Productivity Benefits of Medical Care: Evidence from US-Based Randomized Clinical Trials

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A B S T R A C T

Background: One of the key recommendations of the Second Panel on Cost-Effectiveness in Health and Medicine is to take a societal perspective when evaluating new technologies—including measuring the productivity benefits of new treatments. Yet relatively little is known about the impact that new treatments have on labor productivity. **Objectives:** To examine the relationship between new drug treatments and gains in labor productivity across conditions in the United States and to evaluate which randomized clinical trials (RCTs) collected labor productivity data. **Methods:** We collected data on US-based RCTs with work-ability surveys from searches of Google Scholar, PubMed, Scopus, the Cochrane Central Registry of Clinical Trials, and Clinical-Trails.gov. Combining RCT data with survey data from the Medical Expenditure Panel Survey, we assessed productivity changes from new drug treatments. **Results:** During the last decade, some disease conditions have seen treatments that improve ability to work by as much as 60%. The annual increase in productivity gains attributable to new drug treatments was modest 1.1% (P = 0.53). Of the 5092 RCTs reviewed, ability-to-work measures were collected in 2% of trials. Work productivity surveys were more likely among prevalent medical conditions that affected individuals who worked, earned higher wages, and experienced larger reductions in hours worked as a consequence of disease diagnosis. **Conclusions:** From our data, we estimated that drug innovation increased productivity by 5.5 million work days per year and $233 billion in wages per year. These labor-sector benefits should be taken into account when assessing the socially optimal cost for new drug innovation.

Keywords: drug value, labor productivity, randomized clinical trials, work ability.

Introduction

One of the key recommendations of the Second Panel on Cost-Effectiveness in Health and Medicine is to take a societal perspective when evaluating new technologies [1]. When considering the resource costs associated with the use of health care interventions, one should account for societal benefits from increased productivity, a dimension that is not traditionally captured by preference-based or health-based measures. This societal perspective is important given that medical innovation is a global public good, and efficiently managing resource both across and within countries relies on a complete understanding of the health and nonhealth welfare impacts.

In the United States, non-health considerations are particularly salient because most Americans obtain their health insurance through their employers. In 2015, employers covered, on average, 72% to 83% of average annual premiums, which totaled $6,251 for single coverage and $17,545 for family coverage [2]. Despite the significant subsidies that employers provide, little is known about the impact that medical treatments have on labor productivity. This issue is particularly relevant for employees, who often take prescription drugs for primary or secondary prevention, with the goal of maintaining good function.

US-based estimates of the productivity losses as a result of poor health are large. In 2003, 885 million days were lost because of own or family-related illnesses that prevented employees from concentrating at work or coming into work [3]. An additional 18 million adults aged 19 to 64 years remained unemployed because of health reasons. Both workers and firms bear the burden of these health costs: Individuals experience the impaired or lost ability to work, and firms face the costs of rehiring and retraining replaced workers, which can include higher wages, lost revenues, and idle assets [4,5]. Estimates of health-related productivity losses sum to around $226 to $260 billion every year [3,6,7].

Although the burden is large, it is less clear whether new treatments can alleviate it. Gains in labor productivity are often overlooked when assessing returns to medical innovation. Cost-effectiveness studies, especially those on pharmaceuticals, have focused on gains in short-term and long-term survival, quality of life, disease progression, consumer surplus, and total health

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spending [8–13]. The few studies that do consider labor productivity gains tend to focus on particular conditions; for example, Thirumurthy et al. [14] focused on antiretroviral medication, Berndt et al. [15,16] and Timbie et al. [17] considered mental health medications, and Garthwaite [18] examined antiarthritic medication. Overall, we lack clear, unified evidence on the extent to which medical innovations have improved on-the-job productivity or reduced employee absences [19].

In this study, we systematically identified the relationship between new drug treatments and labor productivity across several disease groups. Using evidence from randomized clinical trials (RCTs), we assessed when ability-to-work measures were collected and determined how those measures have changed over time.

Methods

Data Sources

Our main data source was a systematic collection of work productivity data from RCTs. Following the literature, we identified 26 instruments that measured the effects of ill-health on productivity because of absence from work or reduced performance while at work (see Appendix Table 1 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2018.01.009). Twenty of the listed surveys have been identified in independent, systematic reviews on health-related productivity loss [3,20]. Six additional surveys, which have been extensively validated among specific disease groups, included the Life Functioning Questionnaire for psychiatric illness; Occupational Role Questionnaire and Quality and Quantity Method in Productivity for back pain; Work Productivity Survey for rheumatoid arthritis; and Work Role Functioning Questionnaire and Workstyle Scale for pain at work [21–24].

