The impact of biopharmaceutical innovation on disability, Social Security recipiency, and use of medical care of U.S. community residents, 1998-2015

Frank R. Lichtenberg

frank.lichtenberg@columbia.edu

Columbia University,
National Bureau of Economic Research, and CESifo

21 October 2021

The research reported herein was performed pursuant to grant RDR18000003 from the US Social Security Administration (SSA) funded as part of the Retirement and Disability Research Consortium. The opinions and conclusions expressed are solely those of the author and do not represent the opinions or policy of SSA, any agency of the Federal Government, or NBER. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof.

The impact of biopharmaceutical innovation on disability, Social Security recipiency, and use of medical care of U.S. community residents, 1998-2015

Abstract

88% of privately-funded U.S. funding for biomedical research came from pharmaceutical and biotechnology firms. This study analyzes the overall impact that biopharmaceutical innovation had on disability, Social Security recipiency, and the use of medical services of U.S. community residents during the period 1998-2015. Most of the data come from the Medical Expenditure Panel Survey.

The effect of biopharmaceutical innovation is identified by differences across over 200 medical conditions in the growth in the lagged number of drug classes ever approved. The FDA believes that 70% of first-in-class drugs offer a "significant improvement" compared with products already on the market.

The estimates indicate that the probability of disability, Social Security recipiency, and medical care utilization is inversely related to the number of drug classes previously approved. The length of the estimated lag is generally 6-9 years, which is not surprising, due to the gradual diffusion of new drug classes. The effect of biopharmaceutical innovation related to a medical condition on the overall health of a person with that condition depends on the number of (other) medical conditions a person has: the smaller the number of conditions, the larger the effect.

Previous innovation is estimated to have reduced: the number of people who were completely unable to work at a job, do housework, or go to school in 2015 by 4.5%; the number of people with cognitive limitations by 3.2%; the number of people receiving SSI in 2015 by 247 thousand (3.1%); and the number of people receiving Social Security by 984 thousand (2.0%). Previous innovation is also estimated to have caused reductions in home health visits (9.2%), inpatient events (5.7%), missed school days (5.1%), and outpatient events (4.1%).

We estimate the value in 2015 of some of the reductions in disability, Social Security recipiency, and use of medical care attributable to previous biopharmaceutical innovation. This value ($115 billion) is fairly close to 2015 expenditure on drug classes that were first approved by the FDA during 1989-2006 ($127 billion). However, for a number of reasons, the costs are likely to be lower, and the benefits are likely to be larger, than these figures.

I. Introduction

Numerous studies have shown that the use of certain drugs can reduce disability. For example, etanercept (approved by the FDA in 1998) was shown to reduce brain inflammation and neurological disabilities in stroke victims.[1] Long-term treatment with siponimod (approved by the FDA in 2019) reduced the risk of disability progression of patients with secondary progressive multiple sclerosis.[2] And people taking new migraine medications experienced about 50% fewer migraine headache days per month, compared with people who weren't taking them.[3]

In this study, we will attempt to determine the *overall* impact that pharmaceutical innovation had on disability, Social Security recipiency[1], and the use of medical services of U.S. community residents[2] during the period 1998-2015. A previous study[6] examined the impact of access to prescription drugs on disability in 11 European countries, and showed that, in general, the larger the number of drugs for a disease that were launched during 1982-2015 in a country, the lower the average disability in 2015 of patients with that disease in that country, controlling for the average level of disability in each country and from each disease, and the number of patients with the disease and their mean age. The present study will build upon and extend this line of research: it will be based on a completely different research design and data, and examine different (and a larger number of) outcome measures.

Key differences between the previous study and current study are summarized in Table 1. Both studies use 2-way fixed effects designs, but the previous study analyzed disability by medical condition and country in a single year (2015), while the current study analyzes disability by medical condition and year in a single country (the USA). In the previous study, the measure of pharmaceutical innovation was the number of drugs (WHO ATC5 chemical substances) previously launched; in the current study, the measure of pharmaceutical innovation is the number of drug

---

[1] People with disabilities may be eligible to receive two types of Social Security benefits: Supplemental Security Income (SSI) and Old Age and Survivors Disability Income (OASDI). SSI is a Federal income supplement program funded by general tax revenues (not Social Security taxes). It is designed to help aged, blind, and disabled people, who have little or no income. It provides cash to meet basic needs for food, clothing, and shelter. Based on their analysis of the 2001 OASDI Public Use Microdata File, Pizer et al[4] found that 80% of people ages 25–61 with OASDI receive it because of disability.

[2] A previous study[5] examined the effect of pharmaceutical innovation on the functional limitations of nursing home residents.

"classes" (WHO ATC4 chemical subgroups) previously launched.[3] In the previous study, estimates were obtained from aggregate data; in the current study, estimates will be obtained from individual-level data. The previous study sample only included people age 50 and over; the current study sample includes people of all ages.[4] The sample size of the current study is about 26 times larger. The previous study sample included about 46 thousand people, and up to 31 medical conditions were identified, so there were about 62 thousand person-conditions. The current study sample includes about 376 thousand people, and up to 216 medical conditions are identified, so there are about 1.65 million person-conditions. The previous study analyzed a small number of person-level disability measures, and did not allow the effect of innovation for a condition on a person's disability to depend on how many conditions the person had. The current study will analyze a larger number of person-level disability measures, and will allow the effect of innovation for a condition on a person's disability to depend on how many conditions the person had. The current study will also analyze several condition-specific disability and healthcare utilization measures.

The research design of the current study is depicted in Figure 1. As shown there, the models we estimate will include medical condition and year fixed effects, so the effect of biopharmaceutical innovation will be identified by differences across medical conditions in the *growth* in the lagged number of drug classes ever approved. The heterogeneity of biopharmaceutical innovation is illustrated by Figure 2, which shows the number of WHO ATC4 chemical subgroups ever FDA-approved for 12 diseases during the period 1995-2015. The same number (13) of chemical subgroups had ever been approved for all 12 diseases by 1995. During the next 20 years, 10 new

---

[3] In the ATC classification system, the active substances are classified in a hierarchy with five different levels. The system has fourteen main anatomical/pharmacological groups or 1st levels. Each ATC main group is divided into 2nd levels which could be either pharmacological or therapeutic groups. The 3rd and 4th levels are chemical, pharmacological or therapeutic subgroups and the 5th level is the chemical substance. The 2nd, 3rd and 4th levels are often used to identify pharmacological subgroups when that is considered more appropriate than therapeutic or chemical subgroups. The complete classification of metformin illustrates the structure of the code:

A	Alimentary tract and metabolism (1st level, anatomical main group)
A10	Drugs used in diabetes (2nd level, therapeutic subgroup)
A10B	Blood glucose lowering drugs, excl. insulins (3rd level, pharmacological subgroup)
A10BA	Biguanides (4th level, chemical subgroup)
A10BA02	Metformin (5th level, chemical substance)

Thus, in the ATC system all plain metformin preparations (including extended-release preparations) are given the code A10BA02. A medicinal substance can be given more than one ATC code if it is available in two or more strengths or routes of administration with clearly different therapeutic uses. For example, prednisolone in single ingredient products is given seven ATC codes due to different therapeutic use and different formulations.[7] The complete ATC classification system can be viewed on Wikipedia[8].

[4] The mean ages of people in the previous study and current study are 68 and 35, respectively.

chemical subgroups used to treat diabetes mellitus without complications were approved, 5 new chemical subgroups used to treat chronic kidney disease were approved, and no new chemical subgroups used to treat menstrual disorders were approved.

In the next section, we will describe the econometric model we will estimate. Data sources and descriptive statistics will be discussed in section III. Empirical results will be presented in section IV. Key implications of the estimates will be discussed in section V. The final section provides a summary and conclusions.

II. Econometric model

To determine the impact that pharmaceutical innovation had on disability and the use of medical services by Americans during the period 1998-2015, we will estimate the following probit model:

$$\text{Prob}(Y_{ictae}=1) = \Phi[\beta_k \ln(CUM\_CLASS_{c,t-k}) + \phi\, N\_COND_{ictae} + \rho \ln(PREV_{ct}) + \alpha_c + \delta_t + \pi_a + \gamma_e + \varepsilon_{ictae}] \quad (1)$$

where $\Phi[\ ]$ is the cumulative standard normal distribution function and

Y_{iaect} = a binary measure of disability, Social Security recipiency, or health care use of community resident i of age a and years of education e with medical condition c in year t (t=1998, 1999,…, 2015)

$CUM\_CLASS_{c,t-k}$ = the number of classes (WHO ATC4 chemical subgroups) of drugs used to treat medical condition c ever approved by the FDA by the end of year t-k (k = 0, 3, 6,…,15)
= $\sum_g (APPROVED_{g,t-k} * INDIC_{gc})$

$APPROVED_{g,t-k}$ = 1 if any chemical substance in WHO ATC4 chemical subgroup g was approved by the FDA by the end of year t – k

= 0 otherwise

$INDIC_{gc}$ = 1 if any chemical substance in WHO ATC4 chemical subgroup g is used to treat (indicated for) medical condition c[5]

[5] Many drug classes are used to treat multiple medical conditions.

= 0 otherwise

N_COND_{iaect} = the number of medical conditions of person i of age a and years of education e with medical condition c in year t

$PREV_{ct}$ = the prevalence of medical condition c in year t

α_c = a fixed effect for medical condition c

δ_t = a fixed effect for year t

π_a = a fixed effect for single year of age a

γ_e = a fixed effect for single year of education e

The dependent variables—the person-level and condition-specific disability measures and condition-specific use of medical care measures—are listed in Figure 1. The disturbances of eq. (1) will be clustered by medical condition.

ATC4 vs ATC5. The measure of pharmaceutical innovation in eq. (1) is $CUM\_CLASS_{c,t-k}$: the number of *classes* (WHO ATC4 chemical subgroups) of drugs used to treat medical condition c ever approved by the FDA by the end of year t-k. An alternative measure of pharmaceutical innovation is $CUM\_DRUG_{c,t-k}$: the number of *drugs* (WHO ATC5 chemical substances) used to treat medical condition c ever approved by the FDA by the end of year t-k. In addition to estimating eq. (1), we estimated models using this alternative measure. The estimates indicated that our measures of disability, Social Security recipiency, and use of medical care are much more strongly (inversely) related to $CUM\_CLASS_{c,t-k}$ than they are to $CUM\_DRUG_{c,t-k}$. This difference is consistent with Lanthier et al's[9] finding that 70% of first-in-class drugs are priority-review drugs—the FDA believes that they offer a "significant improvement" compared with products already on the market[10]—while only 32% of non-first-in-class drugs are priority-review drugs.

Lagged launches. Eq. (1) allows the effect of pharmaceutical innovation (entry of new drug classes) to be subject to a lag of up to 15 years. There is likely to be a substantial lag between the launch of a new drug class and its maximum impact on the burden of disease. Utilization of recently-launched drug classes tends to be lower than utilization of drug classes launched many years earlier. Evidence about the shape of the age (number of years since launch)-utilization profile can be obtained by estimating the following equation:

$$\ln(N\_SU_{gn}) = \rho_g + \delta_n + \varepsilon_{gn} \quad (2)$$

where

N_SU_{gt} = the number of standard units of drug class g sold n years after it was first launched (n = 0, 1,…, 20)

ρ_g = a fixed effect for drug class g

δ_n = a fixed effect for age n

The expression $\exp(\delta_n - \delta_{20})$ is a "relative utilization index": it is the mean ratio of the quantity of a drug class sold n years after it was launched to the quantity of the same drug class sold 20 years after it was launched. We estimated eq. (2), using annual data for the period 2006-2018 on 113 drug classes. Estimates of the "relative utilization index" are shown in Figure 3. These estimates indicate that utilization of a drug class levels off about 9-10 years after it was first launched. It is used about twice as much then as it was four years after launch.

