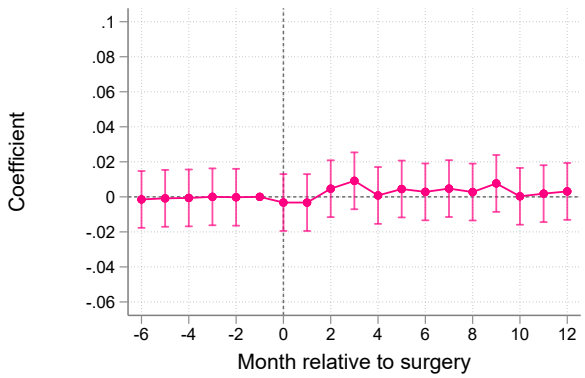
Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level. Spending refers to the allowed amount for Part B services only. Standard errors are clustered at the provider level.

Figure A.8: Effect of seeing an early adopter, relative to a late adopter, on anti-emetic prescriptions and hormone therapy

(a) Anti-emetic prescription in month t

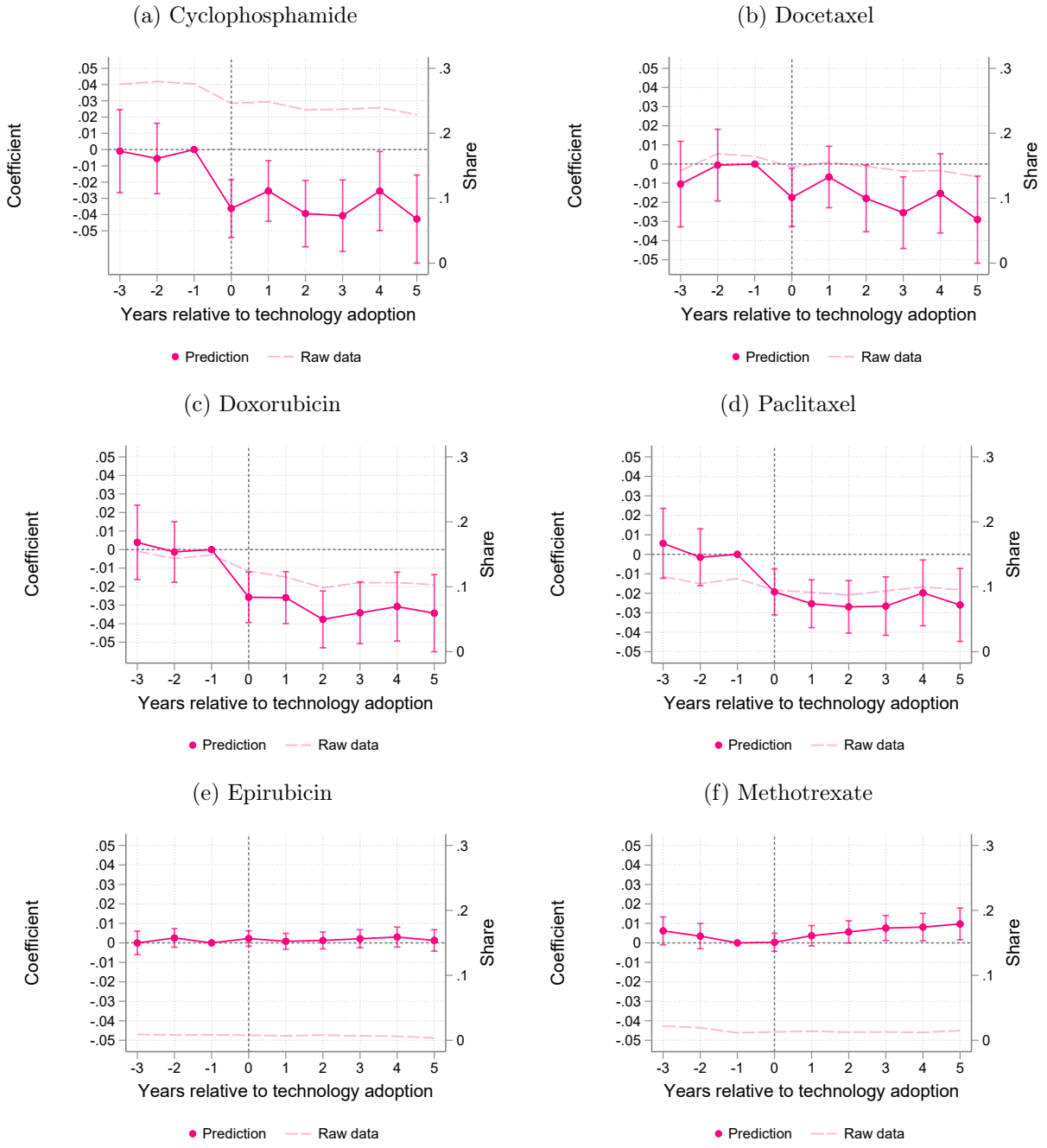


(b) Hormone therapy in month t - Placebo



Note. N=9,074 patients with surgeries in 2007-2009. An observation is a patient. The figure depicts results from estimating Equation (3).

Figure A.9: Effect of technology adoption on the use of specific chemotherapy drugs



Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, any Part D coverage, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery, indicators for the total number of these comorbidities, an indicator for metastasis within 3 months, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level.

Table A.1: Inputs to the classification matrix

	(1) Tested	(2) Chemotherapy	(3) True negative	(4) False negative
Adopted	0.102***	-0.0241***	0.0175***	0.00655
	(0.00502)	(0.00622)	(0.00604)	(0.00399)
Observations	63,062	63,062	63,062	63,062

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note. N=53,315 patients and N=4,228 providers (analysis sample). An observation is a patient-provider. The table shows the results from estimating 2. Controls include: age at surgery, race, medicaid status, Medicare Part D coverage, and disability status. Patient comorbidities include indicators for a history of Alzheimer's or dementia, AMI, chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure, stroke, hypertension, the total number of comorbidities, an