Medical Innovation, Education, and Labor Market Outcomes of Cancer Patients*

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Abstract

Innovations in cancer treatment have lowered mortality, but little is known about their economic benefits. We assess the effect of two decades of improvement in cancer treatment options on the labor market outcomes of breast and prostate cancer patients. In addition, we compare this effect across cancer patients with different levels of educational attainment. We estimate the effect of medical innovation on cancer patients' labor market outcomes employing tax return and cancer registry data from Canada and measuring medical innovation by using the number of approved drugs and a quality-adjusted patent index. We find that innovations in cancer treatment during the 1990s and 2000s reduced the negative employment effects of cancer by 63% to 70%, corresponding to a reduction in the economic costs of prostate and breast cancer diagnoses by 13,500 and 5,800 dollars per year, respectively. The benefits of medical innovation are limited to cancer patients with postsecondary education.

Keywords: Medical Innovation; Breast Cancer; Prostate Cancer; Labor Supply; Employment; Earnings; Returns to Education.

JEL codes: I12; I14; I24; I26; J22; O31.

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1 Introduction

Apart from being one of the major causes of mortality and morbidity, cancer also has important economic consequences because cancer patients often reduce their labor supply. Medical innovations in cancer treatment are primarily designed to lower mortality, but they may also have the benefit of helping cancer patients maintain their pre-cancer labor market activities. Hence, when assessing the costs and benefits of new medical treatments, it is important to take into consideration not just whether the new treatment can extend the lives of cancer patients but also whether it can help patients participate in the labor market and maintain their productivity. However, potential economic benefits may vary across patient with different characteristics, in particular socio-economic status.

In this paper, we address two important questions related to medical innovation in cancer treatment. First, we provide the first evidence on how medical innovation in cancer treatment affects the labor market outcomes of breast and prostate cancer patients. Second, we assess differences in labor market benefits of medical innovation by patients' level of education to determine whether economic gains related to medical innovation differ by socio-economic status. To estimate the effect of medical innovation, we use unique Canadian administrative data from several sources. Our findings imply substantial gains from medical innovation in terms of smaller declines in employment and earnings following a cancer diagnosis. These gains are observed almost exclusively among individuals with postsecondary education.

Cancer research has grown rapidly in recent decades (Sudhakar 2009), leading to a 23% decline in cancer-related death rates in the U.S. between 1991 and 2016 (Siegel, Miller, and Jemal 2016). Lichtenberg (2013, 2014, 2015, 2017, 2018a, 2018b) provides U.S., Canadian, and international evidence directly tying a decline in cancer mortality to an increase in available drugs and cancer research more broadly. This decline in mortality comes at a cost. The median cost of developing a new cancer drug is 800 million U.S. dollars (Prasad and Mailankody 2017). Between 2005 and 2012, total public expenditures on chemotherapy and radiation therapy in Canada increased by factors of 3 and 3.5, respectively, in real terms (de Oliveira et al. 2018).

Existing evidence on the indirect benefits of cancer treatment innovation typically focuses on a single drug or combination of drugs and attempts to estimate patient utilities (Delea et al. 2013; Gharaibeh et al. 2017; Meng et al. 2018; Zhou et al. 2018). Studies that account for productivity loss due to cancer are limited to a decline in employment due to patients' death (Hanly, Soerjomataram, and Sharp 2015; Pearce et al. 2018). In contrast, this is the first paper that explicitly estimates the effect of medical innovation on the labor market outcomes of surviving cancer patients, which is an important determinant of the total benefits of new

treatment options.

We focus on prostate and breast cancer for three reasons. First, they are the most common cancer diagnoses among men and women. Second, survival rates are high compared to other cancer types, so breast and prostate cancer patients are more likely to benefit from improved treatment options in terms of their labor market outcomes. Third, although cancer usually occurs later in life, a substantial fraction of prostate and breast cancer diagnoses occur during working age. Hence, we expect meaningful changes in labor market outcomes in response to improved treatment. Bradley et al. (2002a, 2002b; 2005; 2006; 2007; 2007; 2013) analyze the labor market outcomes of breast and prostate cancer patients, but to our knowledge no study has considered the role of treatment innovation in this context or in the context of any other cancer types. We provide more background on breast and prostate cancer in Section 3.1.

To study the labor market effects of innovation in cancer treatment, we use data linking the Canadian 1991 Census cohort with the Canadian Cancer Registry and individual income tax returns. These data provide a representative sample of individuals diagnosed with breast and prostate cancer in Canada between 1992 and 2010 (see Section 4). We track the labor market outcomes (employment status and annual earnings) of these cancer patients before and after their diagnosis and identify a control group consisting of individuals who were never diagnosed with cancer. We capture the cumulative level of medical innovation related to the treatment of breast and prostate cancer by counting the number of drugs that were approved for the treatment of these cancers and by constructing a quality-weighted patent index (see Section 3.2). To our knowledge, no other study has used patent data to estimate the effect of medical innovation on labor market outcomes.

Using data from the treatment group (cancer patients) before and after the diagnosis and from the control group, we employ difference-in-differences regressions to estimate the impact of cancer diagnosis on labor market outcomes and the degree to which this effect is moderated by medical innovation. To study how the impact of innovation varies by education, we estimate separate regressions for patients with different levels of highest educational attainment: primary, secondary, and postsecondary education. In all regressions, we use Coarsened Exact Matching weights to balance treatment and control group based on observed variables, including pre-treatment labor market outcomes. Section 5 presents a detailed description of our empirical strategy.

Our results confirm the existing evidence of negative labor market effects of breast and prostate cancer diagnoses. More important, we find that medical innovation, measured by the number of approved drugs and patents, reduces the negative employment effect of prostate cancer by about 64% to 70% over our study period. For breast cancer, medical innovation mitigated the negative effect on employment by 63% to 68%, and this effect was concentrated

among women aged 35 to 44 whose breast cancer diagnoses are typically more severe than the diagnoses of older women. We also find effects of medical innovation on earnings that are only statistically significant in the case of prostate cancer. Our results imply that medical innovation between 1992 and 2010 could be associated with a reduction in the economic cost of a cancer diagnosis by about 13,500 and 5,800 dollars per patient and year in the case of prostate and breast cancer, respectively. When estimating separate effects by education, we find that the economic gains of medical innovation arise almost exclusively among patients with postsecondary education. These results are robust to various alternative specifications. We present a comprehensive discussion of our empirical findings in Section 6.

This study contributes to several distinct literatures. First, and most important, we contribute to the small but growing literature on the labor market effects of medical innovation, which focuses on pharmaceutical innovation such as the birth control pill (Goldin and Katz 2002; Bailey 2006), painkillers (Garthwaite 2012; Bütikofer and Skira 2018), HIV treatment (Papageorge 2016; Thirumurthy, Graff Zivin, and Goldstein 2008), antidepressants (Bütikofer, Cronin, and Skira 2019) and hormone replacement therapy (Daysal and Orsini 2014), as well as minimally invasive surgery (Epstein et al. 2013). These studies use the introduction of a specific medical technology as a natural experiment. In contrast, we do not focus on one particular innovation but take a broader view on medical innovation and consider the labor market effects of cumulative medical innovation in cancer treatment over two decades.

We also shed light on the value of medical innovation more generally. Cutler and McClellan (2001) show that increased medical spending is cost-effective in many cases. Murphy and Topel (2003) develop a general framework to evaluate the gains from medical innovations and find that the economic benefits of reducing mortality are very large. We contribute to this literature by considering the individual benefits that arise from medical innovation when cancer patients are able to stay economically more active after a diagnosis.

Finally, we contribute to the literature on the nexus among health, education, and economic outcomes. For example, Lundborg, Nilsson, and Vikström (2015) and Parro and Pohl (2019) show that the labor market effects of health shocks differ by education in Sweden and Chile. Heinesen and Kolodziejczyk (2013) find larger negative employment effects among less educated breast and colorectal cancer patients in Denmark. Glied and Lleras-Muney (2008) find that declines in mortality due to health-related technological progress are largest among highly educated individuals and Lleras-Muney and Lichtenberg (2005) show that patients with more education are more likely to use recently launched drugs. We add to this literature by studying how the interaction between medical innovation and education affects cancer patients' labor market outcomes.

2 Conceptual Framework

In this section, we provide a theoretical framework motivating the links among medical innovation, education, and labor market outcomes of cancer patients that we investigate in the empirical portion of this study. First, we consider the effect of improved treatments on labor market outcomes; second, we incorporate education into the framework.