Due to gradual diffusion of new drug classes, the maximum impact of a new drug class on disease burden is likely to occur a number of years after it was launched, but the peak effect could occur either more than or less than 9-10 years after launch. The lag might be longer because some drugs for chronic diseases (e.g. statins) may have to be consumed for several years to achieve full effectiveness. But the lag might be shorter because the impact of a drug class on disease burden is likely to depend on its quality (or effectiveness) as well as on its quantity (utilization), and drug classes launched more recently are likely to be of higher quality than earlier-vintage drug classes.[6, 7]

Other biomedical innovation. Eq. (1) includes a measure of pharmaceutical innovation ($CUM\_CLASS_{c,t-k}$), but it does not include measures of other types of biomedical innovation (e.g. innovation in diagnostic imaging, surgical procedures, and medical devices). Dorsey et al[15] showed that 88% of privately-funded U.S. funding for biomedical research came from

[6] Grossman and Helpman [11] argued that "innovative goods are better than older products simply because they provide more 'product services' in relation to their cost of production." Bresnahan and Gordon [12] stated simply that "new goods are at the heart of economic progress," and Bils [13] said that "much of economic growth occurs through growth in quality as new models of consumer goods replace older, sometimes inferior, models." As noted by Jovanovic and Yatsenko [14], in "the Spence–Dixit–Stiglitz tradition…new goods [are] of higher quality than old goods."

[7] The impact on disease burden may depend on the *interaction* (quantity * quality) of the two variables. The impact will increase with respect to drug class age (time since launch) if the rate of increase of quantity with respect to age is greater than the rate of decline of quality with respect to age; otherwise the impact will decline.

pharmaceutical and biotechnology firms.[8] Also, some previous research indicated that non-pharmaceutical medical innovation is not positively correlated across diseases with pharmaceutical innovation. Nevertheless, controlling for non-pharmaceutical medical innovation would be desirable. Unfortunately, measuring non-pharmaceutical medical innovation is far more difficult than measuring pharmaceutical innovation. We constructed a measure of nonpharmaceutical biomedical innovation, by medical condition and year, using methods described in Lichtenberg (2019)[18]. This measure is the mean vintage[9] of Analytical/Diagnostic/Therapeutic Techniques and Equipment Medical Subject Headings (MeSH Tree branch E) descriptors assigned to MEDLINE/PubMED articles about medical condition c published in year t. When this measure was included as a regressor in eq. (1), its coefficient was not significant, and it had little effect on estimates of β_k.

Disease prevalence. The disease prevalence variable ($\ln(PREV_{ct})$) is included as a regressor in eq. (1) to control for potential variation in disease screening intensity or awareness. Suppose that the severity of a disease is normally distributed, as depicted in Figure 4. If disease screening/awareness is low, only the most severe cases (those with severity $S > S_0$) will be detected and reported, and mean disability from the disease will be high. If disease screening/awareness is high, less severe cases (those with severity $S > S_1$) will be detected and reported, and mean disability from the disease will be lower. Hence one would expect that the higher the relative reported prevalence of a disease, the lower the relative mean disability from the disease. Higher (true or measured) disease prevalence is also likely to cause more drug launches. Therefore, failure to control for prevalence could bias estimates of the drug launch coefficients away from zero. On the other hand, controlling for prevalence may make our estimates of the drug launch coefficients conservative. Targeted efforts and programs to reduce disease burden are likely to depend on disease prevalence, so controlling for prevalence will also control at least to some extent for the effects of those efforts and programs on disability.

Interaction effect. Eq. (1) will be estimated using data on each medical condition of each person in each year. The reported number of medical conditions varies across individuals. Table 2 shows that

---

[8] Much of the rest came from the federal government (i.e. the NIH), and new drugs often build on upstream government research[16]. The National Cancer Institute[17] says that it "has played a vital role in cancer drug discovery and development, and, today, that role continues."

[9] The vintage of a descriptor is the first year in which that descriptor was assigned to any article in MEDLINE/PubMED.

in 2015, 25% of people had no medical conditions, 18% had one medical condition, 13% had 2 medical conditions, 21% had more than 5 medical conditions, and 7% had more than 10 medical conditions. Moreover, only 5% of medical conditions are borne by people with one medical condition, only 21% of medical conditions are borne by people with less than 4 medical conditions, and *almost half (49%) of medical conditions are borne by people with more than 7 medical conditions.*

As shown in Figure 1, some of the outcomes (dependent variables) we will analyze are person-level, rather than condition-by-person-level, measures. Suppose that person A has a single medical condition, e.g. diabetes, and that person B has diabetes and four other medical conditions. We hypothesize that diabetes-related pharmaceutical innovation will have a greater impact on the overall (person-level) health of person A than it will on person B. To allow for this possibility, we will also estimate the following generalization of eq. (1):

$$\text{Prob}(Y_{ictae}=1) = \Phi[\beta_{low,k}\,(N\_COND\_LOW_{ictae} * \ln(CUM\_CLASS_{c,t-k}))$$

$$+ [\beta_{mid,k}\,(N\_COND\_MID_{ictae} * \ln(CUM\_CLASS_{c,t-k})) + [\beta_{high,k}\,(N\_COND\_HIGH_{ictae} * \ln(CUM\_CLASS_{c,t-k}))$$

$$+ \phi\, N\_COND_{ictae} + \rho \ln(PREV_{ct}) + \alpha_c + \delta_t + \pi_a + \gamma_e + \varepsilon_{ictae}] \qquad (3)$$

where

$$N\_COND\_LOW_{ictae} = 1 \text{ if } 1 \leq N\_COND_{ictae} \leq 4$$
$$= 0 \text{ otherwise}$$

$$N\_COND\_MID_{ictae} = 1 \text{ if } 5 \leq N\_COND_{ictae} \leq 8$$
$$= 0 \text{ otherwise}$$

$$N\_COND\_HIGH_{ictae} = 1 \text{ if } 9 \leq N\_COND_{ictae} \leq 60$$
$$= 0 \text{ otherwise}$$

Eq. (3) allows the effect of pharmaceutical innovation related to a medical condition on the overall health of a person with that condition to depend on the number of (other) medical conditions a person has. The observations are divided into 3 groups of roughly equal size: low N_COND (the bearer of that condition has less than 5 medical conditions), medium N_COND (5-8 medical conditions), and high N_COND (more than 8 medical conditions). We expect the magnitude of $\beta_{low,k}$ to be larger than the magnitude of $\beta_{high,k}$.

III. Data sources and descriptive statistics

Data on all variables shown in Figure 1, except data on pharmaceutical innovation, were obtained from the Full-Year Consolidated Data files[19] and Medical Conditions files[20] of the 1998-2015[10] waves of the Medical Expenditure Panel Survey (MEPS),[21] a set of large-scale surveys of families and individuals, their medical providers, and employers across the United States. MEPS is the most complete source of data on the cost and use of health care and health insurance coverage. As noted in the MEPS documentation,[22] "data from [the Medical Conditions file] can be merged with MEPS person-level data to append person-level characteristics such as demographic or health insurance characteristics to each record. Since each record represents a single condition reported by a household respondent, some household members may have multiple medical conditions and thus will be represented by multiple records on this file." In the MEPS Medical Conditions files, conditions are coded by Clinical Classification Code. Table 3 shows the 20 most prevalent medical conditions in 2015.

Data on the FDA approval years of drugs (including their ATC codes) were obtained from the DrugCentral 2021 online drug compendium.[23] Data on approved indications of prescription drugs were obtained from Thériaque,[24] a database produced by France's Centre National Hospitalier d'Information sur le Médicament. In the Thériaque database, indications are coded by ICD10 code. We used the Agency for Healthcare Research and Quality's Clinical Classifications Software Refined for ICD10-CM-Diagnoses[25] to map Thériaque ICD10 codes to MEPS Clinical Classification Codes.

Descriptive statistics are shown in Table 4. The bottom of the table shows the weighted mean number of classes (WHO ATC4 chemical subgroups) of drugs used to treat medical condition c ever approved by the FDA by the end of year t-k (k = 0, 3, 6,…,15), weighted by the prevalence of the condition. It reveals that the rate of pharmaceutical innovation has declined. The mean number of drug classes increased by 15.4% from 1982-1987 to 1995-2000; it increased by only 4.9% from 1997-2002 to 2010-2015.

[10] MEPS data are available through 2018, but the coding of medical conditions changed after 2015.

IV. Empirical results

A. Person-level disability and Social Security recipiency measures

Estimates of β_k (from eq. (1)) and $\beta_{low,k}$ (from eq. (3)) from models of 10 person-level disability and Social Security recipiency measures are shown in Table 5 and graphed in Figure 5. For each measure, we provide 12 estimates: estimates of β_k and $\beta_{low,k}$ for k = 0, 3, 6,…, 15.[11]

In Panel A of Table 5 and Figure 5, the dependent variable is a binary indicator (1 = yes; 0 = no) of whether the person had any limitation. The left side of the Table and Figure shows the estimate of β_k (from eq. (1)); the right side shows the estimate of $\beta_{low,k}$ (from eq. (3)). The estimates of β_6 and β_9 are negative and statistically significant (p-value $\leq$ .01), indicating that the larger the number of drug classes that are used to treat the patient's condition that had ever been launched 6-9 years earlier, the less likely the person had any limitation, *ceteris paribus*. The dependent variable is most strongly related to the number of drug classes launched 9 years earlier. Due to the gradual diffusion of new drug classes, a 9-year lag is not surprising.

The right side of Panel A of Table 5 shows that the estimates of $\beta_{low,6}$, $\beta_{low,9}$, and $\beta_{low,12}$ are also negative and statistically significant. The magnitude of these $\beta_{low,k}$ estimates is about 50% larger than the magnitude of the corresponding β_k estimates. This is consistent with the hypothesis discussed above that innovation related to a medical condition has a larger (negative) effect on the disability of people with fewer medical conditions.

In Panel B of Table 5 and Figure 5, the dependent variable is a binary indicator of whether the person had any limitation in work/housework/school. (Table 4 indicated that this limitation is much less common than whether the person had any limitation at all.) In this case, the estimates of β_k are negative and significant when $3 \leq k \leq 12$, all 6 estimates of $\beta_{low,k}$ are negative and significant, and the magnitude of the $\beta_{low,k}$ estimates is about twice as large as the magnitude of the corresponding β_k estimates. Once again, the dependent variable is most strongly related to the number of drug classes launched 9 years earlier.

In Panels C and D of Table 5 and Figure 5, the dependent variables are indicators of whether the person had physical-functioning and cognitive limitations, respectively. The patterns of

[11] Estimates of $\beta_{mid,k}$ and $\beta_{high,k}$ (from eq. (3)) are shown in Appendix Table 1.

coefficients are similar to those in Panel B. That is also the case in Panel E, where the dependent variable indicates whether the person said that he or she was in fair or poor health.

In Panels F and G of Table 5 and Figure 5, the dependent variables are indicators of whether the person was unable to work, or completely unable to work at a job, do housework, or go to school. Both probabilities are significantly inversely related to the number of drug classes used to treat the person's medical condition launched 3-12 years earlier. The magnitudes of the effects on people with less than 5 conditions are larger than the magnitudes of the effects on all people.

In Panel H of Table 5 and Figure 5, the dependent variable is an indicator of whether the person received SSI. The probability that any person received SSI was significantly inversely related to the number of drug classes used to treat the person's medical condition launched 6-9 years earlier. The probability that a person with less than 5 medical conditions received SSI was significantly inversely related to the number of drug classes used to treat the person's medical condition launched 0-15 years earlier; it was most strongly related to the number of drug classes used to treat the person's medical condition launched 12 years earlier.

In Panel I of Table 5 and Figure 5, the dependent variable is an indicator of whether the person received Social Security income. The probability that any person received Social Security income was significantly inversely related to the number of drug classes used to treat the person's medical condition launched 6-12 years earlier. The probability that a person with less than 5 medical conditions received Social Security income was significantly inversely related to the number of drug classes used to treat the person's medical condition launched 3-15 years earlier; it was most strongly related to the number of drug classes used to treat the person's medical condition launched 12 years earlier.

