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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 improvements 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. While cancer patients are less likely to work after their diagnosis, we find that the innovations in cancer treatment during the 1990s and 2000s reduced the negative employment effects of cancer by 63–70 percent. These benefits of medical innovation are limited to cancer patients with postsecondary education, raising concerns about unequal access to improved treatment options.

JEL Classification Codes: I12; I14; I24; I26; J22; O31

Key Words: medical innovation; breast cancer; prostate cancer; labor supply; employment; earnings; returns to education

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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 precancer 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 successfully participate in the labor market and maintain their productivity. Policymakers may be concerned that not all patients benefit from medical innovation equally and that the economic gains from medical innovation may differ by socioeconomic status.

In this study, we address two important questions related to medical innovation in cancer treatment. First, our study provides 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 socioeconomic 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 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 percent decline in cancer-related death rates in the United States 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). There has been no evidence on the economic benefits of this costly innovation in cancer treatment, such as the effects of new cancer treatments on changes in labor market participation of cancer patients. This paper fills this gap and thereby contributes to our understanding of the cost-effectiveness of new treatments.

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, while cancer usually occurs later in life, a relatively large 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 study has used patent data to estimate the effect of medical innovation on labor market outcomes or any other economic or health 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, reduced the negative employment effect of prostate cancer by about 64 percent to 70 percent over our study period. For breast cancer, medical innovation mitigated the negative effect on employment by 63–68 percent, and this effect was concentrated among women aged 35–44 whose breast cancer diagnoses are typically more severe than the diagnoses of older women. We find marginally statistically significant effects of medical innovation at the intensive labor supply margin. When estimating separate effects by education, we find that the economic gains of medical innovation arise almost exclusively

among patients with postsecondary education. This result raises concerns about unequal access to medical innovation. 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), 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 new 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.

Our results also relate to the large literature on labor market effects of health (see Currie and Madrian 1999 for a summary). Garcia Gomez et al. (2013) and Dobkin et al. (2018) have documented the negative employment and earnings effects of hospitalizations. Jeon (2017) studies the labor market effects of cancer diagnoses using the same data sources as the present paper.

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 (2018) 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. Therefore, she has less time available for market and home production, $T_t^W + T_t^Z$, and likely reduces both.[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 supply caused by a cancer diagnosis.

[1] In a market-based health care system, a sick individual may not reduce her labor supply or may reduce it less in order to afford medical care. In Canada, however, a cancer patient faces almost no out-of-pocket spending for her treatment, so labor supply is not driven by this mechanism. 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.

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— that is, $\partial H_t/\partial M_t$ 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. Second, it 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 cancer are the most common cancer diagnoses among men and women. In 2017, 21,300 men in Canada were diagnosed with prostate cancer (21 percent of all cancer diagnoses in the country) and 26,300 women were diagnosed with breast cancer (25 percent of all cancer diagnoses in the country). In the same year, 4,100 men and 4,900 women in Canada died from prostate and breast cancer. The survival rates for these two types of cancer are relatively high compared to other types of cancer, with a 95 percent five-year survival rate for prostate cancer and a 87 percent 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 very uncommon in men under the age of 50 and occurs most often among those aged over 65; however, 40 percent 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 49–60 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 percent of breast cancer cases occur before age 50 and 4 percent before age 40.[4] Breast cancer tends to be more aggressive in younger women. In our empirical analyses, we include women aged 35–60. As most of the recent innovations in breast cancer relate to more severe types of the disease (see the following section), we focus our main analyses on a sample of younger women, aged 35–44.

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 50–69. This recommendation was largely unchanged throughout our sample period, from 1992 to 2010 (Canadian Task Force on the Periodic Health Examination 1994, Chapter 65; Canadian Task Force on Preventive Health Care 2011). For women aged 35–44, who constitute the focus of our analysis, no breast cancer screening was recommended throughout our sample period. We can therefore attribute any impact on labor market outcomes of young breast cancer patients to changes in technology and not in screening recommendations.