indicator for metastatic cancer within 3 months of surgery, physician age at surgery, metropolitan status of the patient's county of residence, and hospital referral region. Standard errors are clustered at the provider level. *, **, ***, indicate significance at the 10%, 5% and 1% level.

A.4.1 Benchmark to clinical trial

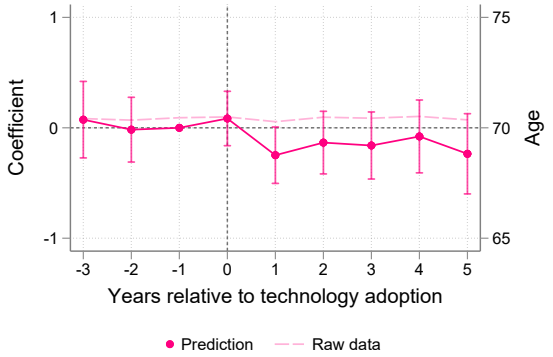
How does this result compare to the evidence from clinical trials? I perform a simple back of the envelope calculation. Scaling the chemotherapy reduction (approximately 15 percent decrease) by the testing increase (approximately 122 percent increase), suggest an approximately 12 percent reduction (-0.15/1.22) in chemotherapy use. Prior research suggests the distribution of Oncotype risk scores in a population of 66-80 years old was: 13.5% high-risk, 59.3% intermediate-risk, 27.2% low-risk.[38] The risk-score distribution is relatively similar for ages 36-66. Moreover, as previously noted, the TAILORx estimates suggest the rate of over and undertreatment in the high and low risk groups of, 25 and 43 percent, respectively. Before 2018, there was little guidance on how to treat patients with intermediate-level risk score. If one assumes the arrival of the technology led to a 43 percent increase in treatment in the high-risk group, a 25 percent reduction in treatment in the low-risk group, and no change in treatment in the intermediate group, this would correspond to a lower bound of a 1 percentage point reduction at the population level. Assuming instead that the arrival of the technology led to a 50 percent reduction in the chemotherapy rate in the intermediate risk-score would imply a 31 percentage point reduction in chemotherapy use at the population level.