In the last panel (Panel J) of Table 5 and Figure 5, the dependent variable is an indicator of whether the person was retired.[12] The probability that a person was retired is *positively* correlated with the number of drug classes used to treat the person's medical condition launched 0-3 years earlier. This is somewhat surprising, since the probability that a person received Social Security is *negatively* correlated with the number of drug classes used to treat the person's medical condition previously launched. (Moreover, pharmaceutical innovation had a *smaller* estimated

[12] We considered a person to be retired if the MEPS variable NWK31 ("Reason not working during RD 3/1") was equal to 2 ("retired").

effect on the probability that people with less than 5 medical conditions were retired than it had on the probability that all people were retired.) However, some retired people don't qualify for Social Security benefits. To qualify for Social Security retirement benefits, a worker must accumulate 40 quarters of coverage. Never-beneficiaries who lack the required work credits may be divided into three mutually exclusive categories: late-arriving immigrants, infrequent workers, and noncovered workers. The majority (55.2%) of never-beneficiaries are late-arriving immigrants, or those who arrive in the United States at age 50 or older.[26]

B. Condition-specific disability and medical care utilization measures

Estimates of β_k (from eq. (1)) from models of 9 condition-specific disability and medical care utilization measures are shown in Table 6 and graphed in Figure 6. For each measure, we provide 6 estimates of β_k for k = 0, 3, 6,…, 15.

The dependent variables in the first 3 panels of Table 6 and Figure 6 are condition-specific disability measures. The estimates in Panel A indicate that the probability that a person had any bed days associated with a condition was significantly inversely related to the number of drug classes used to treat that condition that had ever been launched 3-12 years earlier. The estimates in Panel B indicate that the probability that a person had any missed school days associated with a condition was significantly inversely related to the number of drug classes used to treat that condition that had ever been launched 0, 6, and 9 years earlier. The probability of having any missed work days was significantly inversely related to the number of drug classes that had ever been launched 0 years earlier (Panel C).

The dependent variables in the remaining 6 panels of Table 6 and Figure 6 are condition-specific medical care utilization measures. The estimates in Panel D indicate that, not surprisingly, the probability of using any prescribed medicines for a condition was significantly positively related to the number of drug classes used to treat that condition that had ever been launched 3-6 years earlier. However, the probability of having any office-based visits for a condition was unrelated to the number of previously-launched drug classes used to treat that condition (Panel E). The last 4 panels indicate that the probability of having emergency-room visits, home health visits, inpatient events, and outpatient events associated with a condition was inversely related to the number of previously-launched drug classes used to treat that condition. The probability of

having any home health events was inversely related to the number of drug classes that had ever been launched 3-12 years earlier. The probability of having any inpatient events was inversely related to the number of drug classes that had ever been launched 0-15 years earlier.[13]

V. Discussion

Many of the estimates in Tables 5 and 6 indicated that the probability of disability, Social Security recipiency, and medical care utilization is inversely related to the number of drug classes previously launched. As shown in Table 4, the weighted (by condition prevalence) mean number of drug classes previously launched increased during our sample period, 1997-2015. Our estimates of β_k enable us to estimate what the rates of disability, Social Security recipiency, and medical care utilization would have been in the absence of that increase in the number of drug classes previously launched. The difference between the counterfactual, "no innovation," rate and the actual rate in 2015 can then be used to calculate the reduction in disability, Social Security recipiency, and medical care utilization in 2015 attributable to previous pharmaceutical innovation.

The estimated probability of an outcome in 2015 in the absence of previous pharmaceutical innovation ($\hat{Y}_{no\_innov,2015}$) is:

$$\hat{Y}_{no\_innov,2015} = \Phi[\Phi^{-1}(\hat{Y}_{actual,2015}) - \beta_k * (\text{mean}(\ln(CUM\_CLASS_{2015-k})) - \text{mean}(\ln(CUM\_CLASS_{1997-k})))]$$

where $\Phi[\ ]$ is the cumulative standard normal distribution function and

$\hat{Y}_{actual,2015}$ = the actual probability of outcome Y in 2015

$\text{mean}(\ln(CUM\_CLASS_{t-k}))$ = the weighted (by condition prevalence) mean value of $\ln(CUM\_CLASS)$ in year t – k (t = 1997, 2015)

The percentage reduction in the probability of outcome Y attributable to previous pharmaceutical innovation is $(\hat{Y}_{no\_innov,2015} / \hat{Y}_{actual,2015}) - 1$. The absolute reduction in prevalence of the outcome attributable to previous pharmaceutical innovation can be estimated by multiplying this percentage reduction by the actual prevalence of the outcome in 2015.

[13] New drugs diffuse more rapidly in the hospital sector than they do in the retail sector.

These calculations are performed in Table 7. For each outcome, we select the lag length (k) for which β_k is most significant. The outcome shown in row 1 is an indicator of whether the bearer of the condition has any limitation. As shown in Table 5, this outcome is most significantly inversely related to the number of drug classes ever approved 9 years earlier (k = 9). The mean value of this outcome in 2015 was 46.1%.[14] The estimates imply that, if the number of drug classes ever approved had not increased from 1988 (= 1997 - 9) to 2006 (= 2015 – 9), the mean value of this outcome in 2015 would have been 1.6% percent higher: 46.9%. In 2015, 66.1 million Americans had a limitation. Hence, we estimate that if the number of drug classes ever approved had not increased from 1988 to 2006, about 1.1 million (= 1.6% * 66.1 million) more Americans would have had a limitation in 2015.

As shown in rows 4-8 of Table 7, previous pharmaceutical innovation is estimated to have yielded larger percentage reductions (between 2.9% and 4.5%) of other outcomes. For example, previous innovation is estimated to have reduced the number of people who were completely unable to work at a job, do housework, or go to school in 2015 by 4.5%. But this outcome is much less common than having any limitation, so the estimated reduction in 2015 prevalence of this outcome is smaller: about 718 thousand people.

As shown in rows 8 and 9, previous innovation is estimated to have reduced the number of people receiving SSI in 2015 by 247 thousand (3.1%), and the number of people receiving Social Security by 984 thousand (2.0%).

Rows 11-18 of Table 7 show similar calculations for condition-specific measures of disability and medical care utilization. In these rows, actual prevalence means the number of medical conditions that caused each outcome. For example, as shown in row 11, 134 million medical conditions caused one or more bed days in 2012.[15] Previous innovation is estimated to have reduced prevalence by 5.6%; due to that innovation, 7.6 million fewer medical conditions are estimated to have caused bed days in 2012. Previous innovation is also estimated to have

[14] This figure is more than twice as high as the mean reported in Table 4 (about 19%). For the person-level measures in Table 4, each person contributes one observation. In the dataset from which our models were estimated, a person with N conditions contributes N observations. People with more conditions are more likely to have disabilities. We believe that multiplying the *percentage* reduction in the rate (which is based on the *ratio* of $\hat{Y}_{no\_innov,2015}$ to $\hat{Y}_{actual,2015}$) by the actual prevalence of (number of people with) the outcome in 2015 yields valid estimates of the absolute reduction in prevalence of the outcome attributable to previous pharmaceutical innovation.

[15] MEPS discontinued providing data on bed days, school loss days, and work loss days after 2012, so for these 3 measures, actual prevalence is estimated for 2012.

caused substantial (> 4.0%) reductions in home health visits (9.2%), inpatient events (5.7%), missed school days (5.1%), and outpatient events (4.1%).

We can estimate the value in 2015 of some of the reductions in disability, Social Security recipiency, and use of medical care attributable to previous pharmaceutical innovation. These calculations are shown in Table 8. As shown in row 1, we estimate that new drug classes launched during 1988-2006 reduced the number of people who were unable to work in 2015 by 512,337 (3.9%). According to the Bureau of Labor Statistics' Quarterly Census of Employment and Wages,[27] annual wages per employee in 2015 were $52,942. So, the value of the reduction in inability to work may have been about $27 billion (= 512,337 * $52,942). The remaining values in Table 8 are obtained by multiplying the estimated percentage reductions in prevalence ($(\hat{Y}_{no_innov,2015} / \hat{Y}_{actual,2015}) - 1$) by the corresponding 2015 aggregate expenditure figure. For example, according to MEPS, total SSI expenditure in 2015 was $73.6 billion, and we estimate that new drug classes launched during 1988-2006 reduced the number of people who received SSI in 2015 by 3.1%, so the reduction in SSI expenditure may have been about $2.3 billion (= 3.1% * $73.6 billion). The reduction in Social Security expenditure may have been $14.0 billion (= 2.0% * $713 billion).

The reduction in hospital expenditure had the greatest value. We estimate that innovation reduced the number of 2015 inpatient events by 5.7%. According to the CMS National Health Expenditure Accounts,[28] total U.S. hospital expenditure was $989 billion in 2015, so the reduction in hospital expenditure may have been $56.1 billion (= 5.7% * $989 billion). The estimated reductions in expenditure on home health care, outpatient events, and emergency room events are $8.2 billion, $5.5 billion, and $1.5 billion, respectively. The sum of the 7 sources of value listed in Table 8 is $115 billion.[16]

The costs, as well as the benefits, of pharmaceutical innovation should be considered. Data from the IQVIA MIDAS database indicate that 2015 expenditure on drug classes that were first approved by the FDA during 1989-2006 (i.e. between (1997 – 9 + 1) and (2015 – 9)) was $127 billion.[17] This is 10% larger than the sum of the 7 sources of value listed in Table 8.

---

[16] To the extent that SSI and Social Security replace lost wages, this figure may be overstated due to "double-counting". If we exclude SSI and Social Security, the sum of the sources of value is about $99 billion.

[17] This is 38% of the IQVIA figure for total prescription drug expenditure in 2015 ($331 billion), which is quite similar to the CMS National Health Expenditure Accounts estimate of total prescription drug expenditure ($324 billion).

However, for a number of reasons, the costs are likely to be lower, and the benefits are likely to be larger, than these figures. Regarding costs: (1) Entry of new drugs reduces utilization of older drugs. (2) Prices of old (generic) drugs tend to be reduced by entry of new drugs.[29] Regarding benefits: (1) The cost figure ($127 billion) includes nursing home drug cost, but the benefit figure is based only on community residents; it does not include benefits to nursing home residents. (2) The total value figure shown in Table 8 does not include the value of some of the disability reductions we identified (e.g. reduced cognitive limitations and bed days), whose value is more difficult to measure. (3) The total value figure shown in Table 8 does not include the value of increased longevity resulting from pharmaceutical innovation, which may be far larger.[30]

VI. Summary and conclusions

88% of privately-funded U.S. funding for biomedical research came from pharmaceutical and biotechnology firms. This study analyzed the overall impact that biopharmaceutical innovation, had on disability, Social Security recipiency, and the use of medical services of U.S. community residents during the period 1998-2015. Most of the data come from the Medical Expenditure Panel Survey.

The effect of biopharmaceutical innovation was identified by differences across over 200 medical conditions in the growth in the lagged number of drug classes ever approved. The FDA believes that 70% of first-in-class drugs offer a "significant improvement" compared with products already on the market.

The estimates indicated that the probability of disability, Social Security recipiency, and medical care utilization is inversely related to the number of drug classes previously approved. The length of the estimated lag was generally 6-9 years, which is not surprising, due to the gradual diffusion of new drug classes. The effect of biopharmaceutical innovation related to a medical condition on the overall health of a person with that condition depends on the number of (other) medical conditions a person has: the smaller the number of conditions, the larger the effect.

Previous innovation is estimated to have reduced: the number of people who were completely unable to work at a job, do housework, or go to school in 2015 by 4.5%; the number of people with cognitive limitations by 3.2%; the number of people receiving SSI in 2015 by 247

thousand (3.1%); and the number of people receiving Social Security by 984 thousand (2.0%). Previous innovation is also estimated to have caused reductions in home health visits (9.2%), inpatient events (5.7%), missed school days (5.1%), and outpatient events (4.1%).