For prostate cancer, the guidelines recommend neither the inclusion nor exclusion of the digital rectal exam in/from periodic health examinations for men aged 50–70. 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, Chapter 67; Canadian Task Force on Preventive Health Care 2014). 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 and prostatectomy), radiotherapy, chemotherapy, and hormone therapy (antiestrogen 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 watchful waiting. This course of action may especially be used among older patients with co-morbidities that are more lethal than prostate cancer. In the

[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.

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

age range that we consider (49–60), 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 percent of prostate cancer patients under the age of 55 were treated with a radical prostatectomy.

3.2 Measuring Innovation in Cancer Treatment

Treatment options for many types of cancer have vastly improved over the past 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 at 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).

More recent pharmaceutical innovations in breast cancer treatment may be highly effective but they are also more expensive than older drugs. For example, Durkee et al. (2016) find that adding pertuzumab to a treatment of metastatic breast cancer with docetaxel and trastuzumab leads to an average cost increase of almost US$300,000. Therefore, it is particularly important to evaluate the economic benefits that these treatment innovations may yield.

Denmeade and Isaacs (2002) describe the history of prostate cancer treatment that includes the use of hormonal therapy such as luteinizing hormone-releasing hormone analogues (triptorelin) since the early 1980s. 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, especially in the case of prostate cancer, hormone therapy in treating these cancers, drugs that are available for treatment of a specific type of cancer are an important measure of medical innovation. Lichtenberg (2015) provides a list of all drugs that are 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.

To account for the delay between the approval of a drug and its widespread use in treatment, we consider lags of 5 and 10 years. Lichtenberg (2015) finds that lags of 10 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. 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.

Pharmaceutical innovation is an important driver for improved treatment of breast and prostate cancer, but there are additional medical innovations that are not captured by the number of available drugs. To capture the improved diagnostics, radiation, and surgical procedures that have also contributed to better treatment of these cancers, our second innovation measure is based on the Cancer Moonshot Patent Data from the U.S. Patent and Trademark Office (USPTO).[7] We identify patents that are relevant for breast and prostate cancer by searching for the key words *prostate* or *prostatic* and *breast* or *mammary*. Our list includes diagnostic procedures, surgical equipment and methods, and pharmaceutical innovation. We include not only patents that were granted but also those that were rejected to capture the full range of cancer-related inventions.

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 patient 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 that are being

[6] Approval of these drugs goes back to 1950, so the list includes all drugs that are relevant for cancer treatment.

[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. While these patents were granted in the United States, the corresponding inventions were also available in Canada even if no patent was granted there.

cited), and forward citations (the number of times a patent has been cited).[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. 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.

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 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.[10] Specifically, the CCDB contains the year of the diagnosis and the site of the cancer.[11] 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.[12]

To construct the estimation sample, we first restrict the age range of individuals diagnosed with cancer for the first time. We select men aged 49–60 for our prostate cancer sample and women aged 35–60 for our breast cancer sample. (In our main results, we focus on the subsample of women diagnosed with breast cancer at the age of 35–44). The lower threshold is justified by a very small number of individuals diagnosed at younger ages. The upper

[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.

[10] In our robustness analysis based on five-year survivors, we use individual death information from both CCMD and tax data, which include death information up to 2015.

[11] While 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 to nonrandom missing values.

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

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 percent of the earnings distribution.[13] Our restricted samples consist of 734,188 men and 915,880 women (626,801 in the 35–44 age group). Among these individuals, 7,908 men were diagnosed with prostate cancer and 19,163 women were diagnosed with breast cancer during the 1992–2010 sample period (3,436 in the 35–44 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 below, the final control group contains fewer duplicate individuals after matching.