In the Grossman (1972) model, health capital H_t evolves over an individual's life according to

$$H_t = H((1-\gamma_t)H_{t-1}, T_t^H, M_t),$$

where γ_t is the period-specific depreciation rate, T_t^H is time spent on investing in health, and M_t denotes market health inputs such as surgeries and pharmaceuticals. Here, it is useful to interpret M_t in terms of quantity and quality of health care. That is, a higher value of M_t could reflect more treatment but also better and more effective treatment options. The individual's health status affects her labor supply through a time constraint, given by

$$T_t^W + T_t^Z + T_t^H + T_t^S = \Theta,$$

where T_t^W is time spent working, T_t^Z is time spent on household production, T_t^S is unproductive sick time, and Θ is the total available time per period.

A negative health shock such as a cancer diagnosis (captured by a temporary increase in the depreciation rate γ_t) raises sick time T_t^S. At the same time, it is likely that the individual decides to increase her health investment time T_t^H to offset at least a portion of the decline in her health capital. As an increase in T_t^S reduces full income, this leads to a decline in time spent on market production T_t^W if consumption is a normal good (O'Donnell 1995).[1]

In this model, medical innovation leads to an increase in the quality of health care M_t, so conditional on γ_t, H_{t-1}, and T_t^H, the individual's health capital H_t is higher than in the absence of medical innovation. It is possible that the individual lowers her time input into health investment in response to a higher M_t, but it is more likely that M_t cannot be easily substituted for T_t^H, particularly in the case of cancer treatment such as chemotherapy. As medical innovation reduces the decline in health capital, the effect of a health shock on T_t^W is also smaller. Thus, in this model, medical innovation leads to a smaller decrease in labor

[1] In a health care system where health insurance is contingent on employment, a cancer patient may be less likely to reduce labor supply or even increase it in order to maintain her insurance coverage as she may otherwise not be able to afford treatment. This is not relevant in the present context, however, because Canada has a universal health care system. In addition, a cancer patient faces almost no out-of-pocket spending for her treatment, which would otherwise also affect her labor supply. Although self-administered prescription drugs are not covered by the public health care system, drugs that are administered by a medical provider, including chemotherapy drugs for cancer treatment, are covered.

supply caused by a cancer diagnosis.

Education (or, more generally, human capital) has two main effects in the Grossman (1972) model. First, it raises the efficiency of the production of health, i.e. $\partial H_t/\partial M_t$ increases in education. This higher efficiency may arise from a better capacity to process information in order to seek out high-quality medical providers or innovative treatments. Education may also improve adherence to treatment. In the extended model of Galama and van Kippersluis (2019), it also increases the wage or the marginal benefit of time spent working, T_t^W. Both of these effects imply that, following a cancer diagnosis, more educated individuals reduce their labor supply by a smaller amount because they produce more health with the same amount of medical care and because the loss of earnings resulting from a decline in labor supply is higher. When a novel treatment option becomes available, highly educated cancer patients are better able to take advantage of the new treatment as they are more efficient producers of health than less educated patients. Hence, highly educated patients can mitigate the negative labor market impact of cancer to a greater degree than less educated patients.

3 Cancer and Measuring Innovation in Cancer Treatment

This section provides background information about the incidence, diagnosis, and treatment of prostate and breast cancer. We summarize innovation in the treatment of these diseases and describe the innovation measures used in the empirical analyses below.

3.1 Prostate and Breast Cancer

Prostate and breast cancers are the most common cancer diagnoses among men and women. In 2017, 21,300 men in Canada were diagnosed with prostate cancer (21% of all cancer diagnoses in the country) and 26,300 women were diagnosed with breast cancer (25% of all cancer diagnoses in the country). The survival rates for these two types of cancer are relatively high compared to other types of cancer, with a 95% five-year survival rate for prostate cancer and a 87% rate for breast cancer.[2] Although patients with localized breast and prostate cancers have relatively good prospects for successful treatment, cancers that have already metastasized lead to much higher death rates (Bubendorf et al. 2000; Redig and McAllister 2013).

[2]See http://www.cancer.ca/en/cancer-information/cancer-type/prostate/statistics/ and http://www.cancer.ca/en/cancer-information/cancer-type/breast/statistics/.

Prostate cancer is uncommon in men under the age of 50 and occurs most often among those aged over 65; however, 40% of prostate cancer cases occur before age 65.[3] As we are interested in the labor market effects of cancer and medical innovation, we restrict the sample to men aged 49 to 60 at the time of the diagnosis. That is, considering a five-year follow-up period, these men are below typical retirement age. Breast cancer is also more common in older women: 16% of breast cancer cases occur before age 50 and 4% before age 40.[4] Breast cancer tends to be more aggressive in younger women (Anders et al. 2009; Brandt et al. 2015). In our empirical analyses, we include women aged 35 to 60. As most of the recent innovations in breast cancer relate to more severe types of the disease (see below), we focus our main analyses on a sample of younger women, aged 35 to 44.

Routine screenings are available for prostate and breast cancer. For breast cancer, the current Canadian guidelines do not recommend routine screening for women under the age of 49 but do recommend regular mammography every two to three years for women aged 50 to 69. This recommendation was largely unchanged throughout our study period, from 1992 to 2010 (Canadian Task Force on the Periodic Health Examination 1994, chap. 65; Canadian Task Force on Preventive Health Care 2011). For women aged 35 to 44, who constitute the focus of our analysis, no breast cancer screening was recommended throughout our sample period. Moreover, Zakaria and Shaw (2019) show that the breast cancer screening rate barely changed throughout between 1990 and 2012: among Canadian women aged 35 to 39 it declined by 1.8% annually and among women aged 40 to 49 it increased by 0.4% annually. We can therefore attribute any impact on labor market outcomes of young breast cancer patients to changes in technology and not in screening behavior.

For prostate cancer, the guidelines recommend neither the inclusion nor exclusion of the digital rectal exam in/from periodic health examinations for men aged 50 to 70. Due to the high false positive rate, the guidelines do not recommend routine prostate-specific antigen tests for men of any age. These recommendations remained unchanged throughout our sample period (Canadian Task Force on the Periodic Health Examination 1994, chap. 67; Canadian Task Force on Preventive Health Care 2014). In addition, LeBlanc, Demers, and Shaw (2019) find no significant change in the age-standardized incidence rate of prostate cancer from 1992 to 2001 and a 1.6% annual decline from 2001 to 2011 in Canada, suggesting no meaningful changes in screening rates. Therefore, any impact on the labor market outcomes of prostate cancer patients is likely to have been caused by improvements in treatment and diagnostics and not by changing attitudes towards screening.

For both types of cancer, treatment options include surgery (mastectomy or lumpectomy

[3]See https://www.cancer.org/cancer/prostate-cancer/about/key-statistics.html.

[4]See https://seer.cancer.gov/csr/1975_2015/browse_csr.php?sectionSEL=4&pageSEL=sect_04_table.11.

and prostatectomy, respectively), radiotherapy, chemotherapy, and hormone therapy (anti-estrogen therapy for breast cancer and androgen deprivation therapy for prostate cancer).[5] Increasingly, a combination of two or more options is used (see below). In the case of prostate cancer, an alternative to immediate treatment is active surveillance. This course of action may especially be used among older patients with co-morbidities that are more lethal than prostate cancer. In the age range that we consider (49 to 60), however, it is more common to treat prostate cancer using one or several of the options above. For example, Bechis, Carroll, and Cooperberg (2011) find that 85% of prostate cancer patients under the age of 55 were treated with radical prostatectomy. Moreover, Cooperberg and Carroll (2015) show that active surveillance rates did not exhibit a significant trend during our study period and are around 10% for the lowest risk group and lower for medium and high risk groups.

3.2 Measuring Innovation in Cancer Treatment

Treatment options for many types of cancer have vastly improved over the last few decades (see, e.g., Sudhakar 2009). The combination of surgery and chemotherapy or radiation therapy is one of the major innovations that have lowered cancer mortality rates. Medical innovation has made cancer treatments more effective and reduced their side effects. Zurrida and Veronesi (2015) describe important treatment innovations that happened during our sample period, such as breast-conserving surgery in the 1990s. Chemotherapy has become more effective in targeting cancer cells while causing less harm to healthy cells (for example, by using the drug tamoxifen starting in the 1980s). New drugs that lower the risk of side effects of chemotherapy have also been developed (DeVita and Chu 2008). The majority of new drugs, however, are approved for advanced-stage cancers and not for first-line therapy (Tibau et al. 2018).

Innovations in prostate cancer treatment include the use of hormonal therapy such as luteinizing hormone-releasing hormone analogues (triptorelin) since the early 1980s (Denmeade and Isaacs 2002). More recent drugs such as degarelix provide improved and cost-effective treatment options (Hatoum et al. 2013). Several innovations in surgical methods have also provided additional treatment options for prostate cancer. For example, laparoscopic radical prostatectomy is a minimally invasive surgical technique that leads to better postoperative functional outcomes (Lipke and Sundaram 2005).