[38] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7663955/

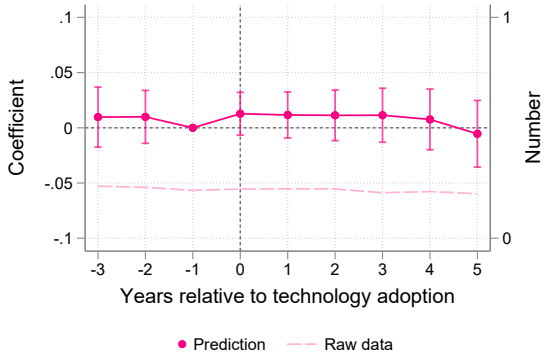
A.5 Robustness

Figure A.10: Technology adoption and patient characteristics

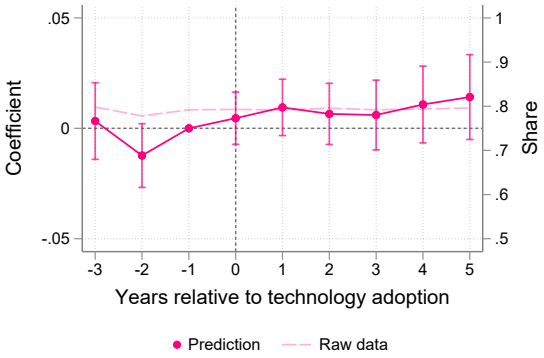
(a) Patient age at surgery



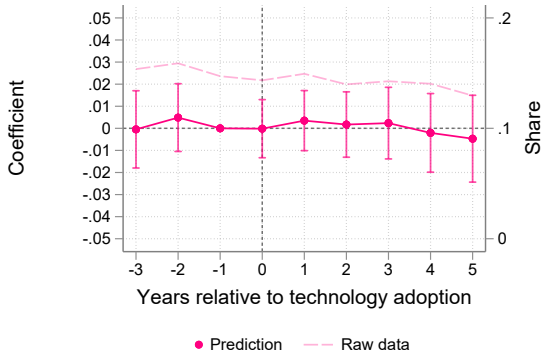
(b) Number of comorbidities



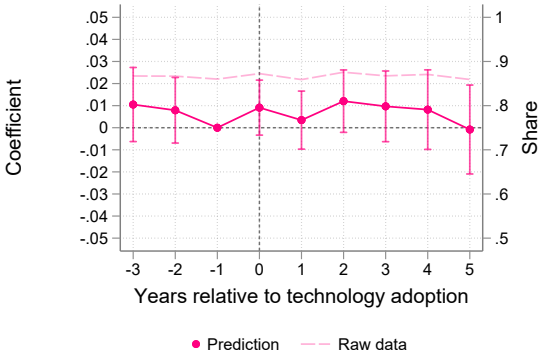
(c) Patient residing in urban county



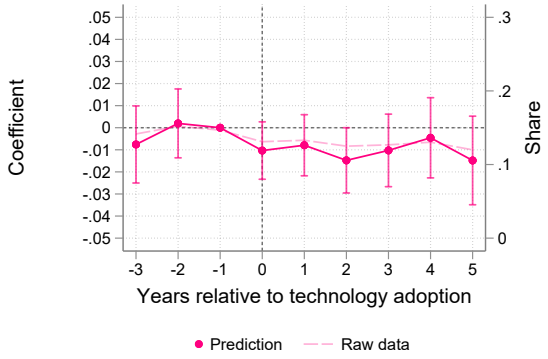
(d) Dual-eligible



(e) White patient



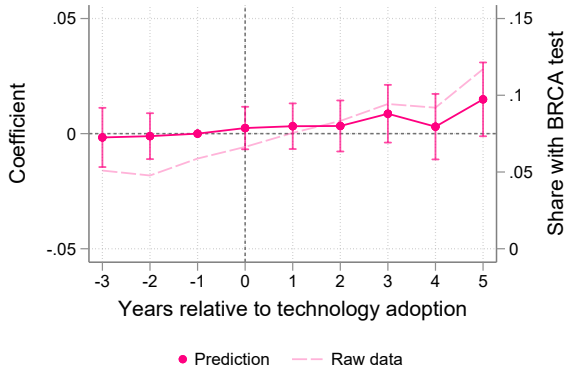
(f) Metastatic cancer within [-90,90] days of surgery



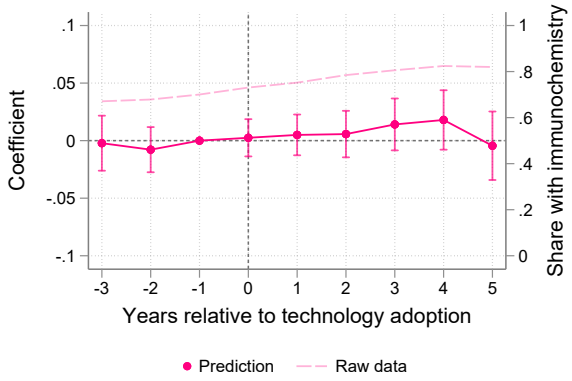
Note. N=53,369 patients and N=4,233 providers (analysis sample). An observation is a patient-provider. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable by relative year, restricted to the sample of providers who adopted the technology at some point. Standard errors are clustered at the provider level.

