Labor Market Effects of Medical Innovation: The Case of Breast and Prostate Cancer*

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Abstract

Innovations in cancer treatment have lowered mortality, but little is know about their economic benefits. In this paper, we assess the effect of improved treatment options over the last three decades on the labor market outcomes of breast and prostate cancer patients. We combine administrative tax return and cancer registry data from Canada with measures of medical innovation (approved drugs, academic publications, and patents) to estimate triple-differences regressions of employment and annual earnings. Our results show that the reductions in these labor market outcomes among cancer patients are partially offset by improved treatment options. Specifically, the decline in employment due to a cancer diagnosis is cut by 50 to 75 percent by the medical innovation that has occurred during the last three decades.

Keywords: medical innovation, labor supply, employment, earnings, breast cancer, prostate cancer.

JEL codes: I10, I18, J17, J22, O30.

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1 Introduction

Medical innovations have led to large declines in mortality and morbidity over the last century. Death rates due to cancer have declined by 23% in the U.S. in the past two decades, for example (Siegel, Miller, and Jemal 2016), while cancer research has grown rapidly (Sudhakar 2009). Lichtenberg (2013), Lichtenberg (2015), and Lichtenberg (2017) shows that cancer mortality has declined in response to an increase in available drugs and cancer research more broadly. In many cases, the value of these innovations in terms of life years gained exceeds the cost of research and development (R&D) and increased medical expenditures (see, for example, Cutler and McClellan 2001).

However, additional economic benefits of medical innovation are often overlooked. Improved treatment option do not only allow patients to live longer and healthier lives but also to be more productive, thereby sustaining higher levels of labor supply and earning higher salaries. In turn, higher earnings imply increased tax revenue and lower reliance on government benefits such as disability insurance. It is therefore important to consider the economic benefits of medical innovation, specifically when it comes to patients' labor market outcomes.

In this paper, we provide the first evidence on how innovations in the treatment of breast and prostate cancer affect the labor market outcomes of individuals diagnosed with these cancers. We employ three measures of innovation: (i) the number of drugs that are approved to treat prostate or breast cancer in Canada in the year of the diagnosis, (ii) the number of medical publications on these cancer types that have been published by the year of the diagnosis, and (iii) the cumulative number of patents related to breast and prostate cancer that have been granted by the year of the diagnosis. To allow for the time that passes between a drug approval, publication, and granting of a patent until the innovation is widely available for treating cancer patients, we also include lagged measures of innovations. We then utilize administrative data from Canada that combines the national cancer registry with longitudinal tax return data to estimate how the effect of a cancer diagnosis on employment and earnings changes with available treatment options and other innovation measures.

We contribute to two distinct literatures. First, our results provide evidence on the labor market effects of health shocks (see Currie and Madrian 1999 for a summary of the older literature). Recently, Garcia Gomez et al. (2013) and Jeon (2016) have documented the negative employment and earnings effects of hospitalizations and cancer diagnoses, respectively.

Second, we shed light on the economic value of medical innovation. Cutler and McClellan (2001) and Cutler et al. (2007) show that increased medical spending is worth it when compared to improved health outcomes including mortality after a heart attack and infant mortality as well as treatment of hypertension. Improved medical treatment options can also

explain part of education gradient in health as shown by Glied and Lleras-Muney (2008).

In particular, we contribute to the small but growing literature that considers the labor market effects of medical innovation. This literature focuses specifically on pharmaceutical innovation. For example, Goldin and Katz (2002) and Bailey (2006) study the labor market effects due to the introduction of the birth control pill. Garthwaite (2012) and Bütikofer and Skira (2016) analyze the effect of Cox-2 inhibitors on labor force participation and absenteeism and disability. Papageorge (2016) exploits the introduction of anti-retroviral drugs for the treatment of HIV positive individuals but also provides a structural analysis of labor supply that accounts for reduced side effects of the new treatment options. Thirumurthy, Zivin, and Goldstein (2008) also studies the labor market effects of AIDS treatment, but in the context of a developing country. Outside of pharmaceutical innovation, Epstein et al. (2013) analyze the effects of minimally invasive surgery on absenteeism. These studies use the introduction (and in the case of Cox-2 inhibitors the market withdrawal) of a specific new medical technology as a natural experiment. In contrast, we do not focus on one particular innovation but rather take a broad view of medical innovation and consider the labor market effects of cumulative medical innovation over three decades. To our knowledge, no study to date has explored the effect of innovation in cancer treatments on labor market outcomes.

We focus on prostate and breast cancer for three reasons. First, they are the most common cancer diagnoses among men and women, respectively, yielding a larger sample size than for other types of cancer. This also implies that the most individuals are affected by medical innovation, so our results are more likely to be economically important. Second, survival rates are relatively high, so there is a good chance that improved treatment does not only lead to lower mortality but also to better outcomes and fewer side effects. Therefore, it is more likely that treatment innovation have an effect on labor supply in addition to reducing mortality. Third, while most cancers occur later in life, a large fraction of prostate and breast cancer diagnoses happen at working age. Hence, we can expect meaningful changes in labor supply in response to improved treatment. Bradley, Bednarek, and Neumark (2002a), Bradley, Bednarek, and Neumark (2002b), Bradley et al. (2005), Bradley, Oberst, and Schenk (2006), Bradley, Neumark, Luo, and Bednarek (2007), Bradley, Neumark, Luo, and Schenk (2007), and Bradley, Neumark, and Barkowski (2013) analyze the labor market outcomes of breast and prostate cancer survivors, but to our knowledge no study has considered the role of treatment innovation in this context.

To study the cumulative effects of medical innovations in the treatment of breast and prostate cancer, we observe cancer diagnoses in Canada between 1992 and 2010. Using administrative data, we are able to merge information on cancer diagnoses with individual tax returns, which allows us to follow cancer survivors before and after their diagnosis. Specifically, we observe

their employment status and total annual earnings as proxies for labor supply. To control for labor market trends, we compare cancer survivors with individuals who were never diagnosed with cancer. We estimate the causal effect of medical innovation on labor market outcomes by exploiting quasi-random assignment of cancer diagnoses over time. In other words, we assume that the exact timing of an individual's cancer diagnosis is uncorrelated with the level of medical innovation present at that point in time. Hence, we employ a triple-differences strategy to identify causal effects. To reduce the influence of any observed differences between individuals with and without cancer diagnoses, we use Coarsened Exact Matching (CEM).

Our results first confirm existing evidence in showing the negative labor market effects of breast and prostate cancer diagnoses. In the five years following the diagnosis, employment rates decline by about 3 to 9 percentage points. More importantly, we find that additional medical innovation, measured by available drugs, academic publication, and patents, reduces this negative effect substantially. In the case of prostate cancer, treatment innovation over our sample period has reduced the negative employment effects by at least one half and almost completely offset any negative effects for some specifications. At the same time, innovation has reduced the negative effect on the annual earnings of prostate cancer survivors by about $2,000. Among breast cancer patients, medical innovation has lowered the negative effect of a cancer diagnosis by three quarters. This effect is concentrated among women aged 35 to 44.

The remainder of this paper proceeds as follows. First, we provide background on the treatment of breast and prostate cancer and discuss our medical innovation measures in Section 2. We then describe the data in Section 3. Section 4 contains a discussion of our empirical strategy, and we provide the results in Section 5. Finally, Section 6 concludes.

2 Measuring Innovations in Cancer Treatment

Treatment options for many types of cancer have vastly improved over the last few decades. Sudhakar (2009) describes the broad developments. The combination of surgery and chemotherapy is one of the major innovations that have lowered cancer mortality rates. More recently, advances in cancer treatment have led to reduced side effects as drugs used in chemotherapy have become better at targeting cancer cells without harming healthy cells (see also DeVita and Chu 2008).

For the case of breast cancer, Zurrida and Veronesi (2015) describe important treatment innovations that fall into our sample period such as breast-conserving surgery in the 1990s. In addition, chemotherapy has become more effective and targeted (for example, by using the drug tamoxifen starting in the 1980s). More recent pharmaceutical innovations such as trastuzumab and pertuzumab may be highly effective but are also more expensive than older

drugs. It is therefore particularly important to evaluate the economic benefits that these treatment innovations may yield.

Similarly, Denmeade and Isaacs (2002) describe the history of prostate cancer treatment that most importantly includes the use of hormonal therapy such as luteinizing hormone-releasing hormone analogues since the early 1980s. Over the same time period, diagnosis of prostate cancer was improved through the use of prostate-specific antigene tests and less invasive surgical methods were developed. More recently, several innovations in chemotherapy and radiation therapy have provided additional and improved treatment options for prostate cancer.