Tables 1–3 in the online appendix display summary statistics for the prostate and breast cancer samples, including the sample fractions for treated and control group members and the normalized differences between them.[15] Most characteristics are sufficiently balanced between treatment and control group even before matching—that is, 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, particularly 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, prediagnosis employment status, and earnings—are relatively balanced. In Section 5 below, we discuss the matching algorithm that ensures a balanced estimation sample.

[13] The lower cutoff is −$41,156 for men and −$20,039 for women, and the upper cutoff is $1,379,726 for men and $422,089 for women. The dollar amounts are in 2010 Canadian dollars.

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

[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.

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 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 (placebo) diagnosis in the set of matching variables allows us to assign a diagnosis-year variable to members of the control group.

Columns (4) and (5) in Tables 1–3 in the online appendix display the means of individual characteristics weighted by CEM weights. For variables that are 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 percent) of the treated individuals in the prostate cancer sample and 18,844 (98.3 percent) 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

[16] See the individual characteristics in Tables 1–3 in the online appendix for a complete list of the variables and how they are coarsened.

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 percent of the men in the prostate cancer sample and 88 percent 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 logarithm 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 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 independent and identically distributed error term. $P_{ts} = \mathbf{1}\{t \geq s\}$ is a postdiagnosis indicator variable. 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 Equation (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. We consider 5-year lags in our main results and 10-year lags in robustness checks. 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

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

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 the regression in Equation (3) with time-varying effects of cancer diagnoses and medical innovation:

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

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 prediagnosis 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 the regression in Equation (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:

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

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 in Equation (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

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

Below, we present these combined effects across years before and after the diagnosis, j, along

with their 95 percent confidence intervals that are calculated using the Delta method.

6 Results

6.1 The Effect of Medical Innovation on Labor Market Outcomes

6.1.1 Prostate Cancer

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 et al. (2007).

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 percent level in 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—that is, a decline of 70 percent, 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 percent. 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 log-annual earnings as the outcome variable (i.e., we consider effects at the intensive margin of labor supply). Unconditional on treatment innovation, we find a decline in annual earning of about 12 percent among employed prostate cancer patients in column (1) of Table 2. This estimate suggests that some prostate cancer patients reduce their hours of work, although we cannot rule out the possibility that their wages declined as our data contain neither hours of work nor wage rates.

The estimates in columns (2) and (3) of Table 2 show that medical innovation reduces the negative effect of a prostate cancer diagnosis on earnings, with the triple interaction terms being statistically significant at the 10 percent level. These estimates imply that the increase in approved drugs is associated with a reduction in the earnings decline from approximately 19 percent to 9 percent and the patent index with a change from 17 percent to 10 percent between 1992 and 2010. While these effects are not very precisely estimated, they suggest

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

that medical innovation also lowers the negative labor market effects of a prostate cancer diagnosis at the intensive margin.

We now consider the dynamic specification in Equation (4). Figure 2 shows the overall effect of a prostate cancer diagnosis on employment and log-earnings at the highest and lowest level of innovation given by Equation (6).[19] 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 not statistically significantly different from 0 (see panels [a] and[b]). The p-values for the test of null hypothesis in Equation (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 0.0487 and 0.0695. Finally, Figure 2 supports the parallel trends assumption as the confidence intervals for the treatment effects in the prediagnosis period include 0.

6.1.2 Breast Cancer

Column (1) of Table 3 shows that the probability of working declined by 3.9 percentage points following a breast cancer diagnosis among women aged 35–60. 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) to (4) 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 35–44 age group. These women constitute only about 18 percent 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 force, 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, and recent innovations have particularly improved treatment for these advanced-stage types of breast cancer (see Section 3). Table 4 presents the regression results for this subsample. The results in column (1) show that a breast cancer diagnosis lowered the probability of working by 3.3 percentage points.

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

Columns (2) and (3) of Table 4 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 63–68 percent decline in the negative employment effect of a breast cancer diagnosis over the 1992 to 2010 time period.