Figure A.11: Technology adoption and the use of other technologies

(a) BRCA testing within 90 days



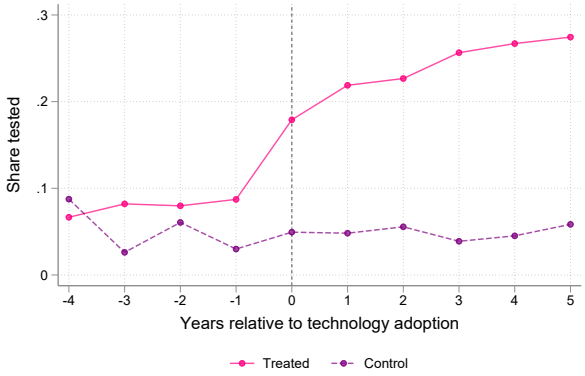
(b) Immunohistochemistry testing within [-5,5] days of surgery



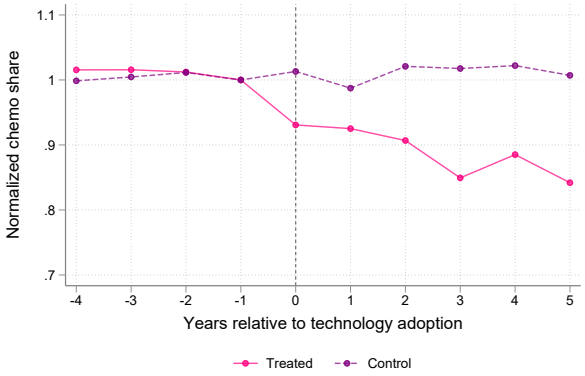
Note. N=66,175 patients, N=4,102 oncologists. The figure depicts results from the event studies ("prediction"). The dashed line ("raw data") depicts the average across providers of the outcome variable (e.g. number of patients tested divided by the total number of atrisk patients seen) by relative year, restricted to the sample of providers who adopted the technology at some point. The regressions include controls for proxies for patient SES including Medicaid status, disability status, any Part D coverage, eligibility for the Part D Low Income Subsidy, an indicator for a screening mammogram in the 180 days prior to surgery, patient comorbidities including age at surgery, chronic conditions present at the time point of surgery (Alzheimers, AMI, Cancers (lung, colorectal, endometrial), chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure), indicators for the total number of these comorbidities, and proxies for healthcare access, including HRR fixed effects and whether or not the patient resides in a metropolitan county, and physician age at the time point of surgery. Standard errors are clustered at the provider level. Standard errors are clustered at the provider level.

Figure A.12: Technology adoption and treatment decisions - control vs treated diseases

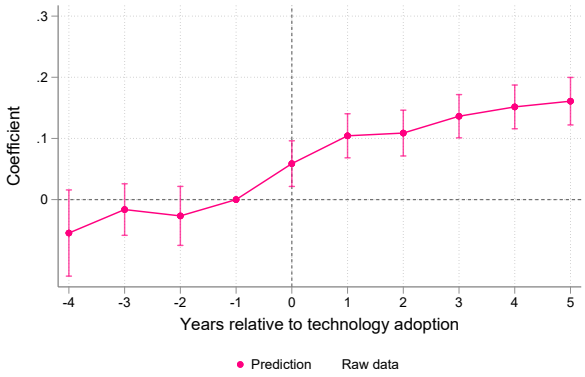
(a) Genomic testing within 90 days - raw data