These improvements in treatment options for breast and prostate cancer are also reflected in the innovations measures that we use in our empirical analyses below. Here, we describe how our three innovations measures are constructed and the rationale for their use. Due to the growing importance of chemotherapy in treating these cancers and in reducing potential side effects, drugs that are available for treatment of a specific type of cancer are a good measure of medical innovation. Lichtenberg (2015) provides a list of all drugs that are available for cancer treatment along with the year when they were approved in Canada. We use this information to calculate the cumulative number of drugs that were approved for treatment of breast and prostate cancer in the year of an individual's diagnosis. To account for the delay between approval of a drug and its wide use in treatment, we consider lags of 5, 10, and 15 years in this and our other innovation measures. Lichtenberg (2015) finds that lags of 10 and more years yield statistically significant results when regressing years of potential life lost before age 75 on the cumulative number of drugs. His results imply a cost of life-year before age 75 gained due to pharmaceutical innovation of about 2,700 dollars.

As described above, pharmaceutical innovation is an important driver for improved treatment options for breast and prostate cancer, but there are additional medical innovations that are not captured by the number of available drugs. Improved diagnostics, radiation, and surgical procedures have also contributed to better treatment of these cancers. Therefore, our second innovation measure takes a broader approach by counting all academic publications about breast and prostate cancer, respectively, that received any type of research support. These publications include studies that describe new treatment options and randomized trials that may compare existing alternatives in treating a specific type of cancer. We restrict publications to those with research support because it is more likely that they contributed to improved treatment options. Overall, the underlying rationale in using the cumulative number of publications is that this measures broadly reflects the amount of medical knowledge that is available at any given point in time. Lichtenberg (2013) and Lichtenberg (2017) uses this measure to study the effect of cancer research on mortality and hospitalization and

finds that higher research output lowers both adverse health outcomes. Cutler, Meara, and Richards-Shubik (2012) also use this measure for medical innovation in the context of infant mortality.

To find publications about specific types of cancer, we performed searches on PubMed limiting results to publications that listed the specific cancer (prostate or breast cancer) as a Medical Subject Headings (MeSH) Major Topic and received any kind of research support.[1] We then calculated the cumulative number of publications over all years.

Our third innovation measure also uses a broad definition of medical innovation by relying a patents that are related to breast and prostate cancer. Specifically, we use the Cancer Moonshot Patent Data from the U.S. Patent and Trademark Office (USPTO).[2] Patents are a commonly used measure for innovation (see Hall and Harhoff 2012 for a recent overview on the economics of patents). We identify patents that are relevant for breast and prostate cancer by searching for the key words "prostate" or "prostatic" and "breast" or "mammary," respectively. To our knowledge, no study has used patent data in the context of measuring the effect of medical innovation on labor market or any other economic or health outcomes.

In Figure 1, we plot our three innovation measures for breast and prostate cancer from 1972 to 2010.[3] The innovation patterns for the two cancers are broadly similar but also show some significant differences. The number of available drugs grew approximately linearly, especially during the 1980s and 1990s with a more recent slow-down. Whereas the number of drugs was initially similar for both cancer types, the growth in breast cancer drugs has outpaced that for prostate cancer drugs. Breast cancer research is overall more active than prostate cancer research as evidenced by the growth in cumulative publications. In 2010, about 50,000 publications on breast cancer had been published compared to about 23,000 on prostate cancer. In contrast, the growth in the number of patents since 2000 has been slightly faster for prostate-related innovations with about 1,200 patents compared to 1,000 that are related to breast cancer.[4]

[1] See https://www.ncbi.nlm.nih.gov/pubmed. The relevant MeSH Major Topics are "breast neoplasms" and "prostatic neoplasms." In order to restrict the searches to publications that received research support, we limited publication type to "research support, american recovery and reinvestment act," "research support, n i h, extramural," "research support, n i h, intramural," "research support, non u s gov't," "research support, u s gov't, non p h s," "research support, u s gov't, p h s," or "research support, u s government." We then downloaded the by-year counts of resulting publications.

[2] 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.

[3] In order to make our estimates below more easily comparable across innovation measures, we divide the cumulative number of publications by 1,000 and the cumulative number of patents by 100.

[4] Figure 1 also shows that medical innovation for breast and prostate cancer treatment has not evolved linearly. Can we exploit this feature of the data to identify the causal effect of innovation on labor market outcomes? For example by including non-linear functions of innovation measures.

3 Data Description and Summary Statistics

The individual-level data come from three main 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]).[5] Statistics Canada linked these data sources based on the 1991 Canadian Census. First, individuals who were aged 25 and above in the 1991 census were linked to the CCDB and CMDB. The CCDB and CMDB data provide cancer diagnoses up to 2010 and death records up to ????. Second, individuals in the census were linked to LWF and T1FF tax records 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.[6]

To construct the estimation sample, we first restrict the age range among individuals who were diagnosed with cancer. Specifically, we select men aged 40 to 62 at the time of their prostate cancer diagnosis and women aged 35 to 62 at the time of their breast cancer diagnosis. We pick the lower threshold such that very few individuals were diagnosed at younger ages. The upper threshold limits the role of early retirement during the follow-up period after a cancer diagnosis.[7] To reduce the influence of outliers, we drop individuals whose earnings fall into the top and bottom 0.05% of earnings.[8] Our restricted samples consist of 918,160 men and 941,878 women, respectively. Among these individuals, 11,156 men were diagnosed with prostate cancer and 21,093 women were diagnosed with breast cancer during the sample period.

We then construct the treatment and control groups as follows: For each year between $s = 1992$ and $s = 2010$, we assign individuals who were diagnosed with breast or prostate cancer as their first cancer diagnosis 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. That is, our control group contains many duplicate individuals. However, as described in Section 4 below, we are not able to match every observation in the control group with a treated individual, so the final estimation sample contains fewer duplicate individuals.

Tables 1 and 2 display summary statistics for the prostate and breast cancer samples,

[5] We have used and described these data sources in Jeon (2016) and Jeon and Pohl (2017). See also the detailed description in the Online Appendix to Jeon and Pohl (2017). In contrast to our earlier studies, here we use a larger sample over a longer sample period.

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

[7] In the regression results in Section Section 5, we also report estimates for various age groups.

[8] The lower cutoff is –41,481 dollars for men and –20,206 dollars for women and the upper cutoff is 1,353,213 dollars for men and 413,628 dollars for women.

respectively. Columns (1) and (2) of each table show the sample fractions for treated and control group members and column (3) contains the normalized differences between them.[9] Most characteristics are balanced between treatment and control group, i.e. their normalized difference is 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 older, in particular in the prostate cancer sample. In addition, older individuals are less likely to list dependent children on their tax return, so more control groups members are classified as having no children. In the breast cancer sample, the difference in fraction without children could be reinforced by 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, and pre-diagnosis employment status and earnings, are relatively balanced. In Section 4 below, we discuss the matching algorithm that ensures a balanced estimation sample.

4 Empirical Strategy

In this section, we describe how we estimate the labor market effects of medical innovations in the treatment of breast and prostate cancer. First, we discuss the weighting and second, we detail the triple-differences regressions.

To make the treatment and control group, we use Coarsened Exact Matching (CEM). Iacus, King, and Porro (2011) and Iacus, King, and Porro (2012) propose this matching algorithm that splits the sample into strata based on coarsened observables and matches treatment and control group within each bin. The CEM algorithm yields control group weights equal to $n_T^k/n_C^k \times N_C/N_T$ for stratum k, where n_T^k and n_C^k are the number of individuals in the treatment and control group in the specific stratum and N_T and N_C are the respective numbers of observations in the entire sample. Treated individuals receive a CEM weight of one and individuals who cannot be matched receive a weight of zero. Using CEM weights therefore yields estimates of the average treatment effect on the treated (ATET).

We use the following variables to calculate CEM weights:[10] age (coarsened into 7 groups for the prostate cancer sample and into 8 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

[9] 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.

[10] See the individual characteristics in Tables 1 and 2 for a complete list of the variables and how they are coarsened.

the diagnosis, earnings quintiles in the two years before the diagnosis (including an indicator 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.

Columns (4) and (5) in Tables 1 and 2, respectively, display 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 difference in column (6) of each table is substantially smaller. 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 11,028 (99%) of the treated individuals in the prostate cancer sample and 20,711 (98%) in the breast cancer sample. Among control group members, we match far fewer individuals, but this is not an issue since we have sample individuals multiple times as explained in Section 3 above.

Next, we discuss our estimation approach. We model the labor market outcome (employment status or annual earnings) of individual i in year t. The year of the cancer diagnosis is denoted by s, so C_{is} is an indicator variable that equals one if i was diagnosed in year $s = 1992, \ldots, 2010$ and zero otherwise. That is, $C_{is} = 0, \forall s$ for members of the matched control sample. We also refer to year s as the placebo diagnosis year among control group members. We denote the innovation measures described in Section 2 by I_s, i.e. the cumulative number of drugs, publications, or patents in the year of an individuals' cancer diagnosis. We also consider 5-, 10-, and 15-year lags of this variable (I_{s-5}, I_{s-10}, and I_{s-15}).