These improvements in treatment of breast and prostate cancer are also reflected in the innovation measures that we use in our empirical analyses below. Due to the significance of chemotherapy and hormone therapy in treating these cancers, drugs available for treatment

[5] See https://www.cancer.gov/types/prostate/hp/prostate-treatment-pdq and https://www.cancer.gov/types/breast/hp/breast-treatment-pdq.

of a specific type of cancer are an important measure of medical innovation. Lichtenberg (2015) provides a list of all drugs available for treatment by cancer type along with the year when they were approved in Canada.[6] We use this information to calculate the cumulative number of drugs that were available for the treatment of breast and prostate cancer in the year of an individual's diagnosis.

One limitation in using only drugs approved for the treatment of prostate and breast cancer, respectively, arises from the fact that off-label use, i.e. the use of drugs approved for a different indication, is widespread (Saiyed, Ong, and Chew 2017; Bradford, Turner, and Williams 2018). To account for this possibility, we conduct a robustness check in Section 6.3, where we include drugs that were approved for the treatment of any type of cancer.

To account for the delay between the approval of a drug and its widespread use in treatment, we lag our innovation measures. Lichtenberg (2015) finds that lags of ten and more years yield statistically significant results when regressing years of potential life lost on the cumulative number of drugs in Canada. Using data from 36 countries, Lichtenberg (2018b) also estimates a negative relationship between the number of drugs launched at least five years earlier and cancer-related mortality. In addition to mortality, Lichtenberg (2017) finds that cancer research reduces hospitalizations due to cancer at all lags considered, including no lag at all, but that this relationship becomes stronger at longer lags. We therefore use a lag of five years in our preferred specification and show robustness checks with a lag of ten years and no lag in the Online Appendix. Using a five-year lag, Figure 1 shows that the number of prostate cancer drugs increased from 14 to 27 and the number of breast cancer drugs rose from 17 to 39 between 1992 and 2010.

To capture the improved diagnostics, radiation, and surgical procedures that have also contributed to better treatment of these cancers, we construct a quality-adjusted patent index. Using the Cancer Moonshot Patent Data from the United States Patent and Trademark Office (USPTO),[7] we identify patents relevant for breast and prostate cancer by searching for the key words "prostate" or "prostatic" and "breast" or "mammary." The resulting list of patents includes diagnostic procedures, surgical equipment and methods, and pharmaceutical innovation. We include not only patents that were granted but also those that were unsuccessfully applied for to capture the full range of cancer-related inventions.

[6] Approval of these drugs goes back to 1950, so the list includes all drugs relevant for cancer treatment. See Online Appendix Table A.1 for a list of prostate and breast cancer drugs approved during the study period.

[7] See https://www.uspto.gov/learning-and-resources/electronic-data-products/cancer-moonshot-patent-data. The USPTO specifically assembled this data set to summarize the state of cancer-related innovation. It includes patents for drugs, diagnostics, surgical devices, data analytics, and genomic-based inventions. Although these patents were granted in the United States, the corresponding inventions were also available in Canada even if no patent was granted there.

Not every invention contributes to medical innovation equally. To account for a patent's importance, we construct a quality index as proposed by Lanjouw and Schankerman (2004). Specifically, we estimate the common factor q_j that we interpret as the quality of patent j in

$$y_{jk} = \mu_k + \lambda_k q_j + \epsilon_{jk},$$

where y_{jk} is the kth characteristic of patent j. As suggested by Lanjouw and Schankerman (2004) and Squicciarini, Dernis, and Criscuolo (2013), we use scope (the number of International Patent Classification subclasses the invention is allocated to), claims (the number of specific aspects of technology), backward citations (the number of patents being cited), and forward citations (the number of times a patent has been cited) to measure the quality of each patent.[8] A higher value in these four measures tends to be associated with a higher quality or more important invention. To account for truncation, we apply the adjustment factor developed by Hall, Jaffe, and Trajtenberg (2005) to forward citations. For each characteristic y_{jk}, we normalize the measure by its year-specific maximum as in Squicciarini, Dernis, and Criscuolo (2013). Finally, we sum up the estimated quality factors q_j by year and cumulate them over years separately for prostate and breast cancer. Again, we use a five-year lag in our main results and a ten-year lag and no lags in robustness checks.

Figure 1 shows that the growth in the quality-adjusted patent index was slightly faster for prostate cancer-related innovations after 2000. Since 2005, however, innovation as measured by the cumulative patent index has slowed for both cancer types. Of course, patents are not a perfect measure of medical innovation. First, not all innovations result in a patent application, and such innovations cannot be captured by our index. Second, some patented innovations may not be used in the clinical practice and are therefore irrelevant for cancer patients' outcomes. The quality adjustment of our patent index accounts for the latter issue.

4 Data and Summary Statistics

The individual-level data come from three sources: the 1991 Canadian Census, the Canadian Cancer Database (CCDB) and Mortality Database (CMDB), and tax return data (including the Longitudinal Worker File [LWF] and the T1 Family File [T1FF]).[9] The 1991 Canadian Census Cohort derived from these data sources consists of individuals who were aged 25 and

[8] Data on scope, claims, and citations stem from the NBER Patent Data Project and are available at https://sites.google.com/site/patentdataproject/ (Hall, Jaffe, and Trajtenberg 2001).

[9] We have used and described these data sources in Jeon (2017) and Jeon and Pohl (2017). The Online Appendix to Jeon and Pohl (2017) and Peters et al. (2013) also provide a detailed description. In contrast to our earlier studies, here we use a larger sample over a longer sample period.

older in the 1991 census and who were linked to the CCDB and CMDB. The CCDB and CMDB data provide cancer diagnoses up to 2010 and death records up to 2011. Specifically, the CCDB contains the year of the diagnosis and the site of the cancer.[10] In addition, all individuals aged 25 and older in the 1991 census were linked to LWF and T1FF tax records from 1989 to 2015 irrespective of whether they appeared in the CCDB or CMDB. Hence, we have access to a representative sample of the Canadian population including individuals who were diagnosed with breast or prostate cancer between 1992 and 2010.[11]

To construct the estimation sample, we first restrict the age range of individuals diagnosed with cancer for the first time.[12] We select men aged 49 to 60 for our prostate cancer sample and women aged 35 to 60 for our breast cancer sample. In our main results, we focus on the youngest ten cohorts, i.e. women diagnosed with breast cancer at the age of 35 to 44. The lower threshold is justified by a very small number of individuals diagnosed at younger ages. The upper threshold limits the role of early retirement during the follow-up period after the cancer diagnosis. To reduce the influence of outliers, we drop individuals whose annual earnings fall into the top and bottom 0.05% of the earnings distribution.[13] We also set negative earnings values to zero. Our restricted samples consist of 734,188 men and 915,880 women (626,801 in the 35 to 44 age group). Among these individuals, 7,908 men were diagnosed with prostate cancer and 19,163 women were diagnosed with breast cancer during the sample period, from 1992 to 2010 (3,436 in the 35 to 44 age group).

We then construct the treatment and control groups as follows: For each year from $s = 1992$ to $s = 2010$, we assign individuals who were diagnosed with breast or prostate cancer for the first time in year s to the treatment group. We then assign individuals who were not diagnosed with cancer to the control group for year s if their earnings for years $s-1$ and $s-2$ are observed.[14] The control group in our sample initially includes many duplicate individuals as the same individuals can be controls in multiple s; however, as described in Section 5.1 below, the final control group contains fewer duplicate individuals after matching.

Tables A.4 to A.6 in the Online Appendix display summary statistics for the prostate and breast cancer samples including the sample fractions for treated and control group members

[10] Although the CCDB also contains a variable indicating the stage of the cancer at the time of the diagnosis, this variable is unusable in practice due a large fraction of missing values.

[11] We drop individuals who were diagnosed with other types of cancer from our samples.

[12] Data from the CCDB date back to 1969, so we can reliably exclude individuals who were diagnosed with cancer during the 23 years before our study period.

[13] The very high and very low earnings values stem from measurement error in the tax return data, for example due to missing decimal points. The lower cutoff is −41,156 dollars for men and −20,039 dollars for women and the upper cutoff is 1,379,726 dollars for men and 422,089 dollars for women. All dollar amounts are in 2010 Canadian dollars. When estimating the effect of cancer and innovation on earnings, we replace negative earnings with zeros.