Next, we consider annual log-earnings as the outcome variable in Table 5. Conditional on being employed, a breast cancer diagnosis leads to a substantial decline in earnings of 29 percent ($= exp(-0.336) - 1$) in column (1). In contrast to the results in our prostate cancer sample, we find that medical innovation is associated with an increase in the negative earnings effects of a breast cancer diagnosis as indicated by negative coefficients on the triple interaction terms in columns (2) and (3). They are statistically significant at the 10 level and suggest that the earnings decline due to a breast cancer diagnosis increased from -24 percent to -33 percent when using number of approved drugs and when using the patent index as the measure of medical innovation.

Taken together, the results in Tables 4 and 5 suggest that innovation in breast cancer treatment allowed some women affected by this disease to stay employed. At the same time, the women who remained employed most likely reduced the number of hours they worked because new treatments required more time for recovery from a physically demanding therapy, compelling women to reduce their labor supply at the intensive margin.

Finally, we consider dynamic treatment effects in the breast cancer sample for women aged 35–44, 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 in Equation (5) equal 0.0184 and 0.0598 for drugs and patents, pointing to a significant overall effect of medical innovation.

Turning to log-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 to the effect at the lowest innovation level is not statistically significant. The postdiagnosis effects of medical innovation are jointly marginally significant with p-values of

0.0791 and 0.0633 for drugs and patents.

Based on the estimated employment effects in panels (a) and (b) of Figure 3, 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 0. At the highest innovation level and for the earnings effects in panels (c) and (d), 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 in Equations (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 6 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 postsecondary 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.[20] For drugs in columns (4) to (6) of Table 6 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 7 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

[20] As the effects of medical innovation in the earnings regressions reveal less significant effects of medical innovation, we only consider employment status as an outcome here. Earnings regressions by educational attainment are available upon request.

approved drugs and patents as measures of innovation; see columns (4) to (9) of Table 7. 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 and receiving treatment from 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 the present context. Highly educated cancer patients may also better understand the benefits of the 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 individuals with low education may be more severe because these individuals are diagnosed at a more advanced stage. We cannot test this hypothesis because of 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. Finding that they do not points to unequal access to new and more effective forms of treatments.

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 (see Section 3). 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 cancer patients with low education work in physically more demanding jobs where it is more difficult to undergo a modern high-intensity cancer treatment while remaining employed. Since our data include neither information on medical providers, treatments, or stage of cancer nor information on occupation, we leave testing these theories to future research.

6.3 Robustness

Due to space constraints, we report the regression results for our robustness checks in the online appendix. We conduct two sets of checks. First, we reestimate all regressions presented in the paper using 10-year lags for the innovation measures. As Figures 1 and 2 and Tables 4–10 in the appendix show, the results are largely unchanged with the exception of the earnings effects of innovation losing their statistical significance in the breast cancer sample. Second, we reestimate all regressions on samples of individuals who survive at least five years after the (placebo) diagnosis to investigate whether our results are sensitive to attrition. In the prostate cancer sample, the estimated coefficients are similar to our main results. For breast cancer, however, the employment effect of a diagnosis becomes smaller in the 35–44 age group, and the effects of innovation become insignificant. This difference is due to the fact that women who survive their breast cancer diagnosis by five years have a less severe form of cancer and therefore reduce their labor supply by less and also benefit less from medical innovation. The educational gradient persists in this sample, although the difference is not as significant. (See Figures 3 and 4 and Tables 11–17 in the online appendix.)

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 labor supply at the extensive margin following a prostate or breast cancer diagnosis and at the intensive margin in the case of prostate cancer. We also show that only cancer patients with postsecondary education appear to benefit from medical innovation.

While 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. 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 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.

Nevertheless, our findings suggest that the economic value of medical innovation as measured by the labor market effects among cancer patients is high. The economic benefits that we find are in addition to the reduced mortality due to improved cancer treatment and imply that innovative and expensive cancer treatment may be more cost-effective than previously thought. Future research should disentangle these benefits further to show if any specific innovations account for particularly large changes in labor market outcomes.