To estimate the causal effect of medical innovations on labor market outcomes, we run two types of regressions. First, we restrict the effect of a cancer diagnosis and of treatment innovation to be constant over time. Hence, we run the following regressions:

$$Y_{its} = \beta_1 P_{ts} + \beta_2 C_{is} P_{ts} + \beta_3 P_{ts} I_s + \beta_4 C_{is} P_{ts} I_s + \alpha_i + \gamma_t + u_{its}, \tag{1}$$

where Y_{its} is the labor market outcome of individual i in year t when the (placebo) diagnosis year is s, 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 post-diagnosis indicator variable.[11] The effect of a cancer diagnosis, β_2, and of available (lagged) medical innovations, β_4, do not vary over time.

It is likely 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 his or her labor supply after a few years. In addition, the effect of medical innovation may affect labor market outcomes differentially over time. For

[11] We also run robustness checks where we define $P_{ts} = \mathbf{1}\{t > s\}$, i.e. the year of the cancer diagnosis is part of the pre-period.

instance, the pattern of innovations that mostly reduce side effects may differ from that of improved treatments that reduce mortality. To account for these dynamic effects, we estimate a version of regression (1) with time-varying effects of cancer diagnoses and medical innovation. We therefore estimate regressions of the following form:

$$Y_{its} = \sum_{j=-J}^{J} \beta^j T_{ts}^j + \sum_{j=-J}^{J} \gamma^j T_{ts}^j C_{is} + \sum_{j=-J}^{J} \delta^j T_{ts}^j C_{is} I_s + \alpha_i + \gamma_t + u_{its} \tag{2}$$

where $T_{ts}^j = \mathbf{1}\{t = s + j\}$ is an indicator that equals one if j years have elapsed since the diagnosis. In our main specification, we set $J = 5$. Including the pre-diagnosis interactions between treatment, period dummies, and the medical innovation measures also allows us to assess the parallel trends assumptions that is required for difference-in-differences or triple-differences regressions. That is, we can test if the γ^js and δ^js are statistically insignificant for $j < 0$.

The coefficients of interest in regression (2) are the δ^js. They measure the effect of increasing innovation by one unit on the difference between the average labor market outcomes of a cancer survivor and a control group member j years after the diagnosis. The δ^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:

$$H_0 : \delta^j = 0, \text{ for } j = 1, \ldots, 5. \tag{3}$$

Rejecting this null hypothesis suggests that improved treatment affects labor market outcomes of cancer patients overall even if the time-varying triple-difference coefficients may not be individually statistically significant. The results in Section 5 below contain p-values for the F-test of hypothesis (3) that show if the hypothesis can be rejected.

This research design constitutes a triple-differences approach. The first difference is between individuals who were diagnosed with breast or prostate cancer and those who were never diagnosed. Since we use CEM weights, members of the control group are observably identical to individuals diagnosed with cancer. The second difference is between pre- and post-diagnosis years. It allows us to control for any common trends in labor market outcomes. The third difference is between different values of the innovation measure. Hence, identification of the causal estimate of the effect of cancer treatment innovation on changes in labor market outcomes comes from the following: the timing of someone's cancer diagnosis is orthogonal to the amount of treatment innovation that exists at that point in time for that particular type

of cancer. Therefore, any unobserved characteristics that may affect someone's labor market outcomes are also uncorrelated with the amount of innovation.

5 Results

In this section, we present and discuss the results from estimating regressions (1) and (2) for the effect of our three medical innovation measures on employment status and annual earnings in the breast and prostate cancer samples.

5.1 Prostate Cancer

Table 3 displays the results from the triple-differences regressions with time-invariant effects for employment. For each of the three innovation measures, we report estimates for the entire sample (aged 40 to 62) and the subsample in the age group 49 to 58. This age groups account for about 50 percent of the treatment group (see Table 1). In this and the other tables for time-invariant effects, we report the estimated coefficients $\hat{\beta}_2$ and $\hat{\beta}_4$ in regression (1), i.e. the interaction between prostate cancer and the post-diagnosis period and the triple interaction with the innovation measures.[12]

Using the number of approved drugs lagged by 10 years as the innovation measure, Table 3 shows that a prostate diagnosis lowers employment by 5 percentage points among all men aged 40 to 62 and each additional drug increases employment by 0.16 percentage points. To interpret this result, we consider the range of this innovation measure. In 1993, 9 drugs were approved for at least 10 years, and this number increased to 26 by 2010. Hence, combining the estimates implies that a prostate cancer diagnosis reduced employment by between 3.6 and 0.9 percentage points.[13] In the age group 49 to 58, the decline ranges between 4.8 and 2.1 percentage points, so men in this age group are more negatively affected by a prostate cancer diagnosis. In both cases, however, medical innovation leads to reduction in the negative employment effect of a cancer diagnosis that is both statistically and economically significant.

When proxying innovation by cumulative publications or patents, we also find a decline in employment due to a prostate cancer diagnosis that is partially offset by improved treatment options. In particular, employment declines by between 2.8 and 0.1 percentage points in the all ages sample and between 3.1 and 0.6 percentage points in the 49 to 58 age group when using cumulative publications. For the cumulative number of patents, these effects amount to

[12] Full regression results are available from the authors.

[13] We calculate these combined effects as $\hat{\beta}_2 + \hat{\beta}_4 \times I_{1993}$ for the lowest level of medical innovation and as $\hat{\beta}_2 + \hat{\beta}_4 \times I_{2010}$ for the highest level.

between 2.4 and 0.3 percentage points in the all ages sample and 2.6 to 0.5 percentage points in the restricted sample.[14] These results confirm the estimates based on available drugs using broader measures of medical innovation.

We then run these regressions with same innovation measures and for the same age groups, but with time-varying effects, see regression (2). These results allow us to track the effect of a cancer diagnosis and medical innovation on labor market outcomes over time. Table 4 displays the estimated $\hat{\gamma}^j$ and $\hat{\delta}^j, j = -5, \ldots, 5$, where $j = -1$, i.e. the year before the cancer diagnosis, is the base year. The results show that the negative effect of a prostate diagnosis on employment increases over time for all age groups and innovation measures. In the year of the diagnosis, the effect is small and mostly not statistically significant. This finding is expected because the employment status in that year includes pre-diagnosis labor supply. The decline in employment then increases over the following five years. Among men aged 49 to 58, for example, the effect ranges between 4.2 and 0.5 percentage points in the first year after the diagnosis (measured at the lowest and highest number of available drugs, respectively) and between 7.3 and 0.2 in the fifth year.[15] These results also imply that as the treatment options for prostate cancer improve, the decline in employment over time following the diagnosis becomes less severe. At the highest level of medical innovation at the end of our sample period, the drop in employment is almost non-existent and does not increase over time. The results for other innovation measures and for the all ages sample are similar in size and direction. At the bottom of Table 4, we report the p-values for the F-tests of hypothesis (3). The results indicate that the triple interactions for $j = 1, \ldots, 5$ are jointly significant at the 10 percent level in the case of available drugs and the cumulative number publications but in the case of the cumulative number of patents.

The second labor market outcome we consider is annual earnings. Table 5 shows the estimation results for time-invariant effects. The results indicate a statistically significant decline in earnings due to a prostate cancer diagnosis, but the relative increase due to medical innovation is only statistically significant at the 10 percent level for the all ages sample but not for the sample consisting of men aged 49 to 58. The results in the first column, for example, imply that earnings are reduced by about \$5,100 at the lowest number of available drugs \$4,650 but by only \$2,100 at the highest number. Hence, the point estimates suggest that medical innovation cuts the earnings losses due to a prostate cancer diagnosis by about one half. Average earnings are about \$52,000 in the year prior to the diagnosis (see Table 1), so these effects are economically significant.

In Table 6, we report estimation results for annual earnings with time-varying effects. Similar

[14] We also use 10-year lags here. The numbers of cumulative publications (in 1,000) and patents increased from 0.72 to 7.26 and from 5 to 210, respectively.

[15] These combined effects are calculated as $\hat{\gamma}^j + \hat{\delta}^j \times I_s, j = -5, \ldots, 5, s = 1993, 2010$.

to the employment results in Table 4, we find that the negative impact of a cancer diagnosis and the mitigating effect of medical innovation both increase over time post-diagnosis. For example, when considering available drugs as the innovation in the all ages sample (in the first column), we find a decline in annual earnings in the first year after the prostate cancer diagnosis that ranges between $3,450 at the lowest innovation level to $1,050 at the highest level. In year 5 after the diagnosis, this range is between $5,900 and $150. Hence, these findings suggests that better treatment options do not only lead to lower reductions in earnings, but the increasing decline as time passes after the diagnosis is also reversed.