[14] This includes zero earnings for those who did not work in each year.

and the normalized differences between them.[15] Most characteristics are sufficiently balanced between treatment and control group even before matching, i.e. their normalized differences are below the rule of thumb value of 0.25 (Imbens and Rubin 2015). The two main exceptions are age and number of children. Since the likelihood of a cancer diagnosis increases with age, the control group is younger, in particular in the prostate cancer sample. In addition, older individuals are less likely to list dependent children on their tax return, so fewer controls are classified as having no children. In the breast cancer sample, the difference in the fraction of women without children may partially stem from the fact that childlessness increases the risk of breast cancer (Kampert, Whittemore, and Paffenbarger 1988). Other variables that may affect labor market outcomes after the cancer diagnosis—such as education, pre-diagnosis employment status and earnings—are relatively balanced. In Section 5.1 below, we discuss the matching algorithm that ensures a balanced estimation sample.

5 Empirical Strategy

5.1 Coarsened Exact Matching

To balance covariates across cancer patients and the control group, we use Coarsened Exact Matching (CEM). Iacus et al. (2011, 2012) propose this matching algorithm that splits the sample into strata based on coarsened observed variables and matches treatment and control group within each stratum. The CEM algorithm yields matching weights for individual i equal to

$$w_i^k = \begin{cases} n_T^k/n_C^k \times N_C/N_T & \text{if } i \text{ in control group} \\ 1 & \text{if } i \text{ in treated group} \end{cases} \tag{1}$$

for stratum k, where n_T^k and n_C^k are the number of individuals in the treatment and control group in the stratum and N_T and N_C are the numbers of observations in the entire sample. Individuals who cannot be matched receive a weight of 0. Using CEM weights yields estimates of the average treatment effect on the treated.

We use the following variables to calculate CEM weights: age (coarsened into 4 groups for the prostate cancer sample and into 7 groups for the breast cancer sample), highest level of schooling (4 categories), minority status (3 categories), province or territory of residence in the year of the (placebo) diagnosis (12 categories), working/not working in the two years before the diagnosis, earnings quintiles in the two years before the diagnosis (with a separate

[15] The normalized difference for variable X is defined as $\frac{\bar{X}_C - \bar{X}_T}{\sqrt{\sigma_C^2 + \sigma_T^2/2}}$, where $\bar{X}_j$ is the sample mean for the control or treatment group and σ_j^2 is the sample variance.

category for not working), and year of the (placebo) diagnosis. In addition, we use the number of children (coarsened into 4 groups) for the breast cancer sample.[16] Including the year of the diagnosis in the set of matching variables allows us to assign a diagnosis-year variable to members of the control group who, by definition, did not have a cancer diagnosis. That is, we implicitly select a sequence of annual individual-specific observations that maximizes the similarity between cancer patients and control group members along observed characteristics.

Columns (4) and (5) in Tables A.4 to A.6 in the Online Appendix display the means of individual characteristics weighted by CEM weights. For variables used in the CEM algorithm, the means are identical by construction, but even for other variables, such as union membership, the normalized differences in column (6) of each table are substantially smaller than the raw differences. Hence, the matching algorithm ensures that the treatment and control groups are balanced across a wide range of individual characteristics. We are able to match 7,835 (99.1%) of the treated individuals in the prostate cancer sample and 18,844 (98.3%) in the breast cancer sample. Among controls, we match far fewer individuals, but this is not an issue as we sample the same individuals multiple times as explained in Section 4 above.

After applying the matching algorithm, we construct an annual panel for each treated and control observation, using up to five years before and after the (placebo) diagnosis. Hence, we observe each individual in the sample for up to 11 years. We observe 91.5% of the men in the prostate cancer sample and 88% of the women in the breast cancer sample for the full period of 11 years. To address potential sample attrition, we conduct robustness checks that only include members of the treated and control group who survive at least five years after the diagnosis.

5.2 Labor Market Outcome Regressions

We model the labor market outcome Y_{its} (employment status or the inverse hyperbolic sine of annual earnings) of individual i in year t.[17] The year of the cancer diagnosis is denoted by s. The estimation sample includes annual observations for up to $t = s-5, \ldots, s+5$. C_{is} is an indicator variable that equals 1 if i was diagnosed in year $s = 1992, \ldots, 2010$ and 0 otherwise. That is, $C_{is} = 0$ for all s for the matched controls. We also refer to year s as the placebo diagnosis year for the control group. To obtain the average effect of a cancer

[16] See the individual characteristics in Tables A.4 to A.6 in the Online Appendix for a complete list of the variables and how they are coarsened.

[17] Note that observations for several i in the estimation sample may correspond to the same unique individual in the raw data.

diagnosis on labor market outcomes, we run the following difference-in-differences regression:

$$Y_{its} = \delta_1 P_{ts} + \delta_2 C_{is} P_{ts} + \alpha_i + \gamma_t + u_{its}, \tag{2}$$

where α_i is an individual fixed effect, γ_t is a year fixed effect, and u_{its} is an i.i.d. error term. $P_{ts} = \mathbf{1}\{t \geq s\}$ is a postdiagnosis indicator variable. For the control group, P_{ts} is defined because we use year of diagnosis as one of the matching variables (see above). Intuitively, each match in the control group is assigned a year relative to which we define pre- and postdiagnosis outcomes. In this model, δ_2 is the time-invariant average treatment effect on the treated. All regressions are weighted by the CEM weights given in regression (1). Standard errors in all regressions are clustered at the unique individual level.

To estimate how medical innovations impact the labor market outcomes of cancer patients, we first restrict the effects of a cancer diagnosis and of treatment innovation to be constant over time:

$$Y_{its} = \beta_1 P_{ts} + \beta_2 I_{s-\tau} + \beta_3 C_{is} P_{ts} + \beta_4 P_{ts} I_{s-\tau} + \beta_5 C_{is} P_{ts} I_{s-\tau} + \alpha_i + \gamma_t + u_{its}, \tag{3}$$

where $I_{s-\tau}$ denotes one of the lagged innovation measures described in Section 3.2 τ years before an individual's cancer diagnosis. The effect of a cancer diagnosis, β_3, and of available lagged medical innovations, β_5, do not vary over time in this specification.

It is possible that changes in labor market outcomes after a cancer diagnosis are not constant over time. For example, a cancer patient may stop working immediately after the diagnosis and during treatment but increase her labor supply gradually during the following years. In addition, the effect of medical innovation may affect labor market outcomes differentially over time. To account for these dynamic effects, we estimate a version of regression (3) with time-varying effects of cancer diagnoses and medical innovation:

$$Y_{its} = \sum_{j=-5}^{5} \beta_1^j T_{ts}^j + \beta_2 I_{s-\tau} + \sum_{j=-5}^{5} \beta_3^j C_{is} T_{ts}^j + \sum_{j=-5}^{5} \beta_4^j T_{ts}^j I_{s-\tau} + \sum_{j=-5}^{5} \beta_5^j C_{is} T_{ts}^j I_s + \alpha_i + \gamma_t + u_{its} \tag{4}$$

where $T_{ts}^j = \mathbf{1}\{t = s+j\}$ is an indicator that equals 1 if j years have elapsed since the diagnosis. We take the year before the diagnosis as the base year by setting $\beta_p^{-1} = 0, p = 1, 3, 4, 5$. Including the pre-diagnosis interactions between treatment, period dummies, and the medical innovation measures also allows us to assess the parallel trends assumption that is required for difference-in-differences regressions. That is, we can test if the β_3^js and β_5^js equal 0 for $j \leq -1$.

The coefficients of interest in regression (4) are the β_5^js. They measure the effect of

increasing innovation by one unit on the difference between the average labor market outcomes of cancer patients and controls j years after the diagnosis. The β_5^js may not be individually statistically significant, but that would not necessarily imply that medical innovations have no effect on labor market outcomes of cancer patients. To determine if medical innovation leads to changing labor market outcomes after a cancer diagnosis, we test the following joint null hypothesis:

$$H_0 : \beta_5^j = 0, \text{ for all } j = 0, \ldots, 5. \tag{5}$$

Rejecting this null hypothesis suggests that improved cancer treatment affects labor market outcomes of cancer patients overall even if the time-varying triple interaction coefficients may not be individually statistically significant. The results in Section 6 below contain p-values for the F-test of hypothesis (5) that show whether the hypothesis can be rejected.

To ease the interpretation of the estimated effects, we calculate the overall effect of a cancer diagnosis conditional on a specific value of the innovation measure. In particular, we calculate this effect at the lowest and highest level of innovation during our sample period

$$\beta_3^j + \beta_5^j I_{min} \quad \text{and} \quad \beta_3^j + \beta_5^j I_{max}. \tag{6}$$

Below, we present these combined effects across years before and after the diagnosis, j, along with their 95% confidence intervals calculated using the Delta method.

6 Results

In this section, we present results for the effects of cancer diagnoses and medical innovation on prostate and breast cancer patients' employment and earnings, how these effects vary across education, and we carry out robustness checks.