We estimated the value in 2015 of some of the reductions in disability, Social Security recipiency, and use of medical care attributable to previous biopharmaceutical innovation. This value ($115 billion) is fairly close to 2015 expenditure on drug classes that were first approved by the FDA during 1989-2006 ($127 billion). However, for a number of reasons, the costs are likely to be lower, and the benefits are likely to be larger, than these figures.

References

[1] Technology News and Literature (2011). Drug Reduces Stroke Victim Brain Inflammation, Disability.

[2] Kappos L, et al (2018). Siponimod versus placebo in secondary progressive multiple sclerosis (EXPAND): a double-blind, randomised, phase 3 study. *Lancet* 391(10127):1263-1273. doi: 10.1016/S0140-6736(18)30475-6.

[3] Harvard Health Letter (2019). Are the new migraine medications working?

[4] Pizer SD, Frakt AB, Iezzoni LI (2009). Uninsured Adults with Chronic Conditions or Disabilities: Gaps in Public Insurance Programs. *Health Affairs* (28, No. Supplement 1: Web Exclusives).

[5] Lichtenberg FR (2012). The effect of pharmaceutical innovation on the functional limitations of elderly Americans: evidence from the 2004 National Nursing Home Survey, *Advances in Health Economics and Health Services Research 23*, 71-99.

[6] Lichtenberg FR (2019). The impact of access to prescription drugs on disability in eleven European countries. *Disability and Health Journal*, 12(3): 375-386 (July).

[7] World Health Organization (2021). ATC Structure and Principles.

[8] Wikipedia (2021). Anatomical Therapeutic Chemical Classification System.

[9] Lanthier M, Miller KL, Nardinelli C, Woodcock J (2013). An Improved Approach to Measuring Drug Innovation Finds Steady Rates of First-In-Class Pharmaceuticals, 1987–2011. *Health Affairs* 32 (8), August.

[10] FDA, Center for Drug Evaluation and Research, Review Designation Policy—Priority (P) and Standard (S).

[11] Grossman GM, Helpman E (1993). *Innovation and Growth in the Global Economy.* Cambridge: MIT Press.

[12] Bresnahan TF, Gordon RJ (1996). *The Economics of New Goods.* Chicago: University of Chicago Press.

[13] Bils M (2004). "Measuring the Growth from Better and Better Goods," NBER working paper no. 10606, July.

[14] Jovanovic B, Yatsenko Y (2012). Investment in Vintage Capital. *Journal of Economic Theory* 147(2): 551–569.

[15] Dorsey ER (2010). Financial Anatomy of Biomedical Research, 2003 – 2008. *Journal of the American Medical Association* 303(2): 137–143, January 13.

[16] Sampat B, Lichtenberg FR (2011). "What are the Respective Roles of the Public and Private Sectors in Pharmaceutical Innovation?," *Health Affairs* 2011; 30(2):332-9, Feb.

[17] National Cancer Institute (2021). *Enhancing Drug Discovery and Development*, https://www.cancer.gov/research/areas/treatment/enhancing-drug-discovery.

[18] Lichtenberg FR (2019). The long-run impact of new medical ideas on cancer survival and mortality, *Economics of Innovation and New Technology* 28(7): 722-740.

[19] Agency for Healthcare Research and Quality (2021). Medical Expenditure Panel Survey Full-Year Consolidated Data files.

[20] Agency for Healthcare Research and Quality (2021). Medical Expenditure Panel Survey Medical Conditions files.

[21] Agency for Healthcare Research and Quality (2021). Medical Expenditure Panel Survey (MEPS).

[22] Agency for Healthcare Research and Quality (2021). MEPS HC-180: 2015 Medical Conditions.

[23] Division of Translational Informatics at University of New Mexico (2021). DrugCentral 2021 online drug compendium.

[24] Centre National Hospitalier d'Information sur le Médicament (2021). Thériaque.

[25] Agency for Healthcare Research and Quality (2021). Clinical Classifications Software Refined for ICD10-CM-Diagnoses.

[26] Whitman K, Reznik GL, Shoffner D (2011). Who Never Receives Social Security Benefits? *Social Security Bulletin* 71 (2).

[27] Bureau of Labor Statistics (2021). Quarterly Census of Employment and Wages.

[28] Centers for Medicare & Medicaid Services (2021). National Health Expenditure Accounts.

[29] Lichtenberg FR (2021). Are drug prices subject to creative destruction? Evidence from the U.S., 1997-2017. *Health Economics*, published online 13 May.

[30] Lichtenberg FR (2019). How many life-years have new drugs saved? A 3-way fixed-effects analysis of 66 diseases in 27 countries, 2000-2013. *International Health* 11(5): 403–416 (September).

Table 1

Comparison of features of present study of disability in the U.S. to features of previous study of disability in 11 European countries

	previous study*	present study
2-way fixed effects design	medical condition and country in a single year (2015)	medical condition and year in a single country (USA)
year(s)	2015	1998-2015
countries	11 European countries	USA
micro vs. aggregate data	aggregate	micro
ages	50 and over	all ages
mean age	67.8	35.2
number of persons	45,592	375,828
number of conditions	31	216
number of person-conditions	62,424	1,654,906
pharmaceutical innovation measure	no. of drugs	no. of drug classes
person-level disability measures	yes	yes
allow effect of innovation to depend on no. of conditions?	no	yes
condition-specific disability measures	no	yes
condition-specific health care utilization measures	no	yes

* Lichtenberg FR (2019). The impact of access to prescription drugs on disability in eleven European countries. Disability and Health Journal 12(3): 375-386 (July). https://www.sciencedirect.com/science/article/pii/S1936657419300032

Table 2

Distributions of persons and medical conditions by number of medical conditions borne by person, 2015

N_COND	% of persons with no. of medical conditions = N_COND	cumulative % of persons with no. of medical conditions = N_COND		% of medical conditions borne by persons with no. of medical conditions = N_COND	cumulative % of medical conditions borne by persons with no. of medical conditions = N_COND
0	24.9%	24.9%		0.0%	0.0%
1	18.2%	43.0%		5.2%	5.2%
2	13.3%	56.3%		7.7%	12.9%
3	9.5%	65.8%		8.2%	21.1%
4	7.3%	73.1%		8.4%	29.5%
5	5.5%	78.6%		7.9%	37.4%
6	4.4%	83.0%		7.5%	44.9%
7	3.3%	86.3%		6.6%	51.5%
8	2.7%	89.0%		6.2%	57.7%
9	2.2%	91.2%		5.7%	63.4%
10	1.7%	92.8%		4.8%	68.2%
11	1.3%	94.2%		4.2%	72.4%
12	1.1%	95.3%		3.7%	76.1%
13	1.0%	96.2%		3.7%	79.8%
14	0.7%	96.9%		2.7%	82.6%
15	0.5%	97.5%		2.3%	84.9%
16	0.5%	98.0%		2.3%	87.2%
17	0.4%	98.3%		1.8%	89.0%
18	0.3%	98.6%		1.6%	90.5%
19	0.3%	98.9%		1.4%	91.9%
20	0.2%	99.1%		1.2%	93.1%

Source: Author's calculations based on data from the MEPS 2015 Medical Conditions file.

Table 3

20 most prevalent medical conditions, 2015

Clinical Classification Code	LABEL	UNWEIGHTED frequency	WEIGHTED frequency
98	ESSENTIAL HYPERTENSION	7,006	70,849,016
204	OTHER NON-TRAUMATIC JOINT DISORDERS	6,644	68,644,747
126	OTHER UPPER RESPIRATORY INFECTIONS	6,201	66,810,191
53	DISORDERS OF LIPID METABOLISM	5,264	56,623,122
205	SPONDYLOSIS, INTERVERTEBRAL DISC DIS	3,622	40,118,572
259	RESIDUAL CODES, UNCLASSIFIED	3,738	39,698,327
651	ANXIETY DISORDER	3,391	38,508,722
657	MOOD DISORDERS	3,158	33,769,084
211	OTHER CONNECTIVE TISSUE DISEASE	3,107	33,048,921
134	OTHER UPPER RESPIRATORY DISEASE	3,358	32,163,836
49	DIABETES MELLITUS WITHOUT COMPLICATIONS	3,228	29,160,284
200	OTHER SKIN DISORDERS	2,311	25,937,890
128	ASTHMA	2,422	22,238,337
48	THYROID DISORDERS	1,804	21,961,595
138	ESOPHAGEAL DISORDERS	1,880	21,107,407
244	OTHER INJURIES AND CONDITIONS DUE TO	2,017	20,309,261
255	ADMINISTRATIVE/SOCIAL ADMISSION	1,790	19,755,531
127	CHRONIC OBSTRUCTIVE PULMONARY DISEASE	1,723	19,188,873
133	OTHER LOWER RESPIRATORY DISEASE	1,983	18,572,466
136	DISORDERS OF TEETH AND JAW	1,764	18,200,494

Source: Author's calculations based on data from the MEPS 2015 Medical Conditions file.

Table 4
Descriptive statistics

year	1997-2002	2003-2009	2010-2015	
Person-level measures				
N	175,700	229,505	207,652	
completed years of education	10.5	10.5	10.1	
age	34.0	34.0	34.8	
retired	8.0%	7.2%	6.8%	
unable to work	3.7%	4.0%	3.9%	
completely unable to do activity	4.1%	4.8%	4.5%	
has any limitation	18.7%	20.0%	18.4%	
has any limitation work/housework/school	6.8%	7.5%	7.0%	
has limitation in physical functioning	8.6%	9.6%	8.7%	
has cognitive limitations	3.0%	3.6%	3.7%	
in fair or poor health	11.9%	12.9%	12.4%	
receiving SSI	3.2%	3.0%	3.3%	
receiving Social Security	13.2%	12.2%	12.2%	
Condition-level measures				
N	467,820	665,993	640,420	
any bed days assoc. w/ condition	13.3%	13.7%	12.2%	
any missed school days assoc. w/ condition	8.2%	7.2%	6.6%	
any missed work days assoc. w/ condition	12.5%	10.9%	9.9%	
any inpatient events assoc. w/ condition	3.2%	3.0%	2.5%	
any emergency room events assoc. w/ condition	5.3%	5.4%	5.2%	
any home health events assoc. w/ condition	1.8%	1.9%	2.0%	
any office-based events assoc. w/ condition	48.0%	46.9%	42.7%	
any outpatient events assoc. w/ condition	5.2%	5.1%	4.5%	
any prescribed medicines assoc. w/ condition	52.5%	53.6%	52.0%	
				% change, 1997-2002 to 2010-2015
$CUM\_CLASS_{c,t}$	20.6	20.9	21.6	4.9%
$CUM\_CLASS_{c,t-3}$	19.9	20.5	21.4	7.5%
$CUM\_CLASS_{c,t-6}$	19.1	20.1	21.1	10.3%
$CUM\_CLASS_{c,t-9}$	18.4	19.4	20.8	12.1%
$CUM\_CLASS_{c,t-12}$	17.7	18.6	20.3	14.0%
$CUM\_CLASS_{c,t-15}$	16.9	17.8	19.7	15.4%

Table 5

Estimates of β_k (from eq. (1)) and $\beta_{low,k}$ (from eq. (3)) from models of 10 person-level disability and Social Security recipiency measures