5.2 Breast Cancer

The results for the labor market outcomes in our breast cancer sample follow the same outline as for the prostate cancer results above. In addition to the all ages sample, we report results for the 35 to 44 age group. These women constitute only about 16 percent of the treatment group, but they are likely to be most responsive to improved treatment options for breast cancer because of their stronger attachment to the labor force.

Table 7 displays the coefficient estimates for $\hat{\beta}_2$ and $\hat{\beta}_4$ in regression (1) for employment status as the labor market outcome. While we find statistically significant and negative effects of a breast cancer diagnosis on employment, the mitigating effect of medical innovation is only statistically significant in the 35 to 44 age group. Our estimates imply that going from the lowest to highest level of innovation leads to a change in women's employment decline from 4.3 to 0.8 percentage points for approved drugs, 4.2 to 0.6 percentage points for the number of cumulative publications, and from 4.2 to 0.9 percentage points for the number of cumulative patents.[16] Hence, all results yield the same conclusion that improvements in the treatment of breast cancer between 1993 and 2010 have substantially reduced the negative employment effect among women aged 35 to 44.

Allowing for time-varying effects in Table 8 shows that the mitigating effect of medical innovation on the employment status of breast cancer patients is concentrated in the third year after the diagnosis. When measuring innovation by the number of approved drugs, for example, the third year effect $\hat{\gamma}^2 + \hat{\delta}^3 \times I_s, s = 1993, 2010$ changes from a decline of 5.4 to 1.3 percentage points among women aged 35 to 44. These results suggest that the economic value of better treatment options does not come into effect immediately after the diagnosis but rather appears in the medium term. It is plausible that medical innovation in the treatment of breast cancer has allowed affected women to return to the labor force

[16] We use medical innovation measures that are lagged by 10 years here. The number of approved drugs increased from 13 in 1983 to 36 in 2000, and the numbers of cumulative publications (in 1,000) and patents increased from 2.28 to 20.36 and from 11 to 177, respectively.

faster. This finding is consistent across all three measures of innovation. The testing results for hypothesis (3) reported at the bottom of Table 8 show that the joint effect of medical innovation triple-differences is highly significant with p-values between 0.01 and 0.02.

The results for annual earnings are shown in Table 9. While the effect of a breast cancer diagnosis on earnings is negative as expected, the additional effect of medical innovation is also negative in contrast to our other results. Among the 35 to 44 year olds, the results using drugs as the innovation measure imply that improved treatment increased the earnings decline from \$4,300 to \$7,000, which is a substantial amount given average annual earnings of about \$30,000 (see Table 2).

To further investigate this issue we turn to the time-varying results in Table 10. These estimates show that the negative effect of the triple interactions with all three innovation measures, respectively, are concentrated in the year of the diagnosis and the following year. The point estimates in the subsequent years are also negative but not statistically significant. At the same time, the results reported in Table 8 show positive effects on employment in the later years after the diagnosis. These two sets of results suggest a different pattern for the effects of medical innovation on earnings and employment in the case of breast cancer compared to prostate cancer. Specifically, using improving the options for the treatment of breast cancer may have led to more intensive treatment that forced women to reduce their labor supply at the intensive margins, thereby lowering their earnings. At the same time, these better treatments may have had fewer side effects, which allowed breast cancer patients to stay in the labor force. The drug tamoxifen is an example for such as treatment innovation (see Section 2). The overall effect of medical innovation on the labor market outcomes among breast cancer patients is therefore mixed. While the drop in employment is substantially reduced, innovation leads to lower earnings.

6 Conclusion

This paper is the first to assess the labor market effects of innovation in cancer treatment among cancer patients. 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, academic publication, and patents.

Our results imply a large role of medical innovation in improving the labor market outcomes of cancer survivors. Among men diagnosed with prostate cancer, we find that the decline in employment status is lowered by at least 50 percent and almost disappears completely depending on the age group and innovation measure employed. For breast cancer patients, we find that the negative employment impact is cut by about three quarters. We also investigate

how these effects vary over time and consider the impact of medical innovation on annual earnings as a proxy for the intensive labor supply margin.

These findings show 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 here are in addition to the reduced mortality due to improved cancer treatment and may affect potential cost-benefit-analyses. Future research should disentangle these benefits further to show if any particular innovations account for particularly large changes in labor market outcomes.

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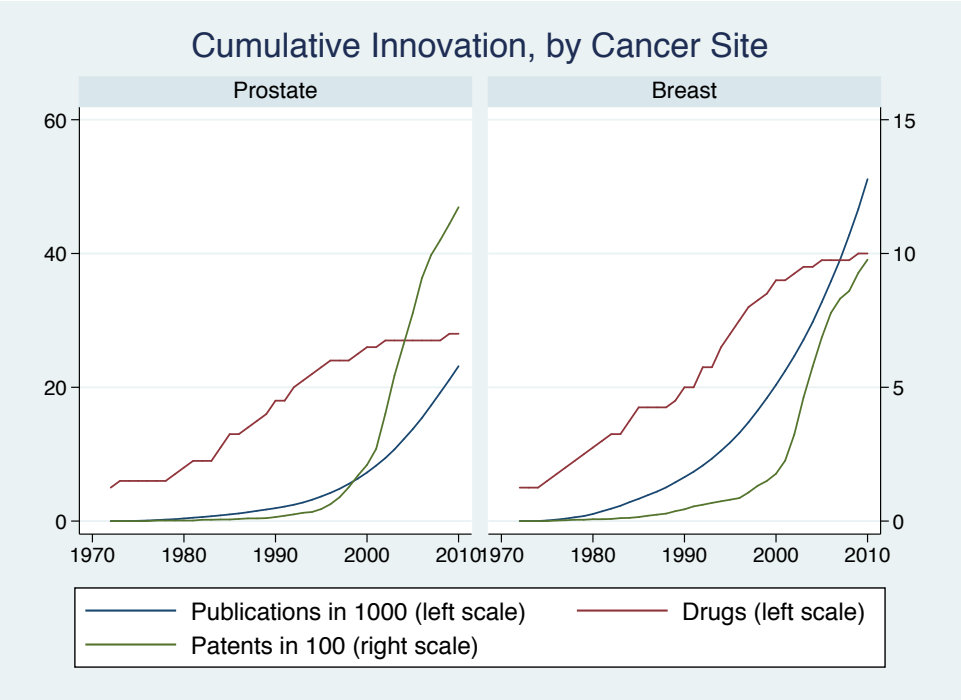