6.1 The Effect of Medical Innovation on Labor Market Outcomes

6.1.1 Prostate Cancer

Panel (A), column (1) of Table 1 shows that men's probability of working declines by 1.8 percentage points during the five years after a prostate cancer diagnosis unconditional on medical innovation.[18] This estimate is consistent with the results in Bradley, Neumark, Luo, and Schenk (2007).

[18] We only display the estimated coefficients $\hat{\delta}_2$, $\hat{\beta}_3$, and $\hat{\beta}_5$ from regressions (2) and (3) in the regression tables. Complete results are available upon request.

Innovation, measured as the number of approved drugs and the patent index five years before the cancer diagnosis, increases the likelihood of being employed among cancer patients during the five years after the year of diagnosis. These coefficients are statistically significant at the 5% level in panel (A), columns (2) and (3) of Table 1. These estimates imply a change in the overall employment effect of a prostate cancer diagnosis from -0.0390 $(= -0.0680 + 14 \times 0.00208)$ in 1992 to -0.0118 $(= -0.0680 + 27 \times 0.00208)$ in 2010, i.e. a decline of 70%, as the number of approved drugs increased from 14 to 27. For patents, the estimated coefficients in column (3) imply a decline in the negative employment effect from -0.0327 $(= -0.0332 + 1.605 \times 0.000329)$ to -0.0117 $(= -0.0332 + 65.350 \times 0.000329)$, or 64%. Hence, we find evidence that medical innovation in the treatment of prostate cancer is associated with alleviating the negative effects of prostate cancer at the extensive margin of labor supply.

Next, we run the same regressions with the inverse hyperbolic sine (arcsinh) of annual earnings as the outcome variable. We include observations with zero earnings, so the estimated coefficients reflect a combination of effects at the extensive and intensive margin and capture the total labor market benefits of medical innovation. Not conditioning on treatment innovation, we find a decline in annual earning of about 27% in panel (B), column (1) of Table 1.[19] The estimates in panel (B), columns (2) and (3) of Table 1 show that medical innovation reduces the negative effect of a prostate cancer diagnosis on earnings. These estimates imply that the increase in the number of approved drugs and the increase in the patent index are associated with a reduction in the earnings decline from approximately 52% to 20% and from 46% to 20%, respectively, between 1992 and 2010. With an average post-diagnosis earnings level among members of the control group of about 46,700 dollars, these results point to an average earnings gain of 13,500 dollars per year associated with cancer treatment innovation.

We now consider the dynamic specification in regression (4). Figure 2 shows the overall effect of a prostate cancer diagnosis on employment and arcsinh-earnings at the highest and lowest levels of innovation given by equation (6).[20] The pattern is similar for both innovation measures. We find that the effect of a cancer diagnosis on employment status is statistically indistinguishable from 0 in the year of the diagnosis irrespective of the level of innovation, but, at the minimum level of innovation, it drops to about -5 percentage points within three years and remains there. In contrast, the medium- to long-run effects at the highest level of innovation are barely statistically significantly different from 0 (see panels (a) and (b)). The

[19] Bellemare and Wichman (2019) show that the semi-elasticity in an arcsinh-linear specification is approximately equal to the corresponding regression coefficient.

[20] The full regression results are available upon request.

p-values for the test of null hypothesis (5) equal 0.0552 and 0.0761 in the regressions using drugs and patents. Similarly, the negative earnings effect is stable over time and more than twice as large at the lowest level of innovation (see panels (c) and (d)). The corresponding p-values equal 0.154 and 0.0989. Finally, Figure 2 supports the parallel trends assumption as the confidence intervals for the treatment effects in the pre-diagnosis period include zero.

6.1.2 Breast Cancer

Column (1) of Table 2 shows that the probability of working declined by 3.9 percentage points following a breast cancer diagnosis among women aged 35 to 60. This estimate is smaller than the one reported in previous studies, but Bradley et al. (2002a, 2002b; 2005) use an older sample (average age 55 versus 50 in our sample). Columns (2) and (3) indicate that medical innovation has no significant effect on the likelihood of employment for breast cancer patients.

As medical innovation does not have any measurable economic benefits in the full sample, we focus on the 35 to 44 age group. These women constitute only about 18% of the treatment group, but they are likely to be most responsive to improved treatment options for breast cancer for two reasons. First, they are more strongly attached to the labor market, so they are more likely to take advantage of innovative treatment options to remain working. Second, breast cancer diagnoses are often more severe among younger women (see Section 3.1) and recent innovations have particularly improved treatment for these advanced-stage types of breast cancer (see Section 3.2). Table 3 presents the regression results for this subsample. The results in panel (A), column (1) show that a breast cancer diagnosis lowered the probability of working by 3.3 percentage points.

Panel (A), columns (2) and (3) of Table 3 show that medical innovation has a positive and statistically significant effect on employment. Calculating the overall effect of a breast cancer diagnosis on employment evaluated at the lowest and highest levels of innovation, we find that the effect decreased (in absolute value) from -0.047 to -0.015 as the lagged number of approved breast cancer drugs increased from 17 in 1992 to 39 in 2010. Evaluated at the minimum and maximum patent index, the employment effect changed from -0.049 to -0.018. Medical innovation is therefore associated with a 63% to 68% decline in the negative employment effect of a breast cancer diagnosis over the 1992 to 2010 time period.

Next, we consider annual arcsinh-earnings as the outcome variable in panel (B) of Table 3. A breast cancer diagnosis leads to a 65% decline in earnings in column (1). The point estimates on the innovation effects are positive, suggesting a mitigating effect of innovation on the earnings decline due to a breast cancer diagnosis, but not statistically significant. Were they significant, they would imply a change from a 72% decline in total earnings in

1992 to a 55% decline in 2010. For average post-diagnosis annual earnings in the control group of about 34,000 dollars, this corresponds to a gain of 5,800 dollars per year.

Finally, we consider dynamic treatment effects in the breast cancer sample for women aged 35 to 44, shown in Figure 3. Panels (a) and (b) indicate that the negative effect of a breast cancer diagnosis on employment increases over time at the lowest level of innovation, reaching about -6 percentage points after four years. At the highest level of innovation, the employment effect is similar until the first year after the diagnosis, becoming less negative and statistically indistinguishable from 0 in later years. The p-values for the test of null hypothesis (5) equal 0.0184 and 0.0598 for drugs and patents, pointing to a significant overall effect of medical innovation.

Turning to arcsinh-earnings in panels (c) and (d) of Figure 3, we find that the increase in the negative earnings effect associated with medical innovation is driven by the first year after the diagnosis when breast cancer patients are most likely to undergo treatment. In later years, the earnings effects are larger in absolute value at the highest innovation level, but the difference between the effects at the highest and lowest innovation levels is not statistically significant. The postdiagnosis effects of medical innovation are jointly marginally significant with p-values below 0.001 for drugs and patents.

There is a slight pre-trend at the lowest innovation level, but except for the effect five years before the diagnosis, the confidence intervals include zero. At the highest innovation level, the parallel trends assumption is satisfied.

6.2 The Role of Education

To investigate how cancer patients' educational attainment affects the relationship among a cancer diagnosis, medical innovation, and labor market outcomes, we estimate the regressions (2) and (3) separately for individuals without a high school degree, with a high school degree but no postsecondary education, and with at least some postsecondary education.

For our prostate cancer sample, columns (1) to (3) of Table 4 show an educational gradient in the effects of prostate cancer on employment. Employment of patients without a high school degree declines by 2.7, those with a high school degree but no postsecondary education by 1.8, and those with post-secondary education by 1.2 percentage points. Heinesen and Kolodziejczyk (2013) find a similar educational gradient in the negative effects on employment among Danish colorectal and breast cancer patients.

Next, we investigate how the mitigating effect of medical innovation on the negative employment effects of a prostate cancer diagnosis varies with education.[21] For drugs in

[21] As the effects of medical innovation in the earnings regressions are not significant in the case of breast cancer, we only consider employment status as an outcome here.

columns (4) to (6) of Table 4 and the patent index in columns (7) to (9), we find that the effect of medical innovation is largest and most statistically significant for men with postsecondary education. For patients with less education, innovation has no statistically significant effect. (The effect of the patent index for high school graduates is the only exception.)

Table 5 shows the regression results for our breast cancer sample. First, we find an educational gradient similar to the one observed for prostate cancer patients. The employment of patients without a high school degree declined by 4.6 percentage points, high school graduates by 4.2 percentage points, and patients with postsecondary education by 1.7 percentage points as seen in columns (1) to (3).

Finally, we consider the relationship among medical innovation, education, and the employment of breast cancer patients. As in the prostate cancer sample, the effect of medical innovation is strongest among women with postsecondary education. This finding applies to approved drugs and patents as measures of innovation; see columns (4) to (9) of Table 5. In both cases, the coefficient on the triple interaction term is highly statistically significant in the highest education subsample, while it is not or only marginally significant for women with a high school degree or less.