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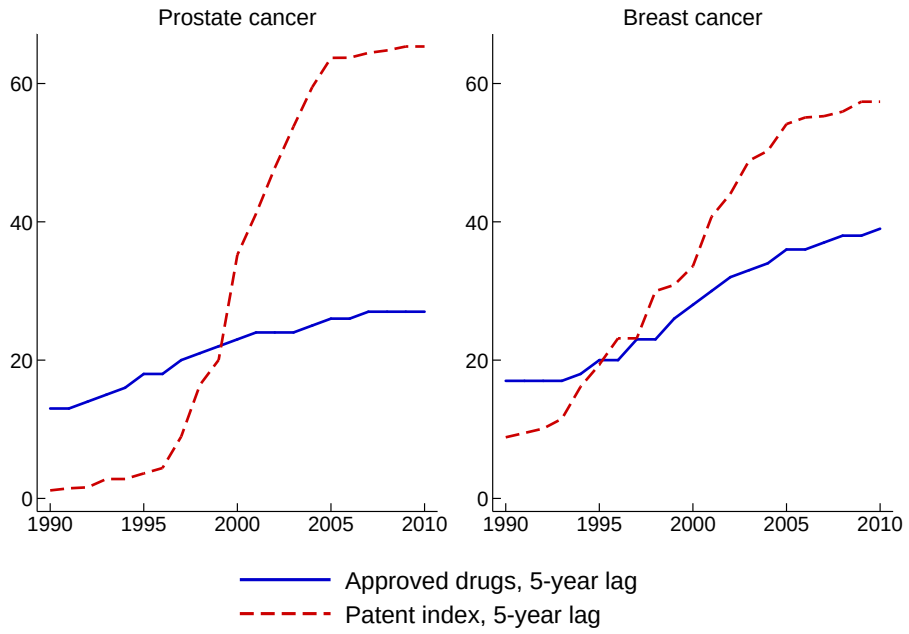
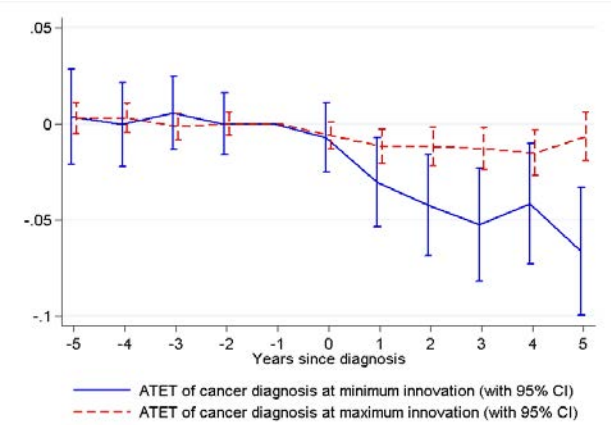
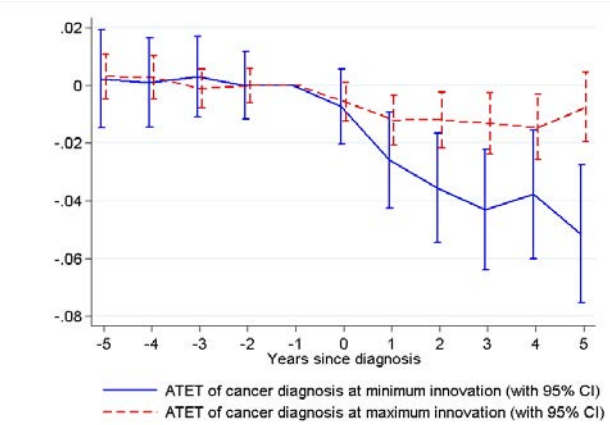


Source: Authors' calculations.