Figure 1: Innovation Measures by Cancer Site and Over Time

Table 1: Summary Statistics: Prostate Cancer Sample

	Unweighted			Weighted by CEM Weights		
	Treat.	Control	Normal. Diff.	Treat.	Control	Normal. Diff.
Coarsened age at s						
35-39						
40-44	0.006	0.237	-0.753	0.006	0.006	0.000
45-48	0.031	0.211	-0.574	0.031	0.031	0.000
49-52	0.102	0.192	-0.257	0.102	0.102	0.000
53-55	0.155	0.126	0.083	0.156	0.156	0.000
56-58	0.244	0.110	0.356	0.244	0.244	0.000
59-60	0.208	0.065	0.427	0.208	0.208	0.000
61-62	0.254	0.059	0.556	0.252	0.252	0.000
Highest level of schooling at s						
no high school	0.258	0.262	-0.010	0.258	0.258	0.000
hs-w/wo trades cert	0.385	0.414	-0.059	0.387	0.387	0.000
postsec non-university	0.143	0.148	-0.016	0.141	0.141	0.000
university degree	0.215	0.176	0.097	0.214	0.214	-0.000
Visible minority						
not a visible minority	0.930	0.919	0.041	0.935	0.935	0.000
Asian	0.030	0.053	-0.116	0.029	0.029	0.000
other	0.040	0.027	0.069	0.037	0.037	0.000
Province/territory at s						
Newfoundland	0.022	0.021	0.007	0.021	0.021	0.000
Prince of Edward Island	0.007	0.005	0.028	0.006	0.006	0.000
Nova Scotia	0.037	0.033	0.026	0.036	0.036	0.000
New Brunswick	0.033	0.027	0.039	0.033	0.033	0.000
Quebec	0.185	0.270	-0.202	0.187	0.187	0.000
Ontario	0.407	0.345	0.130	0.411	0.411	0.000
Manitoba	0.034	0.041	-0.033	0.033	0.033	0.000
Saskatchewan	0.035	0.034	0.006	0.035	0.035	0.000
Alberta	0.108	0.098	0.033	0.108	0.108	0.000
British Columbia	0.126	0.119	0.022	0.127	0.127	-0.000
YK&NWT&NNV	0.004	0.008	-0.059	0.003	0.003	0.000
missing	0.001	0.002	-0.018	0.000	0.000	0.000
Not working at $s = -1$	0.133	0.088	0.144	0.132	0.132	0.000
Working at $s = -1$	0.867	0.912	-0.144	0.868	0.868	0.000
Not working at $s = -2$	0.114	0.079	0.117	0.113	0.113	0.000
Working at $s = -2$	0.886	0.921	-0.117	0.887	0.887	-0.000
Quintiles of earnings at $s = -1$						
not working at $s = -1$	0.133	0.088	0.144	0.132	0.132	0.000
Quintile 1 (lowest)	0.215	0.184	0.079	0.215	0.215	0.000
Quintile 2	0.149	0.178	-0.078	0.150	0.150	0.000
Quintile 3	0.148	0.179	-0.082	0.148	0.148	0.000
Quintile 4	0.161	0.182	-0.056	0.161	0.161	-0.000
Quintiles 5 (highest)	0.193	0.190	0.009	0.194	0.194	0.000
Quintiles of earnings at $s = -2$						
not working at $s = -2$	0.114	0.079	0.117	0.113	0.113	0.000
Quintile 1 (lowest)	0.197	0.184	0.034	0.198	0.198	0.000
Quintile 2	0.155	0.179	-0.064	0.156	0.156	0.000
Quintile 3	0.155	0.180	-0.069	0.153	0.153	0.000
Quintile 4	0.168	0.185	-0.043	0.168	0.168	0.000
Quintile 5 (highest)	0.211	0.193	0.045	0.211	0.211	0.000
Year at s (year of diagnosis)						
1992	0.020	0.041	-0.121	0.020	0.020	0.000
1993	0.029	0.043	-0.076	0.029	0.029	0.000
1994	0.034	0.045	-0.054	0.034	0.034	0.000
1995	0.027	0.046	-0.101	0.027	0.027	0.000
1996	0.031	0.048	-0.088	0.031	0.031	0.000
1997	0.032	0.050	-0.088	0.032	0.032	0.000
1998	0.039	0.051	-0.061	0.038	0.038	0.000
1999	0.041	0.053	-0.054	0.041	0.041	0.000
2000	0.049	0.055	-0.025	0.049	0.049	0.000
2001	0.060	0.056	0.018	0.060	0.060	-0.000
2002	0.059	0.058	0.007	0.059	0.059	0.000

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Table 1 – continued from previous page

	Unweighted			Weighted by CEM Weights		
	Treat.	Control	Normal. Diff.	Treat.	Control	Normal. Diff.
2003	0.058	0.059	-0.002	0.058	0.058	0.000
2004	0.069	0.060	0.037	0.069	0.069	0.000
2005	0.069	0.060	0.035	0.069	0.069	0.000
2006	0.079	0.059	0.079	0.080	0.080	0.000
2007	0.082	0.057	0.097	0.082	0.082	0.000
2008	0.077	0.055	0.089	0.078	0.078	0.000
2009	0.073	0.053	0.084	0.073	0.073	0.000
2010	0.069	0.050	0.078	0.069	0.069	0.000
Number of children at $s = -1$						
no children	0.568	0.385	0.375	0.569	0.548	0.043
1-2 children	0.367	0.476	-0.222	0.367	0.381	-0.030
3+ children	0.052	0.117	-0.235	0.052	0.054	-0.006
missing	0.012	0.022	-0.077	0.012	0.018	-0.045
Age of youngest child at $s = -1$						
no children	0.568	0.385	0.375	0.569	0.548	0.043
age 0-6	0.014	0.080	-0.316	0.014	0.017	-0.022
age 7-17	0.129	0.311	-0.452	0.129	0.138	-0.027
age 18+	0.277	0.202	0.175	0.276	0.280	-0.009
missing	0.012	0.022	-0.077	0.012	0.018	-0.045
Number of children aged 0-17 at $s = -1$						
no child aged 0-17	0.845	0.586	0.598	0.845	0.828	0.047
1 child	0.091	0.168	-0.230	0.092	0.097	-0.019
2+ children	0.051	0.223	-0.516	0.051	0.057	-0.028
missing	0.012	0.022	-0.077	0.012	0.018	-0.045
Union status: no	0.570	0.518	0.106	0.570	0.571	-0.002
Union status: yes	0.430	0.482	-0.106	0.430	0.429	0.002
Marital status: single	0.139	0.189	-0.133	0.139	0.161	-0.061
Marital status: couple	0.848	0.789	0.154	0.848	0.821	0.074
Marital status: missing	0.012	0.022	-0.076	0.012	0.018	-0.045
Self-employed: no	0.790	0.796	-0.015	0.790	0.793	-0.006
Self-employed: yes	0.196	0.177	0.048	0.196	0.188	0.021
Self-employed: missing	0.014	0.026	-0.089	0.013	0.019	-0.047
Age	57.219	50.040	1.356	57.202	57.078	0.030
Earnings at $s = -1$	52,770.916	53,493.807	-0.012	52,863.944	52,560.002	0.005
Earnings at $s = -2$	55,414.838	53,912.087	0.025	55,443.158	55,224.513	0.003
Earnings at $s = -1$ if working	60,873.988	58,657.009	0.036	60,930.557	60,580.237	0.005
Earnings at $s = -2$ if working	62,540.003	58,560.663	0.064	62,537.296	62,290.674	0.004
Number of dependents at $s = -1$	0.688	1.146	-0.427	0.689	0.720	-0.033
Age of youngest dependent at $s = -1$	20.357	15.350	0.596	20.340	20.353	-0.002
Number of dependents aged 0-17 at $s = -1$	0.209	0.718	-0.605	0.209	0.235	-0.043
Observations	11,156	10,873,424		11,028	2,428,119	

Table 2: Summary Statistics: Breast Cancer Sample

	Unweighted			Weighted by CEM Weights		
	Treat.	Control	Normal. Diff.	Treat.	Control	Normal. Diff.
Coarsened age at s						
35-39	0.043	0.154	-0.378	0.044	0.044	0.000
40-44	0.120	0.211	-0.248	0.120	0.120	-0.000
45-48	0.166	0.183	-0.045	0.167	0.167	0.000
49-52	0.198	0.161	0.097	0.200	0.200	-0.000
53-55	0.145	0.103	0.126	0.144	0.144	0.000
56-58	0.139	0.088	0.160	0.138	0.138	0.000
59-60	0.098	0.052	0.176	0.097	0.097	-0.000
61-62	0.091	0.047	0.175	0.090	0.090	0.000
Highest level of schooling at s						
no high school	0.236	0.247	-0.026	0.237	0.237	-0.000
hs-w/wo trades cert	0.380	0.393	-0.027	0.382	0.382	0.000
postsec non-university	0.217	0.214	0.006	0.215	0.215	0.000
university degree	0.167	0.146	0.058	0.166	0.166	0.000
Visible minority						
not a visible minority	0.920	0.915	0.020	0.927	0.927	-0.000
Asian	0.054	0.056	-0.011	0.050	0.050	0.000
other	0.026	0.029	-0.018	0.023	0.023	-0.000
Province/territory at s						
Newfoundland	0.020	0.023	-0.022	0.019	0.019	-0.000
Prince of Edward Island	0.006	0.005	0.009	0.005	0.005	0.000
Nova Scotia	0.033	0.032	0.002	0.032	0.032	0.000
New Brunswick	0.025	0.026	-0.008	0.024	0.024	-0.000
Quebec	0.244	0.264	-0.047	0.247	0.247	-0.000
Ontario	0.375	0.350	0.052	0.379	0.379	0.000
Manitoba	0.040	0.040	0.000	0.039	0.039	0.000
Saskatchewan	0.034	0.036	-0.009	0.033	0.033	-0.000
Alberta	0.095	0.096	-0.004	0.094	0.094	-0.000
British Columbia	0.122	0.119	0.008	0.122	0.122	0.000
YK&NWT&NNV	0.006	0.008	-0.015	0.005	0.005	0.000
missing	0.001	0.001	-0.002	0.000	0.000	0.000
Not working at $s = -1$	0.165	0.153	0.033	0.164	0.164	0.000
Working at $s = -1$	0.835	0.847	-0.033	0.836	0.836	-0.000
Not working at $s = -2$	0.153	0.147	0.017	0.154	0.154	0.000
Working at $s = -2$	0.847	0.853	-0.017	0.846	0.846	-0.000
Quintiles of earnings at $s = -1$						
not working at $s = -1$	0.165	0.153	0.033	0.164	0.164	0.000
Quintile 1 (lowest)	0.163	0.169	-0.018	0.163	0.163	0.000
Quintile 2	0.158	0.169	-0.032	0.157	0.157	-0.000
Quintile 3	0.161	0.170	-0.023	0.161	0.161	-0.000
Quintile 4	0.167	0.169	-0.005	0.168	0.168	-0.000
Quintiles 5 (highest)	0.186	0.169	0.044	0.187	0.187	0.000
Quintiles of earnings at $s = -2$						
not working at $s = -2$	0.153	0.147	0.017	0.154	0.154	0.000
Quintile 1 (lowest)	0.161	0.171	-0.027	0.160	0.160	0.000
Quintile 2	0.162	0.171	-0.024	0.161	0.161	0.000
Quintile 3	0.163	0.171	-0.020	0.163	0.163	-0.000
Quintile 4	0.171	0.171	0.001	0.171	0.171	0.000
Quintile 5 (highest)	0.190	0.170	0.051	0.191	0.191	-0.000
Year at s (year of diagnosis)						
1992	0.038	0.046	-0.041	0.038	0.038	0.000
1993	0.038	0.048	-0.050	0.038	0.038	-0.000
1994	0.045	0.050	-0.023	0.045	0.045	0.000
1995	0.046	0.052	-0.028	0.045	0.045	0.000
1996	0.046	0.053	-0.032	0.046	0.046	0.000
1997	0.051	0.055	-0.016	0.051	0.051	0.000
1998	0.054	0.056	-0.009	0.054	0.054	0.000
1999	0.057	0.057	-0.003	0.057	0.057	0.000
2000	0.055	0.059	-0.018	0.055	0.055	0.000
2001	0.057	0.059	-0.005	0.057	0.057	0.000
2002	0.058	0.057	0.003	0.058	0.058	0.000