Overall, we find that individuals with less than postsecondary education do not seem to benefit from improved treatment options in terms of employment. Our data do not allow us to investigate the mechanisms that explain why, but several pathways are plausible. First, different medical providers may offer different treatments, and identifying providers who offer up-to-date treatments may be more costly for individuals with less education.

Second, Lange (2011) shows that highly educated individuals are more likely to adopt cancer screenings because they better understand scientific evidence. This finding has two implications for our study. Highly educated cancer patients may also better understand the benefits of new treatments and insist that their physician prescribe them. In the same vein, Lleras-Muney and Lichtenberg (2005) find that the more educated use more recently approved drugs. In addition, Lange's (2011) finding implies that cancer diagnoses among less educated individuals may be more severe because these individuals are diagnosed at a more advanced stage. We cannot test this hypothesis due to data limitations, but the medical innovation that took place in the 1990s and 2000s mostly improved the treatment of more severe types of cancer, so, if anything, less educated patients should benefit more from innovation.

Another possible explanation is related to treatment adherence. Innovative cancer treatments are often more complex than older ones; for example, new treatments combine chemotherapy with radiation treatments. Cancer patients with low education may receive the same treatment plans, but they may be less likely to comply with a full treatment regimen.

As a result, the protective effects of medical innovation in terms of reduced negative labor market effects may not materialize for these individuals.

Finally, it is possible that less educated cancer patients work in physically more demanding jobs where it is more difficult to undergo a modern high-intensity cancer treatment while remaining employed. Similarly, more educated individuals may be more attached to their jobs or have "higher quality" jobs, so they take full advantage of innovative treatment options. It is also possible that the innovation effects are driven by diminished labour market opportunities for low educated cancer patients. However, that would only hold if labor market opportunities differed systematically between cancer patients and the control groups, which is unlikely. Since there is no information on medical providers, treatments, stage of cancer or occupation in our data, we leave testing these theories to future research.

6.3 Robustness

We conduct several robustness checks.[22] First, to account for faster and slower diffusion of cancer treatment innovations, we re-estimate the specification with time-invariant treatment effects with ten-year lags and without any lags for both innovation measures. As Tables A.7 and A.8 show, the triple-interaction effects are very similar when we do not include any lags of the innovation measures. When splitting the sample by education, we again find the strongest effects for individuals with postsecondary education (see Tables A.9 and A.10). When we lag the innovation measures by ten years, the results are almost identical to our main specification in Tables A.11 and A.12. Tables A.13 and A.14 show that the innovation effects are again concentrated among highly educated cancer patients. These results suggest that our findings are not very sensitive to the number of years by which our innovation measures are lagged.

One issue in measuring the effect of pharmaceutical innovation is the common off-label use of drugs, see Section 3.2. It is inherently difficult to measure off-label use exactly, but to use a broad set of drugs, we consider those approved for the treatment of any type of cancer. Again, we use the approval dates provided by Lichtenberg (2015). When lagged by five years, the total number of cancer drugs increased from 55 to 108 during our study period. Column (1) in Tables A.15 and A.16 show that the effect of innovation on the employment of cancer patients, as measured by the number of all cancer drugs, is still significantly positive, but the effect of an additional drug is smaller than in our main specification. This finding suggests that off-label use plays a role, but the effect of pharmaceutical innovation is mostly driven by drugs approved specifically for breast and prostate cancer.

[22] Due to space constraints, we report the regression results for our robustness checks in the Online Appendix.

To disentangle the role of innovation in cancer treatment and diagnosis, we next split our patent index into patents related to curative and diagnostic inventions, respectively. We do so by identifying patents in these two categories using an extensive list of key words, such as "prognostic" and "detection" for diagnostic patents and "therapy" and "surgery" for treatment patents, and searching patent titles and descriptions.[23] Column (2) of Tables A.15 and A.16 show the regression results when both patent indices are included and interacted with the treatment and post-diagnosis variables. Although the patent index has a significant mitigating effect on cancer patients' employment in our main specification, this is not the case when we enter treatment and diagnostic patents separately, most likely due to a lack of statistical power.

Last, we account for selective mortality of cancer patients by estimating bounds on the regression coefficients in the spirit of Horowitz and Manski (2000). To this end, we replace employment and earnings values that are missing due to an individual's death with the respective minimum and maximum values for this individual and re-estimate the employment and earnings regressions. For both prostate and breast cancer, we find upper bounds that are very similar to our main specification when we replace missing values with within-individual minima, see Tables A.17 and A.18. The lower bounds, which are obtained from using within-individual maxima, however, are not statistically significant. This is not surprising since using maxima (highest annual earnings and the employment indicator set to one) eliminates any potential negative effects of cancer diagnoses and mitigating effects of innovation on these outcomes. We also find that the innovation effects are mostly restricted to individuals with postsecondary education when we estimate bounds in Tables A.19 and A.20. Hence, our results are overall robust to selective mortality of cancer patients.

7 Conclusion

This paper is the first to assess the labor market effects of innovations in cancer treatment. We use large representative samples of Canadian breast and prostate cancer patients along with control groups and measure medical innovation by the number of approved drugs and a quality-adjusted patent index. We find that medical innovation is associated with a reduction in the decline in employment following a prostate or breast cancer diagnosis and in earnings in the case of prostate cancer. We also show that only cancer patients with postsecondary education appear to benefit from medical innovation.

Although our results point to an important role of medical innovation in improving the labor market outcomes of cancer patients, we cannot be certain that these effects are causal.

[23] The full lists of key words are available by request.

A comparison across different types of cancer would allow us to exploit variation in innovation measures over time and across cancer sites but we would not have sufficient power when restricting the sample to working-age individuals. In addition, due to the lack of information on cancer stage at the time of diagnosis, we cannot fully separate the effects of innovations in treatment options from improvements in diagnostics. Our patent index includes both types of innovations, however, and our results indicate that medical innovation overall (related to treatment and diagnosis) mitigates employment effects. Finally, we do not observe actual treatments, so our results should be interpreted as intent-to-treat effects.

Our findings imply that the cumulative innovation in the treatment of prostate and breast cancer from 1992 to 2010 was associated with a decrease in the economic costs (in terms of labor market income) of these diseases of about 13,500 and 5,800 dollars per patient and year, respectively. When assessing the cost-effectiveness of new cancer treatments, these benefits should be included. With a median annual cost of prostate cancer treatment of about 14,500 dollars (Trogdon et al. 2019), the additional economic benefits alone would almost outweigh the entire cost. It is not clear, however, whether these economic benefits would also compensate for the high cost of most recent pharmaceutical innovations in cancer treatment. For example, Durkee et al. (2016) find that adding pertuzumab, a drug that was approved after 2010, to a treatment of metastatic breast cancer with docetaxel and trastuzumab leads to an average cost increase of almost 300,000 U.S. dollars. Nevertheless, our results imply that policymakers should account for indirect costs such as the labor market outcomes of cancer patients when deciding whether to approve or reimburse new cancer treatments.

Future research should further disentangle these benefits to show if any specific innovations account for particularly large changes in labor market outcomes. Moreover, more recent data should be used to assess the economic benefits of innovation in cancer treatment after 2010 when several promising but also expensive new drugs were approved.