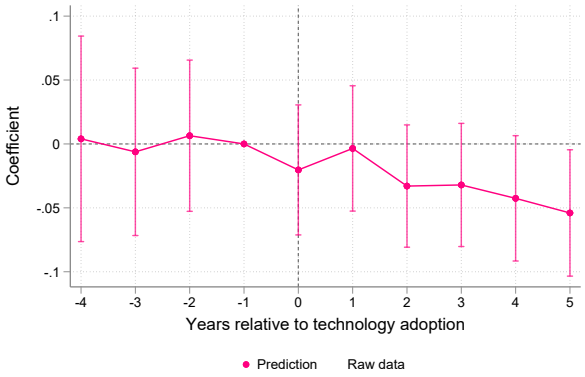
(b) Any chemotherapy within 1 year - raw data



(c) Genomic testing within 90 days



(d) Any chemotherapy within 1 year



Note. Panel (a) shows the share of patients tested separately for patients who are more likely to be indicated for the technology due to a likely negative HER2 status ("treated"), as well as patients who are not indicated for the technology due to a likely positive HER2 status ("control"). Panel (b) shows the normalized share of these patients getting chemotherapy, where the normalization is relative to the shares one year prior to adoption. Panels (c) and (d) show the results from estimating Equation (4).

A.6 Racial gap

Table A.2: Decomposing the racial gap

	(1)	(2)	(3)	(4)	(5)
Black	-0.0988***	-0.0855***	-0.0829***	-0.0683***	-0.0681***
	(0.0074)	(0.0076)	(0.0076)	(0.0075)	(0.0076)
Mean of Y	0.233	0.233	0.233	0.233	0.233
N	34,971	34,971	34,971	34,971	34,971
SES		✓	✓	✓	✓
Comorbidities			✓	✓	✓
Medical appropriateness				✓	✓
Area					✓

Note. The table shows the likelihood of getting tested within 90 days if the patient is Black, relative to white patients, estimated in a sample of patients who saw and adopting provider. All regressions include provider fixed effects. Column (1) displays the raw, unadjusted gap, Column (2) adjusts for patient demographic characteristics including Medicaid status, any Part D coverage, eligibility for the Part D Low Income Subsidy as well as year of surgery indicators. Column (3) additional adjusts for patient comorbidities including patient age at surgery and chronic conditions present at the time point of surgery (Alzheimers, AMI, Cancers (lung, colorectal, endometrial), chronic kidney disease, chronic obstructive pulmonary disease, diabetes, heart failure), indicators for the total number of comorbidities, and disability status. Column (4) additionally adjusts for a the receipt of a mamogram in the 180 days prior to the breast cancer surgery and an indicator for having hormone therapy. Column (5) additionally adjusts for proxies for healthcare access, including HRR indicators and whether or not the patient resides in a metropolitan county. Standard errors are clustered at the provider level.

A.7 Conceptual framework

Let G denote (one of the) gains(s) from using the technology. In the current setting, the gain could be a true negative, and the technology is a genomic test. Assume there are two groups $g \in [a, b]$, and assume that the likelihood that patients within a group gain from innovation is a function of the likelihood that patients within the group 1) have access to a provider who uses the technology (A_g), conditional on access, are appropriate or indicated for the technology (I_g) , 3) conditional on access and appropriateness, are tested (T_g) , and 4) conditional on all of the above, experience a good outcome (G_g) as opposed to a bad one (B_g). In the current setting, the good outcome could a true negative, and the bad outcome could be a false negative. This can be visualized in a patient/provider decision tree (see Figure A.13 below), where the ultimate probability of a good outcome is a product of the probabilities of travelling down the pink branch. Denote this branch probability $\hat{G}$. In other words:

$$P(\hat{G}_g = 1) =$$
$$P(A_g = 1) \times P(I_g = 1|A_g = 1) \times P(T_g = 1|A_g = 1, I_g = 1) \times P(G_g = 1|A_g = 1, I_g = 1, T_g = 1)$$

For a group to fully realize the gains from innovation (i.e. for $P(\hat{G}_g) = 1$), it is straightforward to see that this is achieved when all subcomponents are equal to 1; i.e. all patients have access, all patient are appropriate for the technology, all patients are tested if they are appropriate, and all patients derive value from the test if they are tested, conditional on being appropriate. In practice, not all patients will have access to an adopting provider or be indicated for the technology, rendering $P(\hat{G}_g) < 1$.