		β_k					$\beta_{low,k}$			
row	lag (k)	Coef.	Std. Err.	z	P>|z|		Coef.	Std. Err.	z	P>|z|
	A. has any limitation									
1	0	-0.102	0.090	-1.13	0.26		-0.138	0.097	-1.42	0.16
2	3	-0.099	0.072	-1.39	0.17		-0.140	0.077	-1.82	0.07
3	6	**-0.111**	**0.042**	**-2.65**	**0.01**		**-0.155**	**0.045**	**-3.49**	**0.00**
4	9	**-0.101**	**0.035**	**-2.89**	**0.00**		**-0.146**	**0.037**	**-3.91**	**0.00**
5	12	-0.072	0.037	-1.92	0.05		**-0.115**	**0.040**	**-2.89**	**0.00**
6	15	-0.025	0.038	-0.66	0.51		-0.068	0.040	-1.69	0.09
	B. has any limitation work/housework/school									
7	0	-0.132	0.085	-1.55	0.12		**-0.214**	**0.103**	**-2.07**	**0.04**
8	3	**-0.147**	**0.057**	**-2.61**	**0.01**		**-0.240**	**0.068**	**-3.54**	**0.00**
9	6	**-0.108**	**0.038**	**-2.84**	**0.00**		**-0.208**	**0.042**	**-4.94**	**0.00**
10	9	**-0.088**	**0.027**	**-3.21**	**0.00**		**-0.188**	**0.031**	**-6.08**	**0.00**
11	12	**-0.064**	**0.031**	**-2.03**	**0.04**		**-0.159**	**0.035**	**-4.54**	**0.00**
12	15	-0.030	0.035	-0.86	0.39		**-0.124**	**0.037**	**-3.39**	**0.00**
	C. has limitation in physical functioning									
13	0	-0.126	0.082	-1.54	0.12		**-0.199**	**0.097**	**-2.05**	**0.04**
14	3	**-0.118**	**0.054**	**-2.21**	**0.03**		**-0.200**	**0.064**	**-3.14**	**0.00**
15	6	**-0.108**	**0.031**	**-3.48**	**0.00**		**-0.197**	**0.034**	**-5.75**	**0.00**
16	9	**-0.071**	**0.023**	**-3.09**	**0.00**		**-0.161**	**0.026**	**-6.23**	**0.00**
17	12	**-0.057**	**0.027**	**-2.13**	**0.03**		**-0.143**	**0.030**	**-4.71**	**0.00**
18	15	-0.018	0.034	-0.52	0.60		**-0.103**	**0.037**	**-2.81**	**0.01**
	D. has cognitive limitations									
19	0	-0.147	0.083	-1.78	0.08		**-0.237**	**0.100**	**-2.36**	**0.02**
20	3	**-0.141**	**0.053**	**-2.67**	**0.01**		**-0.239**	**0.064**	**-3.73**	**0.00**
21	6	**-0.121**	**0.038**	**-3.20**	**0.00**		**-0.227**	**0.043**	**-5.33**	**0.00**
22	9	**-0.103**	**0.032**	**-3.23**	**0.00**		**-0.210**	**0.036**	**-5.88**	**0.00**
23	12	**-0.082**	**0.035**	**-2.35**	**0.02**		**-0.186**	**0.038**	**-4.85**	**0.00**
24	15	-0.058	0.030	-1.91	0.06		**-0.161**	**0.032**	**-4.97**	**0.00**
	E. in fair or poor health									
25	0	-0.155	0.095	-1.64	0.10		**-0.208**	**0.106**	**-1.96**	**0.05**
26	3	**-0.158**	**0.059**	**-2.66**	**0.01**		**-0.216**	**0.066**	**-3.28**	**0.00**
27	6	**-0.122**	**0.051**	**-2.41**	**0.02**		**-0.186**	**0.054**	**-3.47**	**0.00**
28	9	**-0.100**	**0.049**	**-2.04**	**0.04**		**-0.163**	**0.051**	**-3.17**	**0.00**
29	12	-0.066	0.049	-1.35	0.18		**-0.127**	**0.052**	**-2.46**	**0.01**
30	15	-0.058	0.037	-1.56	0.12		**-0.118**	**0.038**	**-3.07**	**0.00**

Table 5

Estimates of β_k (from eq. (1)) and $\beta_{low,k}$ (from eq. (3)) from models of 10 person-level disability and Social Security recipiency measures

		β_k					$\beta_{low,k}$			
row	lag (k)	Coef.	Std. Err.	z	P>|z|		Coef.	Std. Err.	z	P>|z|
	F. unable to work									
31	0	-0.135	0.103	-1.31	0.19		-0.236	0.127	-1.87	0.06
32	3	**-0.171**	**0.066**	**-2.58**	**0.01**		**-0.282**	**0.081**	**-3.49**	**0.00**
33	6	**-0.139**	**0.037**	**-3.74**	**0.00**		**-0.258**	**0.043**	**-6.08**	**0.00**
34	9	**-0.127**	**0.031**	**-4.06**	**0.00**		**-0.244**	**0.035**	**-6.88**	**0.00**
35	12	**-0.086**	**0.035**	**-2.46**	**0.01**		**-0.199**	**0.040**	**-5.04**	**0.00**
36	15	-0.041	0.038	-1.08	0.28		**-0.154**	**0.041**	**-3.77**	**0.00**
	G. completely unable to work at a job, do housework, or go to school									
37	0	**-0.178**	**0.085**	**-2.10**	**0.04**		**-0.274**	**0.105**	**-2.62**	**0.01**
38	3	**-0.193**	**0.047**	**-4.13**	**0.00**		**-0.297**	**0.057**	**-5.21**	**0.00**
39	6	**-0.124**	**0.037**	**-3.33**	**0.00**		**-0.235**	**0.042**	**-5.62**	**0.00**
40	9	**-0.102**	**0.029**	**-3.49**	**0.00**		**-0.213**	**0.034**	**-6.32**	**0.00**
41	12	**-0.074**	**0.032**	**-2.31**	**0.02**		**-0.181**	**0.036**	**-5.04**	**0.00**
42	15	-0.045	0.034	-1.31	0.19		**-0.151**	**0.036**	**-4.17**	**0.00**
	H. receives SSI									
43	0	-0.087	0.062	-1.39	0.16		**-0.154**	**0.077**	**-2.00**	**0.05**
44	3	-0.079	0.046	-1.72	0.09		**-0.153**	**0.054**	**-2.83**	**0.01**
45	6	**-0.089**	**0.036**	**-2.45**	**0.01**		**-0.168**	**0.040**	**-4.24**	**0.00**
46	9	**-0.087**	**0.027**	**-3.15**	**0.00**		**-0.167**	**0.032**	**-5.28**	**0.00**
47	12	-0.028	0.033	-0.84	0.40		**-0.105**	**0.038**	**-2.79**	**0.01**
48	15	-0.016	0.036	-0.44	0.66		**-0.092**	**0.038**	**-2.45**	**0.01**
	I. receives Social Security									
49	0	-0.044	0.055	-0.79	0.43		-0.078	0.064	-1.22	0.22
50	3	-0.059	0.042	-1.41	0.16		**-0.098**	**0.047**	**-2.07**	**0.04**
51	6	**-0.091**	**0.027**	**-3.43**	**0.00**		**-0.134**	**0.027**	**-4.98**	**0.00**
52	9	**-0.072**	**0.022**	**-3.21**	**0.00**		**-0.116**	**0.023**	**-5.05**	**0.00**
53	12	**-0.070**	**0.019**	**-3.73**	**0.00**		**-0.112**	**0.020**	**-5.51**	**0.00**
54	15	-0.036	0.020	-1.74	0.08		**-0.077**	**0.022**	**-3.57**	**0.00**
	J. is retired									
55	0	**0.065**	**0.030**	**2.20**	**0.03**		0.044	0.030	1.48	0.14
56	3	**0.080**	**0.029**	**2.74**	**0.01**		**0.059**	**0.030**	**1.97**	**0.05**
57	6	0.012	0.025	0.49	0.62		-0.010	0.025	-0.41	0.68
58	9	0.000	0.022	-0.02	0.99		-0.023	0.022	-1.03	0.30
59	12	-0.005	0.020	-0.25	0.80		-0.028	0.021	-1.34	0.18
60	15	-0.004	0.022	-0.19	0.85		-0.026	0.022	-1.22	0.22

Table 6

Estimates of β_k (from eq. (1)) from models of 9 condition-specific disability and medical care utilization measures

	β_k			
lag (k)	Coef.	Std. Err.	z	P>|z|
A. any bed days?				
0	-0.176	0.123	-1.42	0.15
3	**-0.189**	**0.066**	**-2.88**	**0.00**
6	**-0.182**	**0.059**	**-3.11**	**0.00**
9	**-0.156**	**0.059**	**-2.63**	**0.01**
12	**-0.132**	**0.065**	**-2.02**	**0.04**
15	-0.113	0.060	-1.88	0.06

	β_k			
lag (k)	Coef.	Std. Err.	z	P>|z|
B. any missed school days?				
0	**-0.240**	**0.074**	**-3.26**	**0.00**
3	-0.156	0.096	-1.62	0.10
6	**-0.148**	**0.070**	**-2.13**	**0.03**
9	**-0.166**	**0.071**	**-2.33**	**0.02**
12	-0.058	0.064	-0.91	0.36
15	-0.032	0.066	-0.48	0.63

C. any missed work days?				
0	**-0.128**	**0.059**	**-2.16**	**0.03**
3	-0.021	0.060	-0.36	0.72
6	-0.046	0.049	-0.94	0.35
9	-0.055	0.052	-1.05	0.29
12	-0.046	0.059	-0.77	0.44
15	-0.031	0.051	-0.61	0.54

D. any prescribed medicines?				
0	0.146	0.098	1.49	0.14
3	**0.160**	**0.082**	**1.96**	**0.05**
6	**0.150**	**0.071**	**2.12**	**0.03**
9	0.128	0.074	1.74	0.08
12	0.118	0.070	1.68	0.09
15	0.088	0.090	0.98	0.33

E. any office-based visits?				
0	0.033	0.049	0.66	0.51
3	-0.027	0.047	-0.56	0.57
6	-0.025	0.052	-0.47	0.64
9	-0.005	0.055	-0.10	0.92
12	0.000	0.052	0.00	1.00
15	0.012	0.051	0.23	0.82

F. any emergency room visits?				
0	**-0.103**	**0.032**	**-3.22**	**0.00**
3	**-0.109**	**0.041**	**-2.63**	**0.01**
6	-0.085	0.045	-1.89	0.06
9	-0.065	0.054	-1.22	0.22
12	-0.053	0.044	-1.21	0.23
15	-0.054	0.042	-1.30	0.19

G. any home health visits?				
0	-0.199	0.101	-1.97	0.05
3	**-0.237**	**0.054**	**-4.35**	**0.00**
6	**-0.204**	**0.043**	**-4.78**	**0.00**
9	**-0.152**	**0.032**	**-4.75**	**0.00**
12	**-0.071**	**0.035**	**-2.03**	**0.04**
15	-0.044	0.034	-1.28	0.20

H. any inpatient events?				
0	**-0.184**	**0.058**	**-3.14**	**0.00**
3	**-0.159**	**0.050**	**-3.19**	**0.00**
6	**-0.143**	**0.047**	**-3.04**	**0.00**
9	**-0.106**	**0.042**	**-2.50**	**0.01**
12	**-0.091**	**0.035**	**-2.63**	**0.01**
15	**-0.105**	**0.036**	**-2.95**	**0.00**

I. any outpatient events?				
0	0.012	0.067	0.19	0.85
3	-0.068	0.048	-1.42	0.16
6	**-0.078**	**0.033**	**-2.40**	**0.02**
9	-0.070	0.036	-1.94	0.05
12	**-0.079**	**0.029**	**-2.74**	**0.01**
15	**-0.073**	**0.033**	**-2.20**	**0.03**

Table 7

Estimates of the reduction in disability, Social Security recipiency, and medical care utilization in 2015 attributable to previous pharmaceutical innovation