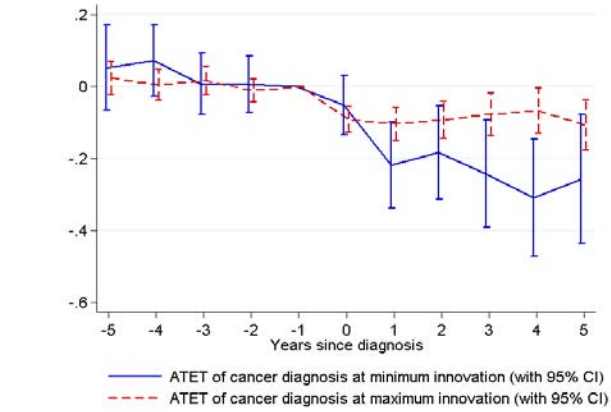
Figure 1: Innovation Measures by Cancer Site and Over Time



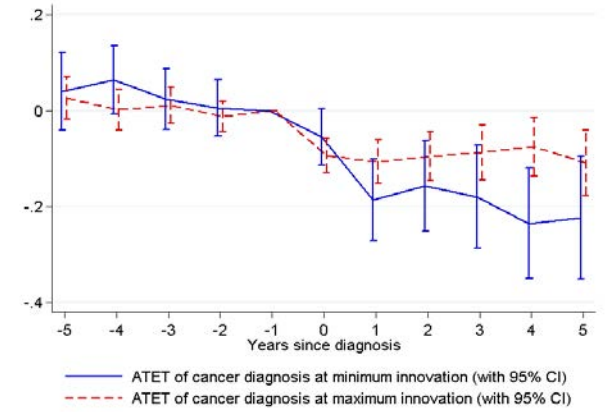
(a) Employment—Innovation Measure: Number of Drugs



(b) Employment—Innovation Measure: Patent Index



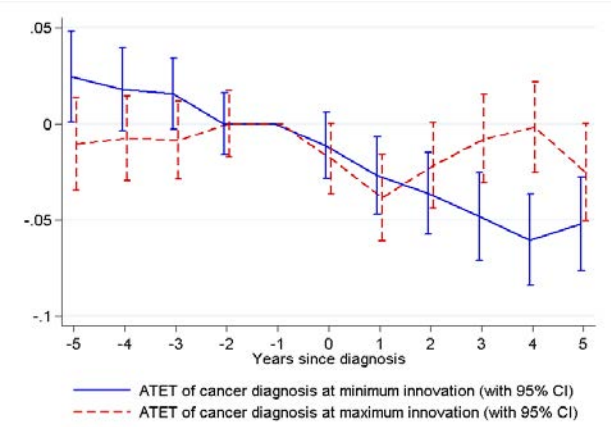
(c) Annual Log-Earnings—Innovation Measure: Number of Drugs



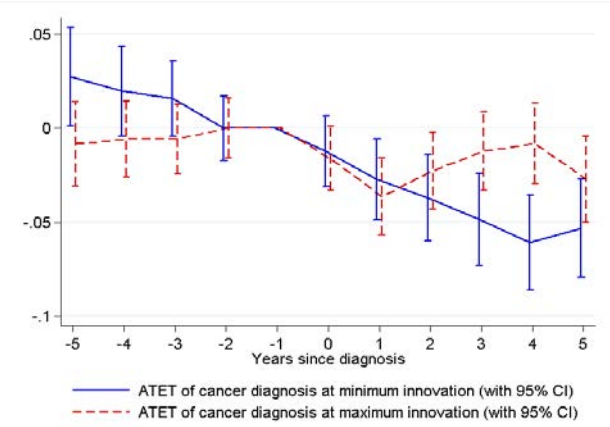
(d) Annual Log-Earnings—Innovation Measure: Patent Index

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.
Source: Statistics Canada and authors' calculations.