It is also straightforward to see that differences in the subcomponents may results in greater gains in one group than the other. For instance, in the extreme, assume all patients in group a have access to the technology, are indicated for the technology, are tested, and experience the intended health outcome (e.g. a true negative in this setting). Then $P(\hat{G}_g = 1) = 1$ and group a fully gains from the technology. The corresponding probabilities are identical in group b, except patients in group b have an 80 percent probability of getting tested. Then, $P(\hat{G}_a) = 1$, $P(\hat{G}_b) = 0.8$ and the relative gains from innovation is lower in group b than group a. If a denotes a group of white patients, and b denotes a group of black patients, a racial disparity arises in the gains from innovation:

$$P(\hat{G}_b) < P(\hat{G}_a) \qquad \textbf{(Racial disparity in gains)}$$

Moreover, introducing two time periods, t and $t-1$, the gains from innovation may increasingly accrue to one group relative to the other, if the subcomponents grow at a faster rate in one group:

$$P(\hat{G}_b^t)/P(\hat{G}_b^{t-1}) < P(\hat{G}_a^t)/P(\hat{G}_a^{t-1}) \qquad \textbf{(Widening of a racial disparity in gains)}$$

In particular, a disparity *emerges* if there are no initial differences in gains $P(\hat{G}_b^{t-1}) = P(\hat{G}_a^{t-1})$. Since G is a the product of a set of probabilities, it is also possible to decompose the racial disparity at a given point in

time into its subcomponent. More specifically, let $G_g \equiv P(G_g = 1)$, $A_g \equiv P(A_g = 1)$, $I_g \equiv P(I_g = 1|A_g = 1)$, $T_g \equiv P(T_g = 1|I_g = 1, A_g = 1)$, and $V_g \equiv P(G_g = 1|T_g = 1, I_g = 1, A_g = 1)$ and log-transforming gives $ln(\hat{G_g}) = ln(A_g) + ln(I_g) + ln(T_g) + ln(V_g)$. The difference in gains is then given by $ln(\hat{G_b}) - ln(\hat{G_a}) = \big(ln(A_b) - ln(A_a)\big) + \big(ln(I_b) - ln(I_a)\big) + \big(ln(T_b) - ln(T_a)\big) + \big(ln(V_b) - ln(V_a)\big)$. In other words, the racial disparity in gains can then be decomposed into the relative importance of 1) access, 2) appropriateness, 3) testing, and 4) value:

$$\Delta\text{gains}_t = \Delta\text{access}_t + \Delta\text{appropriateness}_t + \Delta\text{ testing}_t + \Delta\text{value}_t \quad \textbf{(Static decomposition of the racial disparity in gains)}$$

It is also possible to decompose the rate of change in the racial disparity from time 0 to time 1 as a function of the rate of change in the subcomponents:

$$\Delta\text{gains}_{t-1,t} = \Delta\text{access}_{t-1,t} + \Delta\text{appropriateness}_{t-1,t} + \Delta\text{ testing}_{t-1,t} + \Delta\text{value}_{t-1,t} \quad \textbf{(Dynamic decomposition of the racial disparity in gains)}$$

This framework illustrates two broader points. First, it highlights how the gains from medical innovation can vary across patient subpopulations as a function of factors that can to various degrees by shaped by policy. While increasing "access" and "testing" may be the most straightforward factors to influence, factors like "appropriatenss" may become increasingly important and relevant as precision medicine moves from targeting late-stage diseases to earlier stages of disease, and in the extreme, healthy populations (e.g. emerging technologies that screen for cancer). To the extent that preventive health and screenings ensure timely diagnosis and early detection, making a patient "appropriate" for the technology, the existing case for reducing existing socioeconomic and racial disparities in preventive health becomes increasingly acute.

Second, this framework highlights how the gains from innovation in information technologies, ultimately depend on the value of information that the technology delivers, which may differ across patient groups and providers, both as a result of the inherent characteristics of the technology as well behavioral responses by patients and providers to test results (like adherence).[39] The behavioral dimension that this introduces is somewhat unique to information technologies.

[39]This is particularly relevant for the technology studies in this setting where patients/providers face a difficult decision of forgoing a treatment that has the potential to save a person from dying. Risk-aversion will play a critical role when patients decide whether or not to adhere to a recommendation of forgoing chemotherapy. Another example is that of prenatal testing.

Figure A.13: Clinical pathways to a true negative