Using each of these instruments as search terms, we conducted a search through Google Scholar (additionally including "randomized trial" in the search term), PubMed (focusing exclusively on "clinical trial" article types), Scopus (additionally including "randomized trial" in the abstracts), the Cochrane Central Registry of Clinical Trials, and ClinicalTrials.gov. Our inclusion criteria were RCTs among adults in the United States between 2000 and 2015 that included measures of work impairment, productivity, presentism, or absenteeism from one of the identified survey instruments. We further restricted included studies to those with either pretrial ability-to-work baseline measures or changes in ability to work reported as a percent change.

The last inclusion criterion was important because work productivity surveys use differing scale ranges and directions to measure labor productivity; for example, the Endicott Work Productivity Scale assigns overall scores out of 100, whereas the Work Limitations Questionnaire index ranges from 0 to 28.6. The Work Productivity and Activity Impairment Questionnaire scores have higher numbers corresponding to worsening productivity, whereas the Short-Form Health and Labor Questionnaire defines higher values as corresponding to improvements in productivity. By calculating percent changes where positive values reflect improvements in work productivity, we took into account the coding idiosyncrasies across surveys. Each survey measured productivity from the same basic definitions of perceived impairment, comparative efficiency, unproductive time while at work, and absences from work [3]. The overall improvement attributable to a new drug treatment was then calculated as the difference in percent change between the control and treatment groups. To reduce bias, two researchers independently collected the final data that were analyzed (see Appendix Fig. 1 in

Supplemental Materials found at https://doi.org/10.1016/j.jval.2018.01.009).

Next, to identify when labor productivity surveys were administered, we relied on a broader search of both published and unpublished trials from ClinicalTrials.gov (see Appendix Fig. 2 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2018.01.009). The website, established by the Food and Drug Administration Modernization Act of 1997 and made public in 2000, contains a registry of clinical trials for both federally and privately funded trials conducted under investigational new drug applications from 2000 onward. We again focused on US-based, completed drug-related clinical trials in phase 3 or 4 with randomized interventions between 2000 and 2015, with treatment listed as the primary purpose, and with adults being treated. Data variables included drug name, disease condition, trial funding source, enrollment size, sex distribution, and type of randomization (e.g., single or double blind). We constructed an indicator equal to one if the RCT administered a work productivity survey, defined as including any of the 26 work instruments or the term "work productivity" in the trial entry. We also used the "condition" variable to sort the RCTs into one of 14 disease groups: infectious and parasitic diseases, neoplasms, metabolic diseases, diseases of blood organs and the circulatory system, mental disorders, diseases of the nervous system, diseases of the sense organs, diseases of the respiratory system, diseases of the digestive system, diseases of the genitourinary system, complications of pregnancy, diseases of the skin, diseases of the musculoskeletal system, and injuries (see Appendix Table 2 in Supplemental Materials found at https://doi.org/10.1016/j.jval.2018.01.009).

Finally, we used survey data from the Medical Expenditure Panel Survey (MEPS). The MEPS data from 2000 to 2015 are nationally representative and the most complete source of data on the cost and use of health care. Importantly, the MEPS provides information on a respondent's work, including employment status and self-reported wages, which we converted to 2015 dollars using the Consumer Price Index. It also offers details regarding any office, inpatient, outpatient, or emergency room visit that the respondent had within the year and the International Classification of Diseases (ICD)-9 diagnosis code associated with each visit. We limited this sample to adults aged 18 to 64 years and used the ICD-9 codes to group individuals into the 14 aforementioned disease groups (Appendix Table 2). For each disease group, we calculated the prevalence of disease, propensity to work conditional on having a disease, and average wage conditional on having a disease and working. Using the 2-year panel design of the MEPS survey, we also calculated the annual per-person change in hours worked among those who newly received a diagnosis of a disease (i.e., individuals who did not have the disease diagnosis in the first year and received it the following year). The change in hours worked served as a proxy for diseases where the potential gain in labor productivity is high.

Statistical Analyses

We relied on two types of regression models: linear and logit. Our main analysis of labor productivity gains used a linear regression to estimate the trajectory of productivity improvements over time. Next, we considered whether the collection of work productivity information in RCTs was biased. We focused on two sets of potential predictors: RCT-specific and disease-group characteristics. When assessing the predictive power of RCT-specific characteristics, we estimated logit regression models. The logit models included disease group fixed effects to account for variation in disease-specific drug development and year fixed effects to control for trends in work productivity over time. Using variation within disease groups over time, we determined