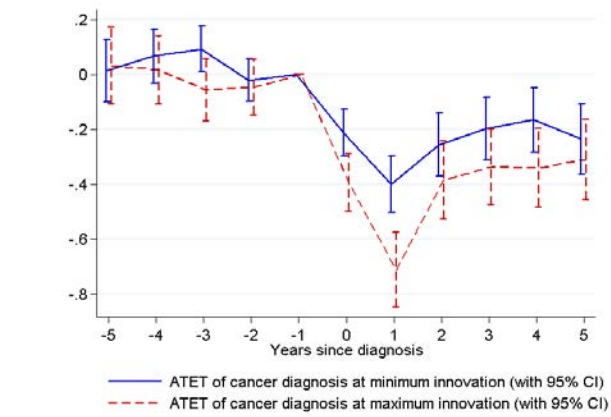
Figure 2: Dynamic Treatment Effects of Prostate Cancer Diagnosis on Labor Market Outcomes, Aged 49–60, by Level of Innovation (Five-Year Lag)



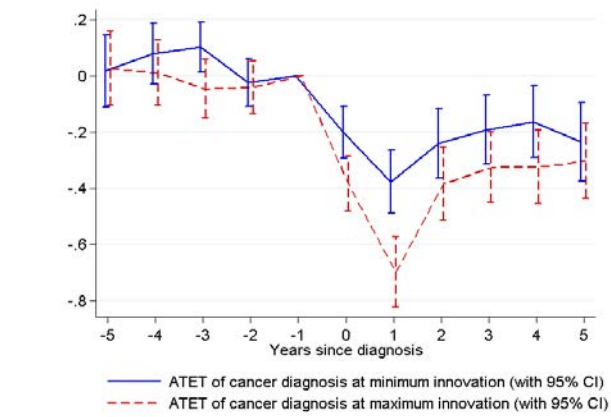
(a) Employment—Innovation Measure: Number of Drugs



(b) Employment—Innovation Measure: Patent Index



(c) Annual Log-Earnings—Innovation Measure: Number of Drugs



(d) Annual Log-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.
Source: Statistics Canada and authors' calculations.

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

Table 1: Prostate Cancer Employment Regressions with Time-Invariant Effects, Aged 49–60

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
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

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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 2: Prostate Cancer Log-Earnings Regressions with Time-Invariant Effects, Aged 49–60

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
Post×Cancer	−0.123***	−0.339***	−0.186***
	(0.0161)	(0.114)	(0.0373)
Post×Cancer×Drugs		0.00890*	
		(0.00470)	
Post×Cancer×Patents			0.00131*
			(0.000715)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.0708	0.0710	0.0710
Number of unique persons	521,311	521,311	521,311
Person-year observations	17,500,524	17,500,524	17,500,524

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from regressions with time-invariant effects. The dependent variable is annual log-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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 3: Breast Cancer Employment Regressions with Time-Invariant Effects, Aged 35–60

	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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 4: Breast Cancer Employment Regressions with Time-Invariant Effects, Aged 35–44

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
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

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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 5: Breast Cancer Log-Earnings Regressions with Time-Invariant Effects, Aged 35–44

	Diff-in-Diff	Triple-Difference	
	(1)	(2)	(3)
Post×Cancer	-0.336^{***}	-0.181^{**}	-0.246^{***}
	(0.0230)	(0.0895)	(0.0536)
Post×Cancer×Drugs		-0.00574^{*}	
		(0.00342)	
Post×Cancer×Patents			-0.00263^{*}
			(0.00159)
Individual fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Within-R^2	0.0112	0.0112	0.0112
Number of unique persons	374,865	374,865	374,865
Person-year observations	9,374,112	9,374,112	9,374,112

Notes: Estimated coefficients and standard errors (clustered on the unique person level) from regressions with time-invariant effects. The dependent variable is annual log-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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 6: Prostate Cancer Employment Regressions with Time-Invariant Effects by Education, Aged 49–60

	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.

Table 7: Breast Cancer Employment Regressions with Time-Invariant Effects by Education, Aged 35–44

	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Statistics Canada and authors' calculations.