			β_k								
row	Person-level measure	lag (k)	Coef.	z	P>|z|	Δmean[ln(cum_class$_k$)]	$\hat{Y}_{actual,2015}$	$\hat{Y}_{no\_innov,2015}$	($\hat{Y}_{no\_innov,2015}$ / $\hat{Y}_{actual,2015}$) – 1	actual prevalence (no. of people) in 2015	reduction in 2015 prevalence due to previous innovation
1	A. has any limitation	9	-0.101	-2.89	0.00	0.188	46.1%	46.9%	1.6%	66,518,606	1,087,194
2	B. has any limitation work/housework/school	9	-0.088	-3.21	0.00	0.188	23.9%	24.4%	2.2%	26,114,266	565,599
3	C. has limitation in physical functioning	6	-0.108	-3.48	0.00	0.182	29.6%	30.3%	2.3%	35,065,504	807,263
4	D. has cognitive limitations	9	-0.103	-3.23	0.00	0.188	13.1%	13.5%	3.2%	14,286,436	453,913
5	E. in fair or poor health	3	-0.158	-2.66	0.01	0.149	27.9%	28.7%	2.9%	35,023,619	1,003,716
6	F. unable to work	9	-0.127	-4.06	0.00	0.188	13.1%	13.6%	3.9%	13,069,508	512,337
7	G. completely unable to work at a job, do housework, or go to school	3	-0.193	-4.13	0.00	0.149	15.8%	16.5%	4.5%	16,066,307	717,536
8	H. receives SSI	9	-0.087	-3.15	0.00	0.188	7.5%	7.8%	3.1%	7,962,496	247,239
9	I. receives Social Security	12	-0.070	-3.73	0.00	0.244	30.8%	31.4%	2.0%	50,188,176	984,418
10	J. is retired	3	0.080	2.74	0.01	0.149	16.2%	15.9%	-1.8%	29,061,321	-523,648
	Condition-specific measure									actual prevalence (no. of conditions) in 2012 or 2015	reduction in 2012 or 2015 prevalence due to previous innovation
11	A. any bed days?	6	-0.182	-3.11	0.00	0.182	12.2%	12.9%	5.6%	134,426,738	7,564,874
12	B. any missed school days?	0	-0.240	-3.26	0.00	0.107	6.5%	6.8%	5.1%	64,262,316	3,287,568
13	C. any missed work days?	0	-0.128	-2.16	0.03	0.107	9.8%	10.0%	2.5%	118,108,129	2,895,970
14	D. any prescribed medicines?	6	0.150	2.12	0.03	0.182	52.5%	51.4%	-2.1%	672,272,630	-13,924,430
15	F. any emergency room visits?	0	-0.103	-3.22	0.00	0.107	5.5%	5.6%	2.3%	65,246,840	1,475,112
16	G. any home health visits?	6	-0.204	-4.78	0.00	0.182	2.3%	2.5%	9.2%	24,957,855	2,286,640
17	H. any inpatient events?	3	-0.159	-3.19	0.00	0.149	2.5%	2.6%	5.7%	32,072,297	1,820,489
18	I. any outpatient events?	12	-0.079	-2.74	0.01	0.244	4.9%	5.1%	4.1%	70,561,790	2,857,771

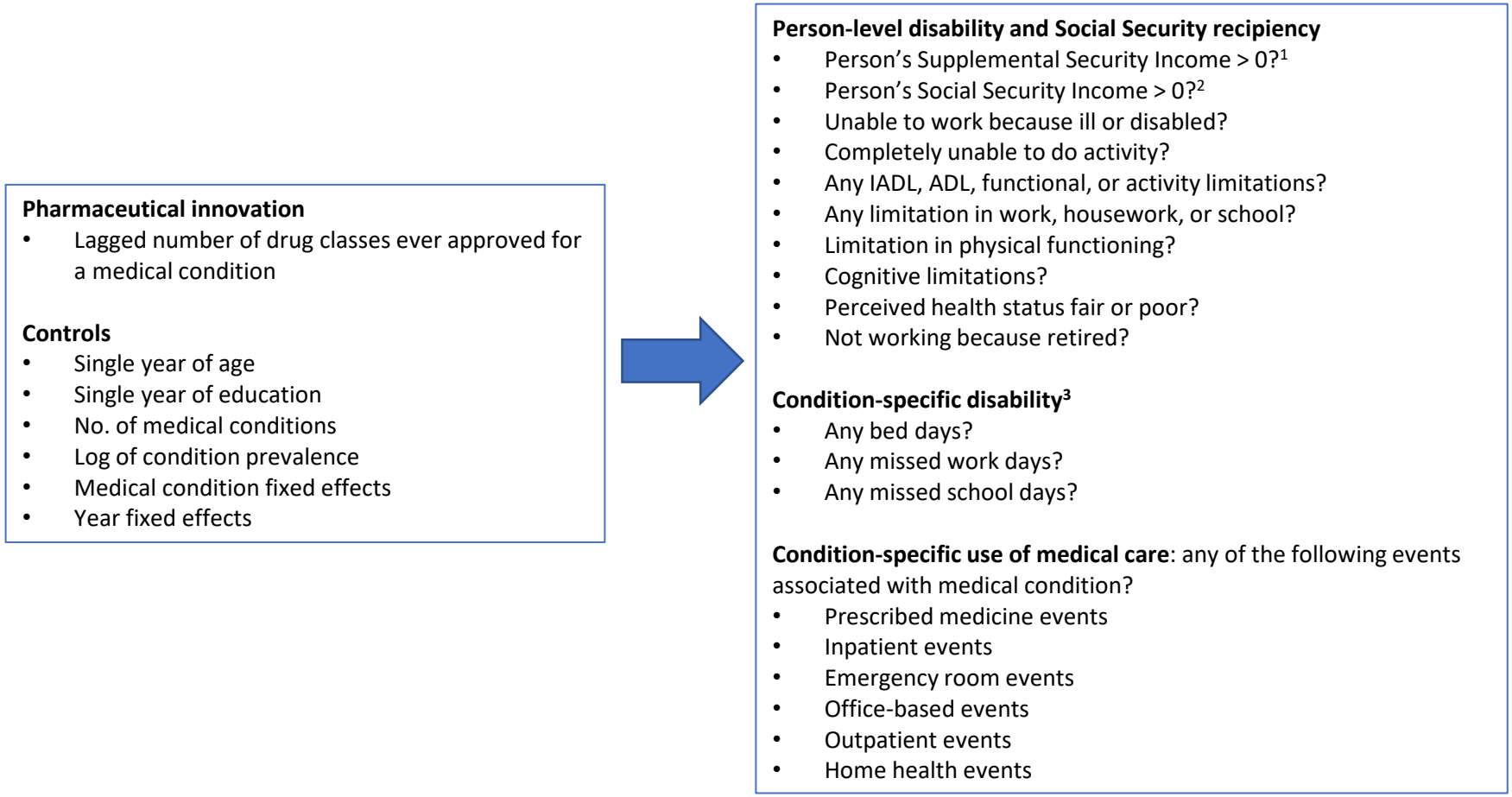
$$\hat{Y}_{no\_innov,2015} = \Phi[\Phi^{-1}(\hat{Y}_{actual,2015}) - \beta_k * (\text{mean}(\ln(\text{CUM\_CLASS}_{2015\text{-}k})) - \text{mean}(\ln(\text{CUM\_CLASS}_{1997\text{-}k})))]$$

Table 8

Estimated value in 2015 of some reductions in disability, Social Security recipiency, and use of medical care attributable to previous pharmaceutical innovation

row	outcome	($\hat{Y}$no_innov,2015 / $\hat{Y}$actual,2015) – 1	estimated value (millions of dollars)	calculation
1	unable to work?	3.9%	$27,124	reduction in no. of people unable to work (3.9% * 13,069,508) * average annual wages per employee ($52,942)
2	receives SSI?	3.1%	$2,287	3.1% * MEPS estimate of aggregate person's SSI ($73,649 million)
3	receives Social Security?	2.0%	$13,990	2.0% * MEPS estimate of aggregate person's Social Security ($713,228 million)
4	any emergency room visits?	2.3%	$1,542	2.3% * MEPS estimate of aggregate emergency room facility and doctor expense (ERTEXP15: $68,192 million)
5	any inpatient events?	5.7%	$56,136	5.7% * CMS estimate of aggregate hospital expenditure ($988,970 million)
6	any home health visits?	9.2%	$8,234	9.2% * CMS estimate of aggregate home health care expenditure ($89,872 million)
7	any outpatient events?	4.1%	$5,482	4.1% * MEPS estimate of aggregate outpatient facility and doctor expense (ERTEXP15: $135,354 million)
	TOTAL		$114,794	

Figure 1
Research design of this study

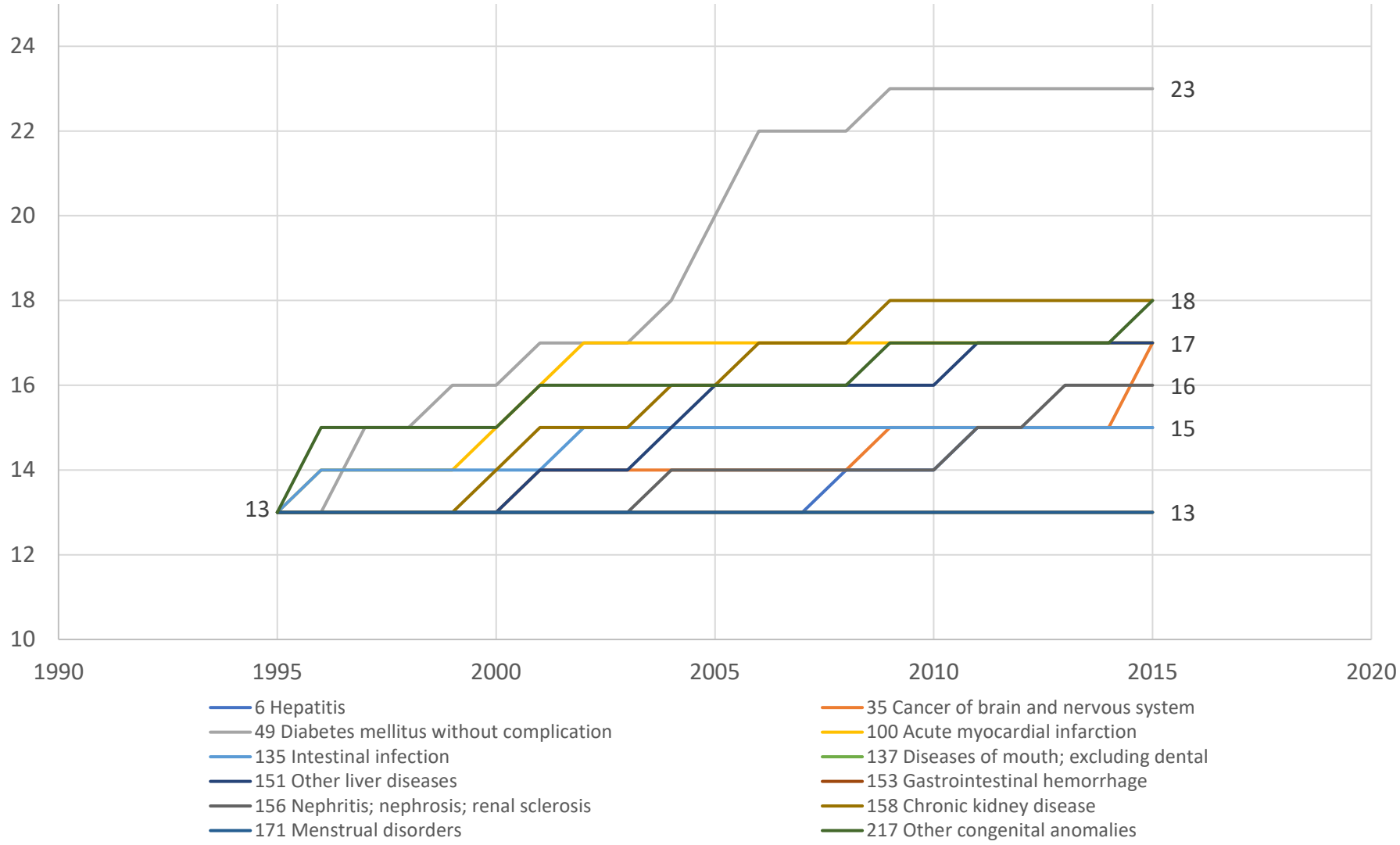


1. Supplemental Security Income is a Federal income supplement program funded by general tax revenues (not Social Security taxes). It is designed to help aged, blind, and disabled people, who have little or no income. It provides cash to meet basic needs for food, clothing, and shelter.