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Table 2 – continued from previous page

	Unweighted			Weighted by CEM Weights		
	Treat.	Control	Normal. Diff.	Treat.	Control	Normal. Diff.
2003	0.054	0.056	-0.009	0.054	0.054	0.000
2004	0.057	0.055	0.009	0.057	0.057	-0.000
2005	0.060	0.053	0.027	0.060	0.060	0.000
2006	0.061	0.052	0.040	0.061	0.061	-0.000
2007	0.058	0.050	0.036	0.058	0.058	0.000
2008	0.058	0.049	0.040	0.058	0.058	-0.000
2009	0.054	0.047	0.031	0.054	0.054	0.000
2010	0.053	0.045	0.037	0.053	0.053	0.000
Number of children at $s = -1$						
no children	0.460	0.367	0.190	0.462	0.462	0.000
1-2 children	0.461	0.506	-0.090	0.462	0.462	-0.000
3+ children	0.079	0.127	-0.159	0.076	0.076	0.000
missing						
Age of youngest child at $s = -1$						
no children	0.460	0.367	0.190	0.462	0.462	0.000
age 0-6	0.051	0.104	-0.198	0.051	0.047	0.018
age 7-17	0.253	0.340	-0.193	0.252	0.251	0.001
age 18+	0.237	0.189	0.116	0.236	0.240	-0.010
missing						
Number of children aged 0-17 at $s = -1$						
no child aged 0-17	0.697	0.556	0.293	0.697	0.702	-0.009
1 child	0.161	0.189	-0.075	0.160	0.155	0.014
2+ children	0.143	0.255	-0.283	0.142	0.143	-0.002
missing						
Union status: no	0.580	0.557	0.047	0.580	0.568	0.025
Union status: yes	0.420	0.443	-0.047	0.420	0.432	-0.025
Marital status: single	0.253	0.255	-0.005	0.253	0.262	-0.021
Marital status: couple	0.747	0.745	0.005	0.747	0.738	0.021
Marital status: missing						
Self-employed: no	0.882	0.883	-0.002	0.882	0.881	0.004
Self-employed: yes	0.117	0.116	0.002	0.116	0.118	-0.004
Self-employed: missing	0.001	0.001	0.002	0.001	0.001	-0.001
Age	51.594	47.835	0.535	51.560	51.490	0.011
Earnings at $s = -1$	30,375.206	29,199.190	0.039	30,480.581	30,346.579	0.004
Earnings at $s = -2$	30,699.945	29,000.532	0.058	30,735.548	30,517.149	0.007
Earnings at $s = -1$ if working	36,364.392	34,460.602	0.065	36,465.071	36,304.759	0.005
Earnings at $s = -2$ if working	36,261.280	34,016.111	0.078	36,319.047	36,060.973	0.009
Number of dependents at $s = -1$	0.933	1.201	-0.239	0.925	0.930	-0.005
Age of youngest dependent at $s = -1$	17.084	14.377	0.317	17.080	17.176	-0.011
Number of dependents aged 0-17 at $s = -1$	0.492	0.803	-0.317	0.490	0.488	0.003
Observations	21,093	12,679,022		20,711	3,654,413	

Table 3: Regression Results for Employment: Prostate Cancer, Time-Invariant Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 49 to 58	All Ages	Age 49 to 58	All Ages	Age 49 to 58
Treat x Post	-0.0503***	-0.0628***	-0.0315***	-0.0341***	-0.0242***	-0.0264***
	(0.0126)	(0.0160)	(0.0058)	(0.0071)	(0.0040)	(0.0048)
Treat x Post x Innovation	0.0016**	0.0021**	0.0042**	0.0039*	0.0001**	0.0001ˆ
	(0.0006)	(0.0007)	(0.0014)	(0.0017)	(0.0000)	(0.0001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,850,758	16,347,520	25,850,758	16,347,520	25,850,758	16,347,520

Table 4: Regression Results for Employment: Prostate Cancer, Time-Varying Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 49 to 58	All Ages	Age 49 to 58	All Ages	Age 49 to 58
Treat x P^{-5}	0.0057	-0.0187	0.0048	-0.0050	0.0046	-0.0005
	(0.0161)	(0.0186)	(0.0070)	(0.0079)	(0.0047)	(0.0053)
Treat x P^{-4}	0.0015	0.0040	0.0034	0.0051	0.0034	0.0060
	(0.0145)	(0.0166)	(0.0065)	(0.0073)	(0.0044)	(0.0050)
Treat x P^{-3}	0.0074	0.0152	0.0055	0.0119^	0.0035	0.0092*
	(0.0126)	(0.0153)	(0.0058)	(0.0067)	(0.0039)	(0.0045)
Treat x P^{-2}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0110)	(0.0131)	(0.0050)	(0.0058)	(0.0034)	(0.0039)
Treat x P^{-1}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0}	-0.0173	-0.0026	-0.0135*	-0.0055	-0.0112**	-0.0060
	(0.0117)	(0.0149)	(0.0054)	(0.0066)	(0.0036)	(0.0043)
Treat x P^{1}	-0.0331*	-0.0617**	-0.0248***	-0.0340***	-0.0207***	-0.0258***
	(0.0147)	(0.0189)	(0.0068)	(0.0083)	(0.0046)	(0.0055)
Treat x P^{2}	-0.0572***	-0.0770***	-0.0337***	-0.0375***	-0.0255***	-0.0275***
	(0.0168)	(0.0218)	(0.0076)	(0.0096)	(0.0051)	(0.0063)
Treat x P^{3}	-0.0640***	-0.0769**	-0.0364***	-0.0386***	-0.0272***	-0.0286***
	(0.0184)	(0.0238)	(0.0084)	(0.0105)	(0.0056)	(0.0069)
Treat x P^{4}	-0.0614**	-0.0674*	-0.0340***	-0.0340**	-0.0250***	-0.0249**
	(0.0205)	(0.0262)	(0.0095)	(0.0118)	(0.0064)	(0.0077)
Treat x P^{5}	-0.0773***	-0.1124***	-0.0440***	-0.0540***	-0.0304***	-0.0358***
	(0.0222)	(0.0294)	(0.0108)	(0.0139)	(0.0073)	(0.0091)
Treat x P^{-5} x Innovation	-0.0001	0.0011	-0.0005	0.0022	0.0000	0.0001
	(0.0007)	(0.0009)	(0.0016)	(0.0018)	(0.0000)	(0.0001)
Treat x P^{-4} x Innovation	0.0000	0.0001	-0.0004	0.0003	0.0000	0.0000
	(0.0007)	(0.0008)	(0.0015)	(0.0017)	(0.0000)	(0.0000)
Treat x P^{-3} x Innovation	-0.0004	-0.0005	-0.0016	-0.0019	-0.0001	-0.0001
	(0.0006)	(0.0007)	(0.0014)	(0.0015)	(0.0000)	(0.0000)
Treat x P^{-2} x Innovation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0005)	(0.0006)	(0.0012)	(0.0013)	(0.0000)	(0.0000)
Treat x P^{-1} x Innovation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0} x Innovation	0.0004	-0.0002	0.0014	-0.0002	0.0000	0.0000
	(0.0005)	(0.0007)	(0.0013)	(0.0016)	(0.0000)	(0.0000)
Treat x P^{1} x Innovation	0.0009	0.0022*	0.0027^	0.0049*	0.0001^	0.0001*
	(0.0007)	(0.0009)	(0.0016)	(0.0020)	(0.0000)	(0.0001)
Treat x P^{2} x Innovation	0.0019*	0.0027**	0.0042*	0.0046*	0.0001^	0.0001
	(0.0008)	(0.0010)	(0.0018)	(0.0023)	(0.0001)	(0.0001)
Treat x P^{3} x Innovation	0.0022*	0.0026*	0.0049*	0.0044^	0.0001*	0.0001
	(0.0009)	(0.0011)	(0.0020)	(0.0025)	(0.0001)	(0.0001)
Treat x P^{4} x Innovation	0.0022*	0.0024*	0.0049*	0.0047	0.0001^	0.0001
	(0.0010)	(0.0012)	(0.0024)	(0.0030)	(0.0001)	(0.0001)
Treat x P^{5} x Innovation	0.0030**	0.0044**	0.0081**	0.0095*	0.0002*	0.0002^
	(0.0011)	(0.0014)	(0.0030)	(0.0039)	(0.0001)	(0.0001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,850,758	16,347,520	25,850,758	16,347,520	25,850,758	16,347,520
F-Test p-Value	0.0782	0.0195	0.0906	0.0853	0.2289	0.1919