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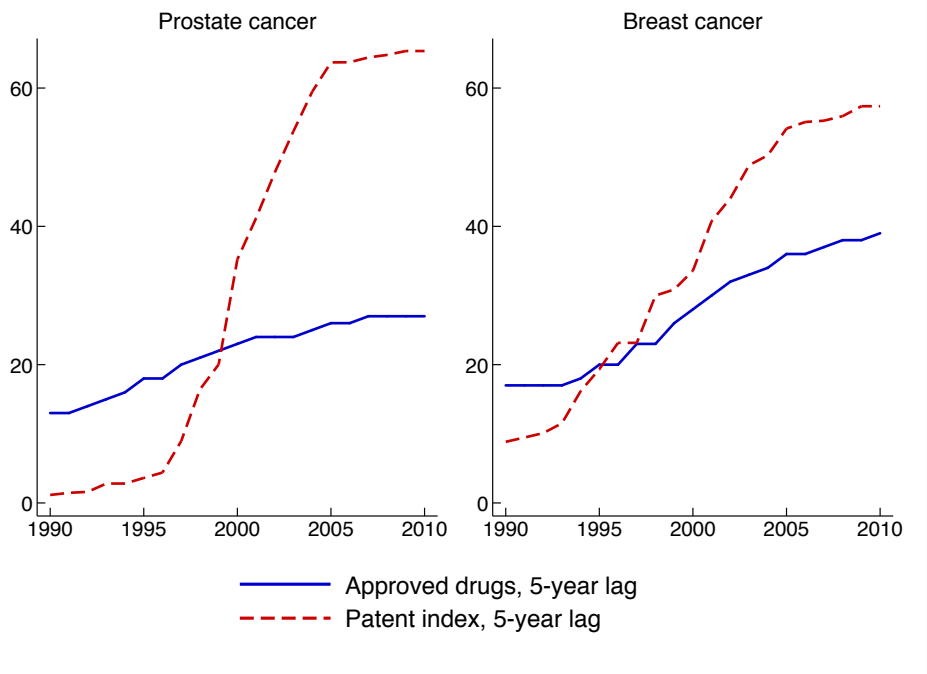
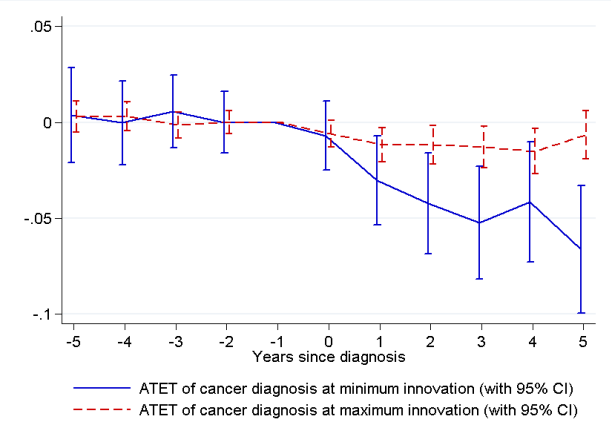
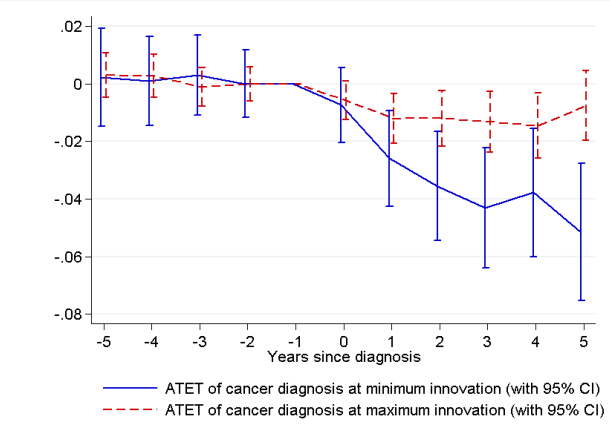


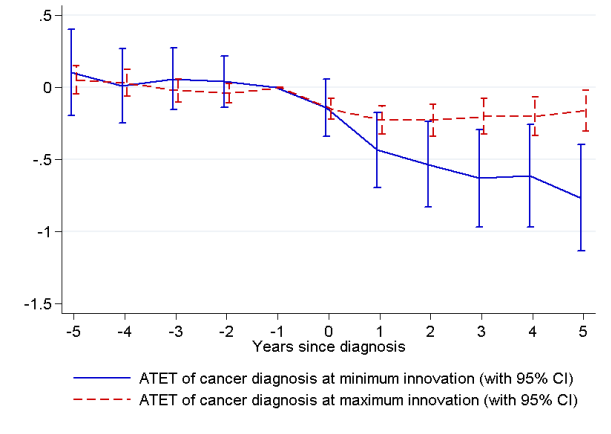
Figure 1: Innovation Measures by Cancer Site and Over Time



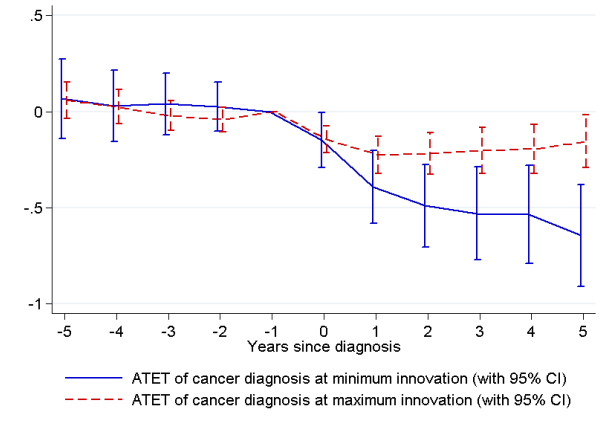
(a) Employment—Innovation Measure: Number of Drugs



(b) Employment—Innovation Measure: Patent Index



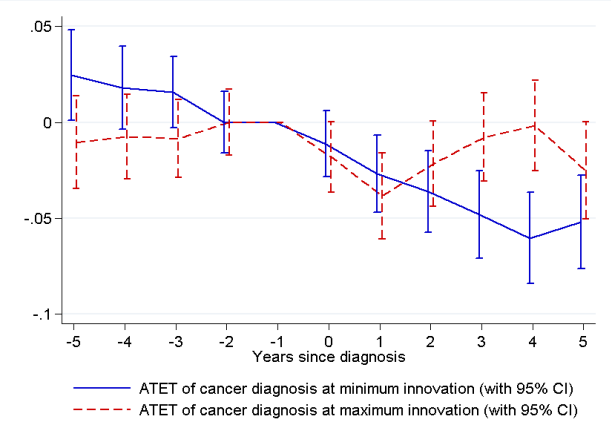
(c) Inverse Hyperbolic Sine of Annual Earnings—Innovation Measure: Number of Drugs



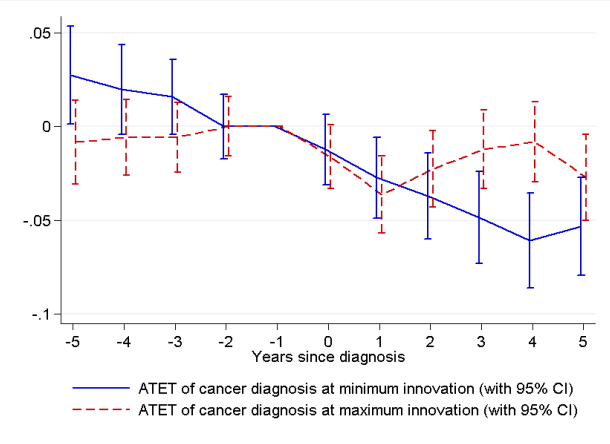
(d) Inverse Hyperbolic Sine of Annual Earnings—Innovation Measure: Patent Index

Notes: The graphs show the estimated effects $\hat{\beta}_3^j + \hat{\beta}_5^j I_{min}$ and $\hat{\beta}_3^j + \hat{\beta}_5^j I_{max}$ for $j = -5, \ldots, 5$, i.e., the effect of a prostate cancer diagnosis on labor market outcomes at the lowest and highest level of medical innovation, along with their 95% confidence intervals.

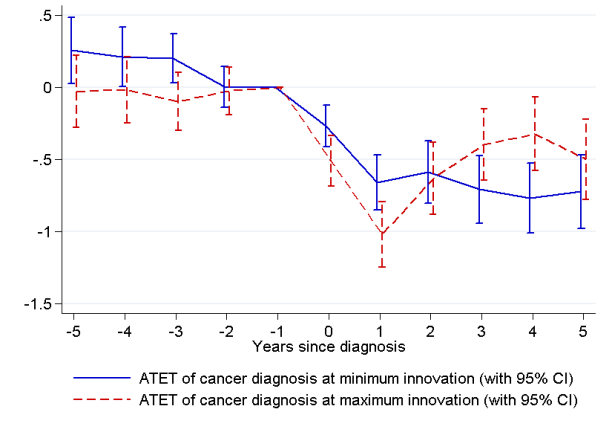
Figure 2: Dynamic Treatment Effects of Prostate Cancer Diagnosis on Labor Market Outcomes, Age 49 to 60, by Level of Innovation (5-Year Lag)



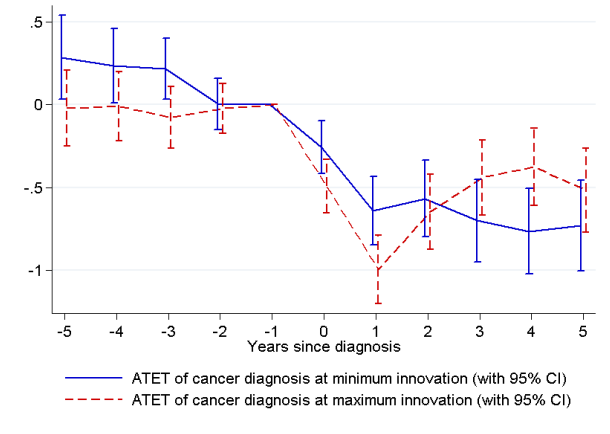
(a) Employment—Innovation Measure: Number of Drugs



(b) Employment—Innovation Measure: Patent Index



(c) Inverse Hyperbolic Sine of Annual Earnings—Innovation Measure: Number of Drugs



(d) Inverse Hyperbolic Sine of Annual Earnings—Innovation Measure: Patent Index

Notes: The graphs show the estimated effects $\hat{\beta}_3^j + \hat{\beta}_5^j I_{min}$ and $\hat{\beta}_3^j + \hat{\beta}_5^j I_{max}$ for $j = -5, \ldots, 5$, i.e., the effect of a breast cancer diagnosis on labor market outcomes at the lowest and highest level of medical innovation, along with their 95% confidence intervals.