2. Based on their analysis of the 2001 OASDI Public Use Microdata File, Pizer et al found that 80% of people ages 25–61 with Old Age and Survivors Disability Income (Social Security) receive it because of disability.

3. Condition-specific disability data are available for the years 1997-2012.

Figure 2
Number of WHO ATC4 chemical subgroups ever FDA-approved for 12 diseases, 1995-2015



Source: Author's calculations based on data in DrugCentral 2021 online drug compendium and Thériaque database.

Figure 3
Mean utilization of a drug class N years after first launch,
relative to utilization of the drug class 20 years after first launch

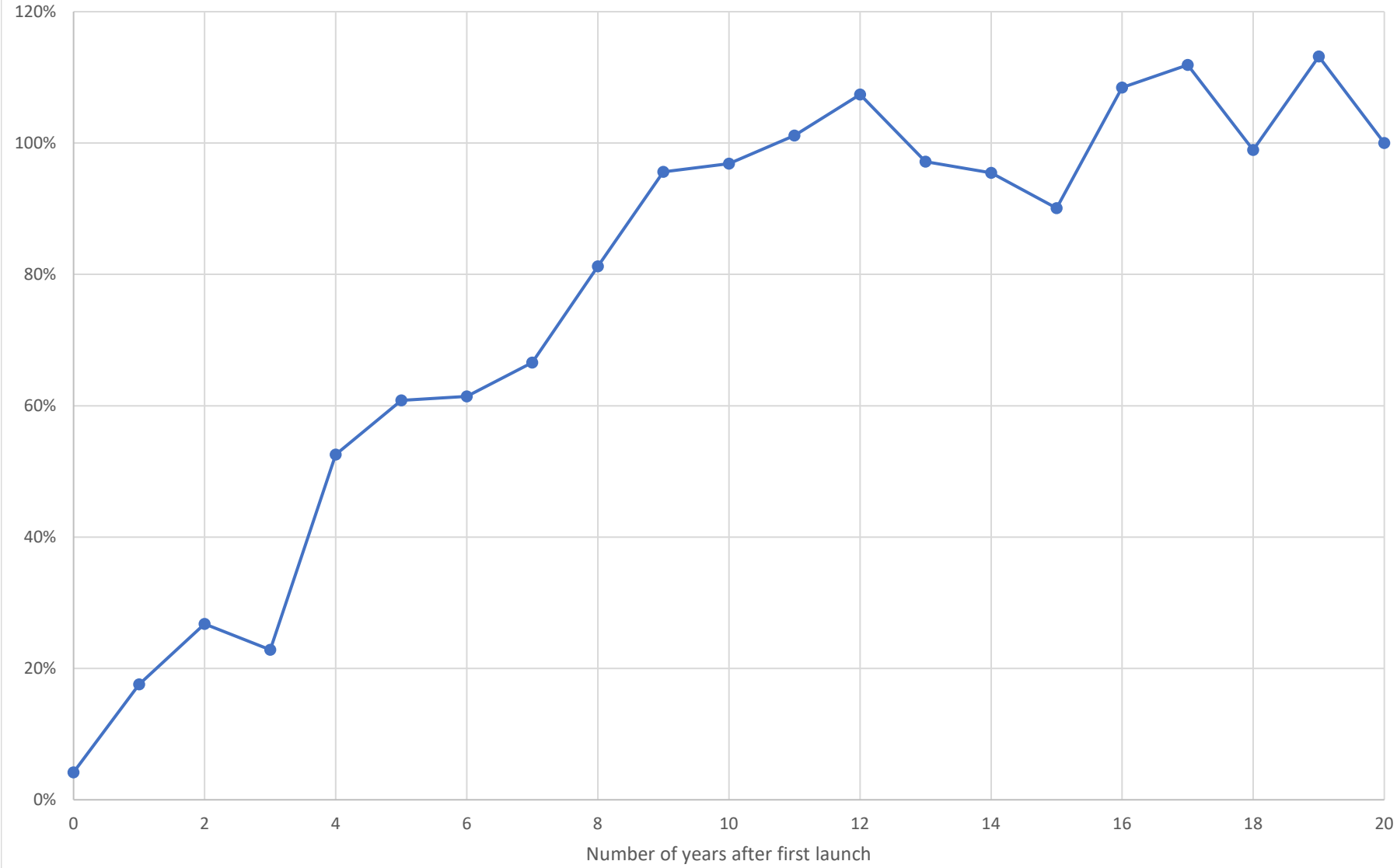


Figure 4

Effect of disease screening/awareness on measured prevalence and mean severity

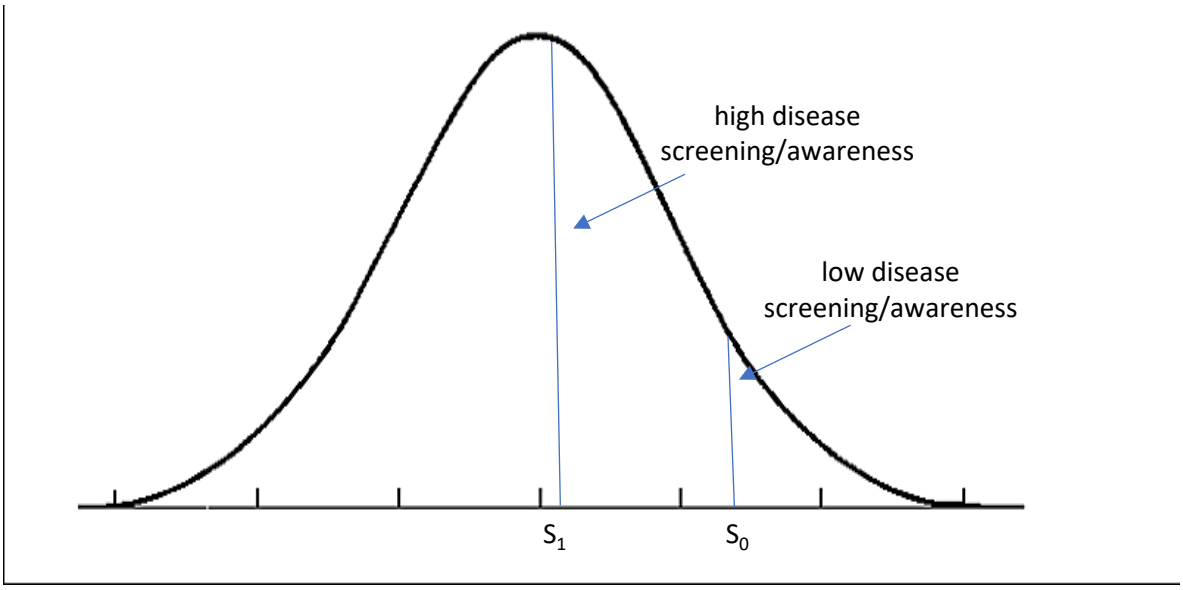
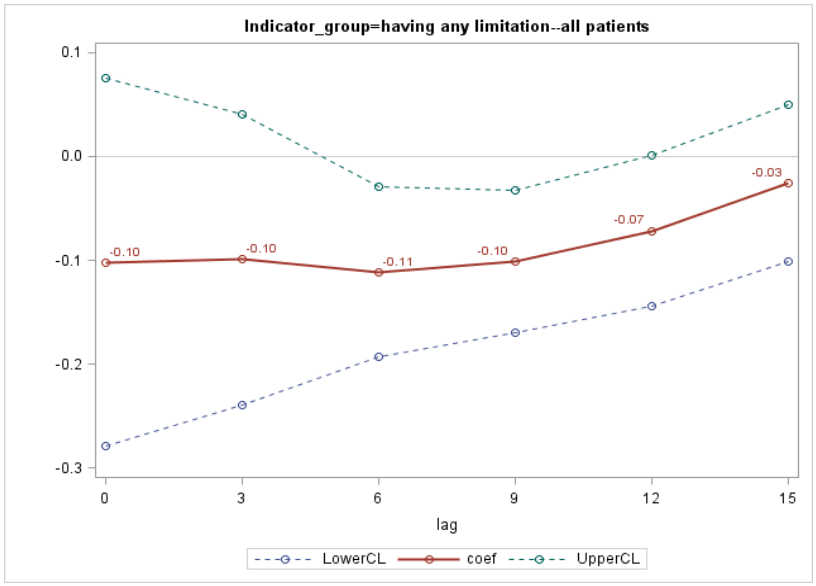
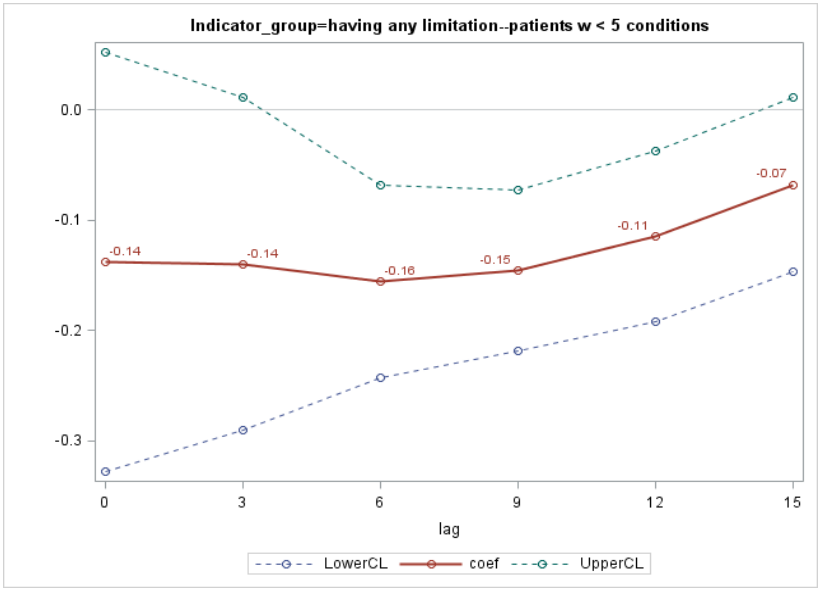