Table 5: Regression Results for Annual Earnings: Prostate Cancer, Time-Invariant Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 49 to 58	All Ages	Age 49 to 58	All Ages	Age 49 to 58
Treat x Post	-5995.225***	-6941.488**	-4392.202***	-5060.447***	-3711.225***	-4344.948***
	(1,625.134)	(2,300.659)	(796.439)	(1,138.301)	(552.114)	(775.172)
Treat x Post x Innovation	149.622^	164.554	415.134^	425.712	12.215^	12.415
	(80.112)	(113.348)	(213.335)	(309.343)	(6.962)	(10.157)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,850,758	16,347,520	25,850,758	16,347,520	25,850,758	16,347,520

Table 6: Regression Results for Annual Earnings: Prostate Cancer, Time-Varying Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 49 to 58	All Ages	Age 49 to 58	All Ages	Age 49 to 58
Treat x P^{-5}	636.934	2937.854	1274.620	2109.986ˆ	1489.307*	1779.377*
	(2,098.379)	(2,719.923)	(965.009)	(1,232.912)	(673.516)	(830.795)
Treat x P^{-4}	-1430.480	1943.449	-85.104	1259.554	393.503	1033.370
	(1,840.188)	(2,596.324)	(904.820)	(1,193.428)	(621.755)	(795.095)
Treat x P^{-3}	294.178	2636.436	499.554	1427.394	514.357	1013.056
	(1,486.300)	(2,011.775)	(776.914)	(1,007.788)	(551.385)	(721.118)
Treat x P^{-2}	-766.793	354.474	-564.086	-48.486	-366.970	-107.346
	(1,131.282)	(1,685.897)	(586.313)	(834.521)	(405.503)	(589.521)
Treat x P^{-1}	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0}	-4729.146***	-3365.378*	-3945.460***	-3814.286***	-3295.546***	-3615.853***
	(1,410.319)	(1,561.949)	(702.021)	(797.520)	(473.615)	(561.121)
Treat x P^{1}	-5812.027***	-5200.732*	-4524.648***	-4909.070***	-3858.400***	-4532.947***
	(1,755.854)	(2,516.190)	(875.474)	(1,241.518)	(592.032)	(815.859)
Treat x P^{2}	-6316.832**	-5712.031*	-4318.572***	-3719.057**	-3508.505***	-3309.425***
	(1,930.080)	(2,775.861)	(975.898)	(1,372.600)	(674.118)	(920.458)
Treat x P^{3}	-6638.457**	-4890.316	-3906.108***	-3721.879*	-2955.453***	-3259.056**
	(2,161.982)	(3,163.846)	(1,088.832)	(1,555.627)	(748.577)	(1,021.549)
Treat x P^{4}	-7718.145***	-7560.266*	-4759.652***	-5036.517**	-3563.601***	-4008.709***
	(2,159.825)	(3,260.695)	(1,127.090)	(1,617.153)	(786.417)	(1,090.744)
Treat x P^{5}	-8998.762***	-9585.702**	-5031.791***	-5846.855**	-3503.287***	-4368.901***
	(2,454.218)	(3,539.502)	(1,300.016)	(1,905.572)	(913.633)	(1,322.313)
Treat x P^{-5} x Innovation	40.949	-76.870	51.606	-216.211	-0.804	-6.998
	(102.247)	(135.053)	(248.090)	(340.695)	(7.810)	(10.823)
Treat x P^{-4} x Innovation	109.348	-53.326	249.204	-117.152	6.071	-3.008
	(91.062)	(129.704)	(245.058)	(337.898)	(7.952)	(10.830)
Treat x P^{-3} x Innovation	3.931	-102.814	-36.779	-252.841	-2.283	-7.448
	(73.927)	(99.823)	(206.668)	(261.152)	(6.773)	(8.196)
Treat x P^{-2} x Innovation	33.877	-24.236	139.463	-25.905	4.560	-0.503
	(59.556)	(87.644)	(177.606)	(241.311)	(6.019)	(7.800)
Treat x P^{-1} x Innovation	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0} x Innovation	121.160ˆ	14.948	481.690*	215.161	16.252*	8.769
	(69.714)	(79.856)	(194.064)	(222.758)	(6.416)	(7.216)
Treat x P^{1} x Innovation	141.232ˆ	72.195	452.521*	336.610	14.370ˆ	12.686
	(84.588)	(125.152)	(229.281)	(354.858)	(7.429)	(11.719)
Treat x P^{2} x Innovation	174.304ˆ	121.005	439.805ˆ	135.681	11.360	1.065
	(93.450)	(136.296)	(250.678)	(372.771)	(8.018)	(11.957)
Treat x P^{3} x Innovation	217.500*	99.748	480.320ˆ	247.339	11.381	6.431
	(106.095)	(158.154)	(290.370)	(447.040)	(9.465)	(14.690)
Treat x P^{4} x Innovation	261.542*	230.716	687.185*	645.436	19.151ˆ	20.243
	(105.988)	(161.490)	(303.598)	(456.794)	(10.463)	(15.623)
Treat x P^{5} x Innovation	341.232**	341.880ˆ	885.315*	991.388ˆ	25.310ˆ	34.623
	(121.581)	(176.262)	(377.626)	(572.998)	(15.227)	(23.921)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,850,758	16,347,520	25,850,758	16,347,520	25,850,758	16,347,520
F-Test p-Value	0.1573	0.4674	0.2164	0.5367	0.3468	0.5109

Table 7: Regression Results for Employment: Breast Cancer, Time-Invariant Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 35 to 44	All Ages	Age 35 to 44	All Ages	Age 35 to 44
Treat x Post	-0.0410***	-0.0622***	-0.0400***	-0.0469***	-0.0397***	-0.0439***
	(0.0071)	(0.0143)	(0.0043)	(0.0081)	(0.0037)	(0.0070)
Treat x Post x Innovation	0.0001	0.0015*	0.0001	0.0020*	0.0000	0.0002*
	(0.0003)	(0.0007)	(0.0004)	(0.0010)	(0.0000)	(0.0001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,024,493	10,513,451	39,024,493	10,513,451	39,024,493	10,513,451