Figure 3: Dynamic Treatment Effects of Breast Cancer Diagnosis on Labor Market Outcomes, Age 35 to 44, by Level of Innovation (5-Year Lag)

Table 1: Prostate Cancer Labor Market Outcome Regressions with Time-Invariant Effects, Age 49 to 60

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
(A) Employment			
Post×Cancer	−0.0179***	−0.0680***	−0.0332***
	(0.00302)	(0.0227)	(0.00745)
Post×Cancer×Drugs		0.00208**	
		(0.000927)	
Post×Cancer×Patents			0.000329**
			(0.000140)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.0665	0.0670	0.0668
Number of unique persons	535,723	535,723	535,723
Person-year observations	19,743,677	19,743,677	19,743,677
(B) Earnings			
Post×Cancer	−0.273***	−0.871***	−0.469***
	(0.0365)	(0.273)	(0.0902)
Post×Cancer×Drugs		0.0249**	
		(0.0111)	
Post×Cancer×Patents			0.00419**
			(0.00169)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.113	0.114	0.114
Number of unique persons	535,723	535,723	535,723
Person-year observations	19,743,677	19,743,677	19,743,677

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from regressions with time-invariant effects. The dependent variable in panel (A) is an indicator for annual employment status that equals one if the person had non-zero earnings in a given year and in panel (B) it is the inverse hyperbolic sine of annual earnings. *Post* is a dummy variable that equals one after the (placebo) cancer diagnosis, *Cancer* is a cancer diagnosis indicator, and *Drugs* and *Patents* are the amount of approved drugs and the cumulative patent index in the year of the diagnosis, lagged by 5 years (see regression (3) in the text). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Breast Cancer Employment Regressions with Time-Invariant Effects, Age 35 to 60

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
Post×Cancer	−0.0386***	−0.0439***	−0.0414***
	(0.00209)	(0.00891)	(0.00589)
Post×Cancer×Drugs		0.000178	
		(0.000289)	
Post×Cancer×Patents			0.0000710
			(0.000136)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.0286	0.0288	0.0288
Number of unique persons	721,377	721,377	721,377
Person-year observations	37,451,015	37,451,015	37,451,015

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from regressions with time-invariant effects. The dependent variable is an indicator for annual employment status that equals one if the person had non-zero earnings in a given year. *Post* is a dummy variable that equals one after the (placebo) cancer diagnosis, *Cancer* is a cancer diagnosis indicator, and *Drugs* and *Patents* are the amount of approved drugs and the cumulative patent index in the year of the diagnosis, lagged by 5 years (see regression (3) in the text). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Breast Cancer Labor Market Outcome Regressions with Time-Invariant Effects, Age 35 to 44

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
	(A) Employment		
Post×Cancer	-0.0329^{***}	-0.0724^{***}	-0.0551^{***}
	(0.00407)	(0.0165)	(0.0103)
Post×Cancer×Drugs		0.00147^{**}	
		(0.000583)	
Post×Cancer×Patents			0.000651^{**}
			(0.000268)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.00862	0.00864	0.00864
Number of unique persons	381,871	381,871	381,871
Person-year observations	10,512,459	10,512,459	10,512,459
	(B) Earnings		
Post×Cancer	-0.644^{***}	-0.855^{***}	-0.753^{***}
	(0.0463)	(0.185)	(0.114)
Post×Cancer×Drugs		0.00788	
		(0.00673)	
Post×Cancer×Patents			0.00323
			(0.00310)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.0115	0.0115	0.0115
Number of unique persons	381,871	381,871	381,871
Person-year observations	10,512,459	10,512,459	10,512,459

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from regressions with time-invariant effects. The dependent variable in panel (A) is an indicator for annual employment status that equals one if the person had non-zero earnings in a given year and in panel (B) it is the inverse hyperbolic sine of annual earnings. *Post* is a dummy variable that equals one after the (placebo) cancer diagnosis, *Cancer* is a cancer diagnosis indicator, and *Drugs* and *Patents* are the amount of approved drugs and the cumulative patent index in the year of the diagnosis, lagged by 5 years (see regression (3) in the text). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Prostate Cancer Employment Regressions with Time-Invariant Effects by Education, Age 49 to 60

	Diff-in-Diff			Triple-Diff: Drugs			Triple-Diff: Patents		
	(1) $<$ HS	(2) $=$ HS	(3) $>$ HS	(4) $<$ HS	(5) $=$ HS	(6) $>$ HS	(7) $<$ HS	(8) $=$ HS	(9) $>$ HS
Post×Cancer	−0.0270***	−0.0180***	−0.0119**	−0.0134	−0.0659*	−0.120***	−0.0250*	−0.0367***	−0.0371***
	(0.00654)	(0.00477)	(0.00483)	(0.0402)	(0.0376)	(0.0416)	(0.0130)	(0.0126)	(0.0131)
Post×Cancer×Drugs				−0.000589	0.00197	0.00442***			
				(0.00170)	(0.00152)	(0.00168)			
Post×Cancer×Patents							−0.0000485	0.000387*	0.000514**
							(0.000267)	(0.000229)	(0.000242)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-R^2	0.0722	0.0648	0.0653	0.0727	0.0655	0.0655	0.0724	0.0652	0.0655
Number of unique persons	145,385	231,645	158,693	145,385	231,645	158,693	145,385	231,645	158,693
Person-year observations	4,542,765	9,090,921	6,109,991	4,542,765	9,090,921	6,109,991	4,542,765	9,090,921	6,109,991

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from difference-in-differences and triple-difference regressions with time-invariant effects. The dependent variable is an indicator for annual employment status that equals one if the person had non-zero earnings in a given year. *Post* is a dummy variable that equals one after the (placebo) cancer diagnosis, *Cancer* is a cancer diagnosis indicator, and *Drugs* and *Patents* are the amount of approved drugs and the cumulative patent index in the year of the diagnosis, lagged by 5 years (see regression (3) in the text). Regressions are by educational attainment: $< HS$ refers to no high school degree, $= HS$ to a high school degree, and $> HS$ indicates more than high school education. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Breast Cancer Employment Regressions with Time-Invariant Effects by Education, Age 35 to 44

	Diff-in-Diff			Triple-Diff: Drugs			Triple-Diff: Patents		
	(1) $<$ HS	(2) $=$ HS	(3) $>$ HS	(4) $<$ HS	(5) $=$ HS	(6) $>$ HS	(7) $<$ HS	(8) $=$ HS	(9) $>$ HS
Post×Cancer	−0.0455***	−0.0420***	−0.0170***	−0.118***	−0.0426*	−0.0775***	−0.0869***	−0.0418***	−0.0515***
	(0.0117)	(0.00641)	(0.00530)	(0.0454)	(0.0255)	(0.0218)	(0.0282)	(0.0160)	(0.0135)
Post×Cancer×Drugs				0.00275*	0.0000219	0.00223***			
				(0.00164)	(0.000904)	(0.000768)			
Post×Cancer×Patents							0.00124*	−0.00000596	0.000999***
							(0.000755)	(0.000418)	(0.000353)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-R^2	0.0224	0.0105	0.00268	0.0225	0.0105	0.00271	0.0225	0.0105	0.00274
Number of unique persons	75,224	177,250	129,397	75,224	177,250	129,397	75,224	177,250	129,397
Person-year observations	1,643,251	5,370,960	3,498,248	1,643,251	5,370,960	3,498,248	1,643,251	5,370,960	3,498,248

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from difference-in-differences and triple-difference regressions with time-invariant effects. The dependent variable is an indicator for annual employment status that equals one if the person had non-zero earnings in a given year. *Post* is a dummy variable that equals one after the (placebo) cancer diagnosis, *Cancer* is a cancer diagnosis indicator, and *Drugs* and *Patents* are the amount of approved drugs and the cumulative patent index in the year of the diagnosis, lagged by 5 years (see regression (3) in the text). Regressions are by educational attainment: $< HS$ refers to no high school degree, $= HS$ to a high school degree, and $> HS$ indicates more than high school education. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.