Table 8: Regression Results for Employment: Breast Cancer, Time-Varying Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 35 to 44	All Ages	Age 35 to 44	All Ages	Age 35 to 44
Treat x P^{-5}	-0.0061	0.0431^	-0.0032	0.0245^	-0.0025	0.0198^
	(0.0090)	(0.0236)	(0.0054)	(0.0131)	(0.0047)	(0.0113)
Treat x P^{-4}	0.0019	0.0298	0.0023	0.0176	0.0026	0.0151
	(0.0081)	(0.0214)	(0.0049)	(0.0122)	(0.0043)	(0.0105)
Treat x P^{-3}	0.0070	0.0291	0.0037	0.0166	0.0030	0.0141
	(0.0071)	(0.0187)	(0.0043)	(0.0106)	(0.0037)	(0.0092)
Treat x P^{-2}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0061)	(0.0160)	(0.0037)	(0.0092)	(0.0032)	(0.0080)
Treat x P^{-1}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0}	-0.0087	-0.0003	-0.0117**	-0.0081	-0.0122***	-0.0098
	(0.0064)	(0.0174)	(0.0039)	(0.0098)	(0.0034)	(0.0084)
Treat x P^{1}	-0.0357***	-0.0208	-0.0398***	-0.0248*	-0.0407***	-0.0254*
	(0.0084)	(0.0206)	(0.0050)	(0.0115)	(0.0044)	(0.0099)
Treat x P^{2}	-0.0465***	-0.0404^	-0.0440***	-0.0341**	-0.0432***	-0.0327**
	(0.0093)	(0.0215)	(0.0056)	(0.0122)	(0.0048)	(0.0106)
Treat x P^{3}	-0.0499***	-0.0653**	-0.0470***	-0.0474***	-0.0461***	-0.0446***
	(0.0101)	(0.0226)	(0.0061)	(0.0130)	(0.0053)	(0.0113)
Treat x P^{4}	-0.0691***	-0.0914***	-0.0595***	-0.0632***	-0.0577***	-0.0589***
	(0.0112)	(0.0230)	(0.0068)	(0.0134)	(0.0059)	(0.0117)
Treat x P^{5}	-0.0495***	-0.0677**	-0.0472***	-0.0538***	-0.0462***	-0.0516***
	(0.0124)	(0.0248)	(0.0074)	(0.0142)	(0.0065)	(0.0124)
Treat x P^{-5} x Innovation	0.0003	-0.0018	0.0004	-0.0023	0.0000	-0.0002
	(0.0004)	(0.0011)	(0.0005)	(0.0015)	(0.0001)	(0.0002)
Treat x P^{-4} x Innovation	0.0001	-0.0012	0.0001	-0.0016	0.0000	-0.0002
	(0.0003)	(0.0010)	(0.0004)	(0.0014)	(0.0000)	(0.0002)
Treat x P^{-3} x Innovation	-0.0003	-0.0012	-0.0003	-0.0017	0.0000	-0.0002
	(0.0003)	(0.0009)	(0.0004)	(0.0013)	(0.0000)	(0.0002)
Treat x P^{-2} x Innovation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0003)	(0.0008)	(0.0003)	(0.0011)	(0.0000)	(0.0001)
Treat x P^{-1} x Innovation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0} x Innovation	-0.0002	-0.0007	-0.0002	-0.0009	0.0000	-0.0001
	(0.0003)	(0.0008)	(0.0004)	(0.0012)	(0.0000)	(0.0001)
Treat x P^{1} x Innovation	-0.0004	-0.0006	-0.0005	-0.0010	-0.0001	-0.0001
	(0.0004)	(0.0010)	(0.0005)	(0.0014)	(0.0001)	(0.0002)
Treat x P^{2} x Innovation	0.0002	0.0005	0.0003	0.0006	0.0000	0.0001
	(0.0004)	(0.0010)	(0.0005)	(0.0015)	(0.0001)	(0.0002)
Treat x P^{3} x Innovation	0.0003	0.0018^	0.0003	0.0025	0.0000	0.0003^
	(0.0004)	(0.0011)	(0.0006)	(0.0015)	(0.0001)	(0.0002)
Treat x P^{4} x Innovation	0.0010*	0.0029**	0.0015*	0.0042**	0.0002*	0.0005**
	(0.0005)	(0.0011)	(0.0006)	(0.0015)	(0.0001)	(0.0002)
Treat x P^{5} x Innovation	0.0003	0.0015	0.0004	0.0021	0.0000	0.0003
	(0.0005)	(0.0012)	(0.0008)	(0.0017)	(0.0001)	(0.0002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,024,493	10,513,451	39,024,493	10,513,451	39,024,493	10,513,451
F-Test p-Value	0.0237	0.0210	0.0164	0.0154	0.0118	0.0090

Table 9: Regression Results for Annual Earnings: Breast Cancer, Time-Invariant Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 35 to 44	All Ages	Age 35 to 44	All Ages	Age 35 to 44
Treat x Post	-3144.773***	-2738.098**	-3665.144***	-3908.863***	-3766.060***	-4074.250***
	(436.087)	(1,017.763)	(258.260)	(546.207)	(224.690)	(467.925)
Treat x Post x Innovation	-49.017**	-119.357*	-62.741*	-165.692*	-7.239*	-21.316*
	(18.968)	(52.189)	(24.900)	(72.267)	(2.847)	(8.718)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,024,493	10,513,451	39,024,493	10,513,451	39,024,493	10,513,451

Table 10: Regression Results for Annual Earnings: Breast Cancer, Time-Varying Treatment Effects

	Drugs		Publications		Patents	
	All Ages	Age 35 to 44	All Ages	Age 35 to 44	All Ages	Age 35 to 44
Treat x P^{-5}	281.053	-632.401	380.714	-144.616	421.182	-36.994
	(521.773)	(1,379.006)	(304.293)	(731.533)	(261.440)	(616.516)
Treat x P^{-4}	455.654	-262.478	440.780ˆ	-127.518	445.823ˆ	-87.782
	(448.622)	(1,188.017)	(264.169)	(627.689)	(228.179)	(530.149)
Treat x P^{-3}	444.059	393.108	400.642ˆ	210.547	399.604*	145.291
	(358.701)	(922.372)	(210.816)	(489.246)	(183.695)	(416.805)
Treat x P^{-2}	24.078	-423.243	67.645	-216.856	78.730	-194.626
	(275.760)	(709.591)	(160.100)	(385.642)	(139.416)	(330.557)
Treat x P^{-1}	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0}	-1929.392***	-1566.464ˆ	-2642.586***	-2807.795***	-2804.210***	-3026.009***
	(306.751)	(818.425)	(177.197)	(433.208)	(153.572)	(367.708)
Treat x P^{1}	-3143.301***	-3282.754**	-4483.028***	-5665.789***	-4785.048***	-6098.705***
	(430.065)	(1,159.250)	(252.943)	(615.800)	(220.296)	(524.858)
Treat x P^{2}	-3251.575***	-2912.467*	-3544.557***	-3767.944***	-3584.992***	-3858.052***
	(485.813)	(1,217.787)	(287.656)	(676.370)	(249.919)	(584.980)
Treat x P^{3}	-3752.478***	-3748.013**	-3742.191***	-4093.919***	-3717.060***	-4110.859***
	(550.788)	(1,337.254)	(324.583)	(742.651)	(281.747)	(644.000)
Treat x P^{4}	-3586.275***	-3142.197*	-3566.442***	-3708.064***	-3516.023***	-3754.336***
	(638.192)	(1,481.633)	(375.437)	(823.801)	(328.348)	(715.678)
Treat x P^{5}	-3307.464***	-3397.247*	-3336.287***	-3985.999***	-3288.357***	-4007.128***
	(721.818)	(1,679.553)	(426.490)	(936.774)	(374.917)	(814.986)
Treat x P^{-5} x Innovation	5.397	43.711	2.768	53.535	-0.164	5.904
	(22.385)	(69.662)	(29.047)	(97.089)	(3.293)	(11.788)
Treat x P^{-4} x Innovation	-2.295	23.101	-3.880	45.102	-0.598	5.967
	(19.436)	(61.575)	(25.448)	(86.353)	(2.899)	(10.506)
Treat x P^{-3} x Innovation	-7.963	-18.214	-14.611	-24.686	-2.020	-2.271
	(15.973)	(48.782)	(21.110)	(69.533)	(2.426)	(8.552)
Treat x P^{-2} x Innovation	2.697	18.866	1.819	23.015	0.086	2.974
	(12.579)	(36.974)	(16.606)	(53.076)	(1.909)	(6.559)
Treat x P^{-1} x Innovation	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Treat x P^{0} x Innovation	-65.857***	-130.804**	-82.473***	-187.386**	-9.046***	-23.391**
	(13.868)	(43.135)	(18.163)	(60.038)	(2.079)	(7.227)
Treat x P^{1} x Innovation	-127.262***	-242.403***	-163.563***	-335.026***	-18.225***	-40.878***
	(19.150)	(60.722)	(25.285)	(84.819)	(2.907)	(10.308)
Treat x P^{2} x Innovation	-27.625	-80.489	-35.293	-101.767	-4.301	-13.323
	(21.178)	(61.023)	(27.877)	(85.699)	(3.191)	(10.440)
Treat x P^{3} x Innovation	3.331	-33.941	6.919	-45.121	0.597	-6.373
	(24.098)	(66.782)	(31.670)	(94.086)	(3.623)	(11.509)
Treat x P^{4} x Innovation	1.730	-51.910	2.330	-63.778	-0.422	-8.504
	(28.540)	(73.951)	(38.623)	(104.281)	(4.581)	(12.809)
Treat x P^{5} x Innovation	-6.699	-61.359	-13.370	-87.160	-2.697	-12.599
	(32.907)	(85.069)	(46.180)	(122.556)	(5.647)	(15.288)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,024,493	10,513,451	39,024,493	10,513,451	39,024,493	10,513,451
F-Test p-Value	0.0000	0.0021	0.0000	0.0021	0.0000	0.0022