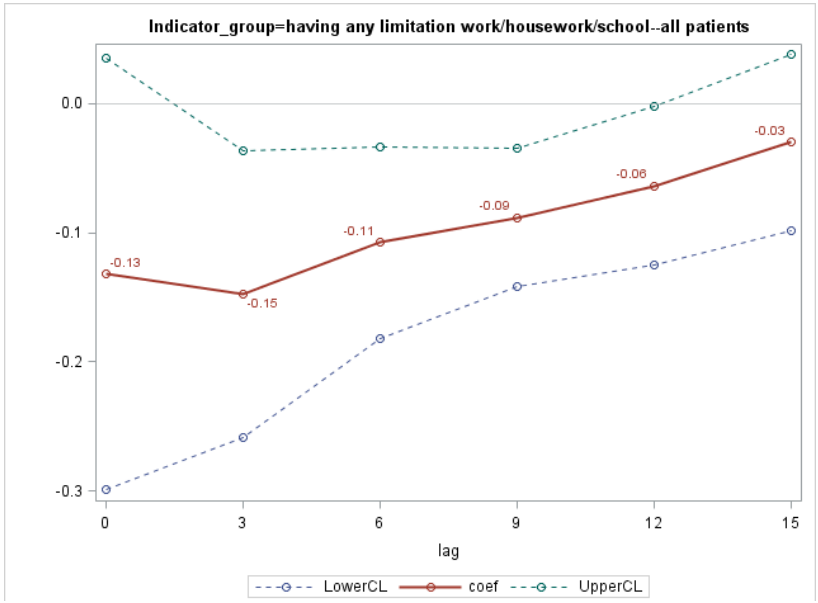
Figure 5

A. has any limitation





B. has any limitation work/housework/school



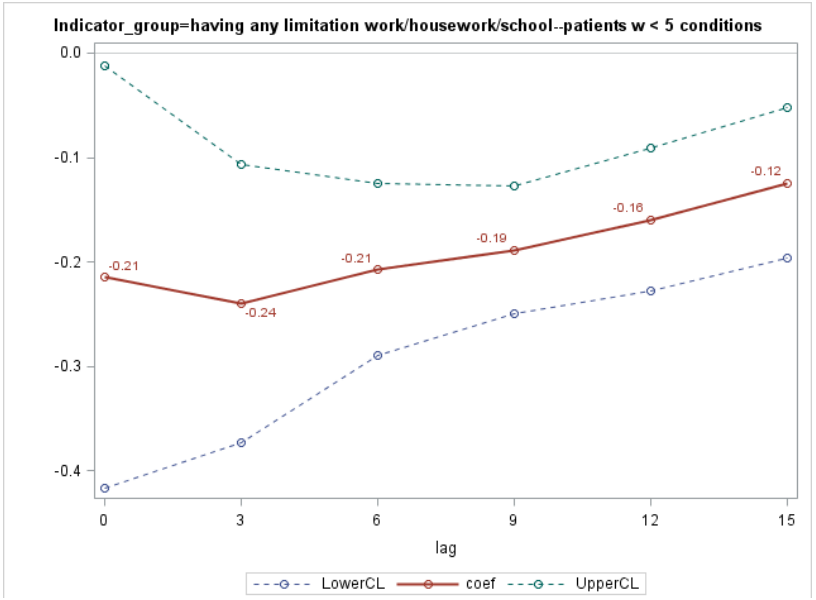
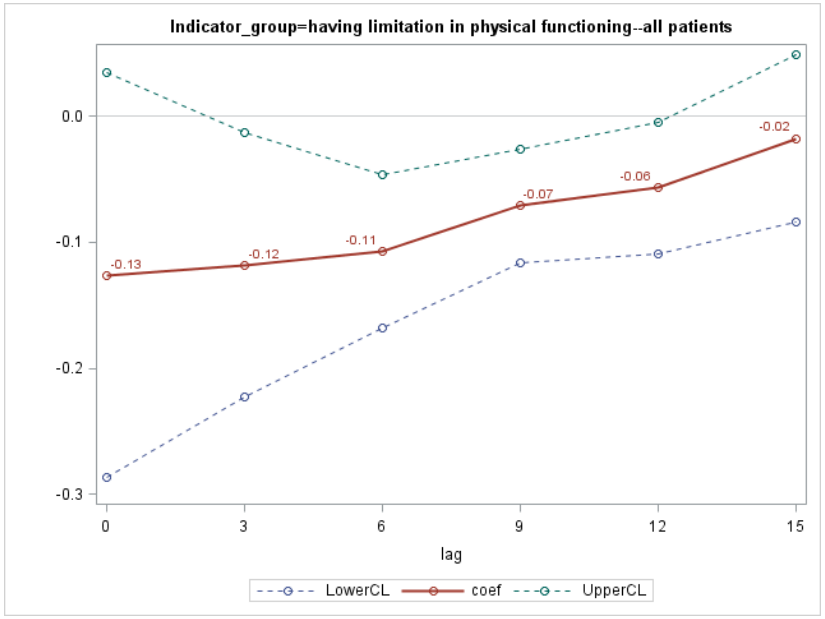
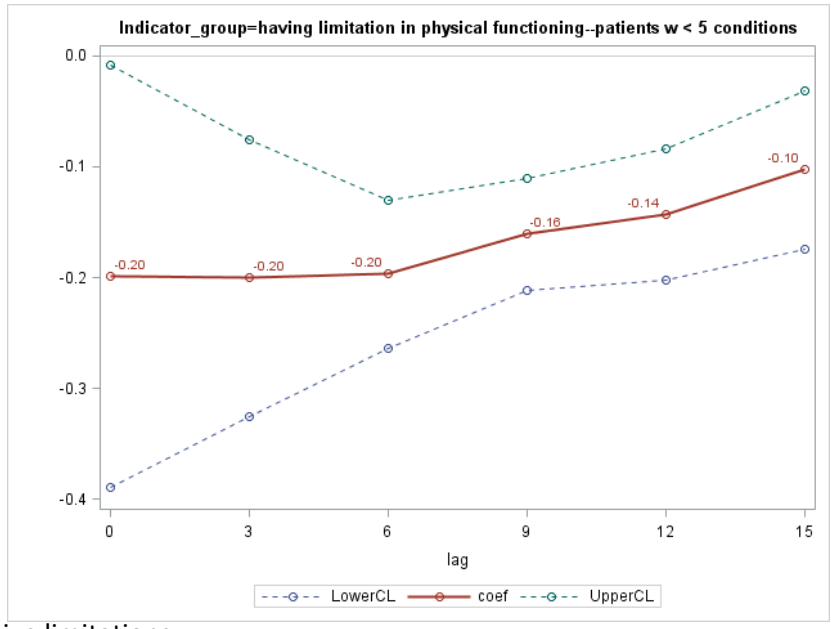


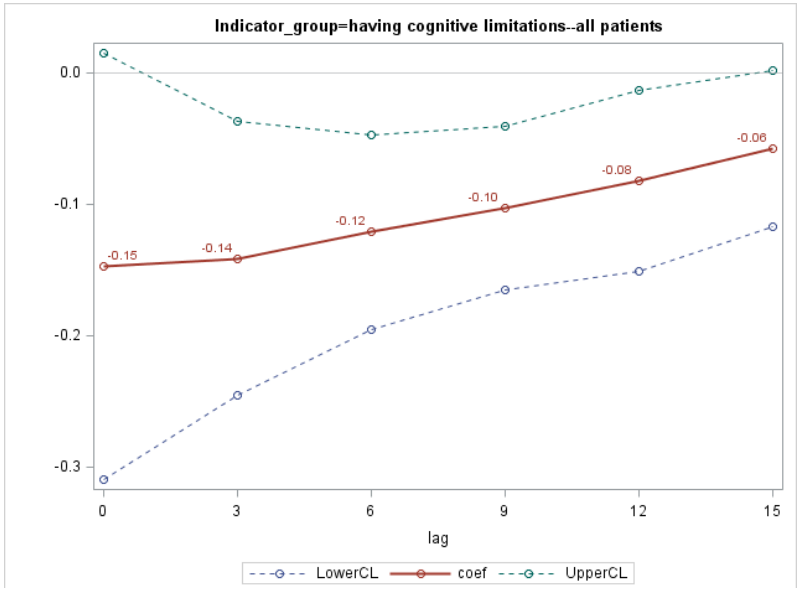
Figure 5

C. has limitation in physical functioning





D. has cognitive limitations



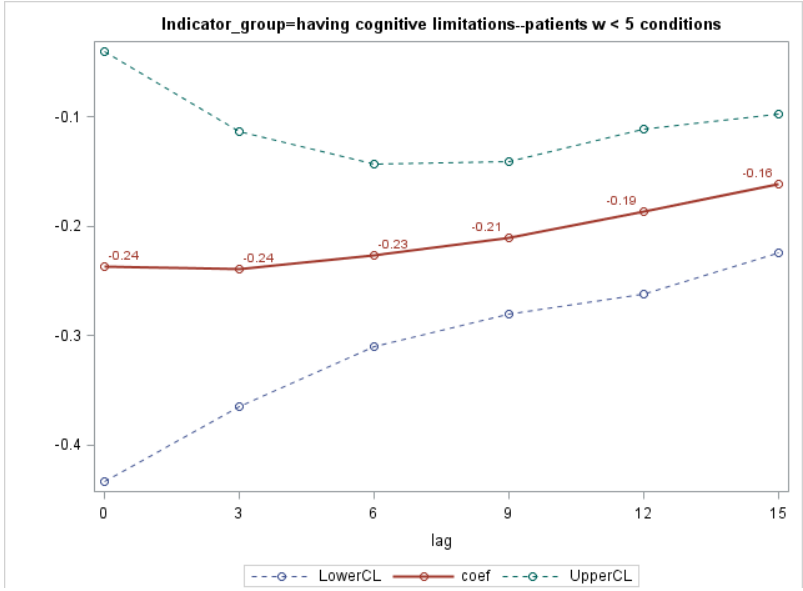
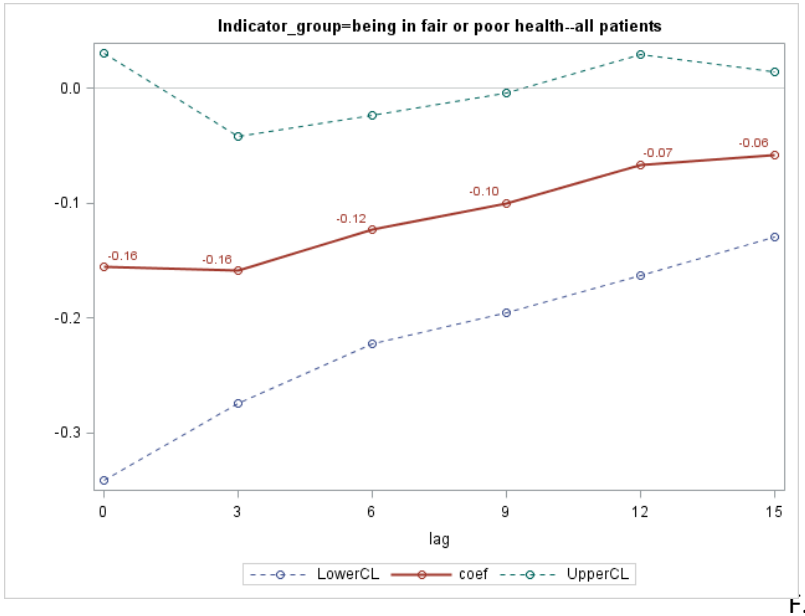
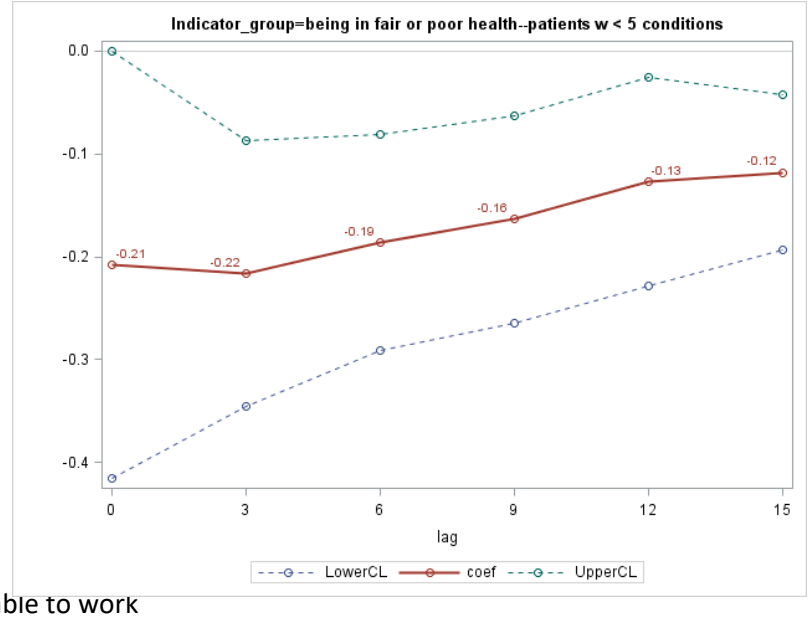


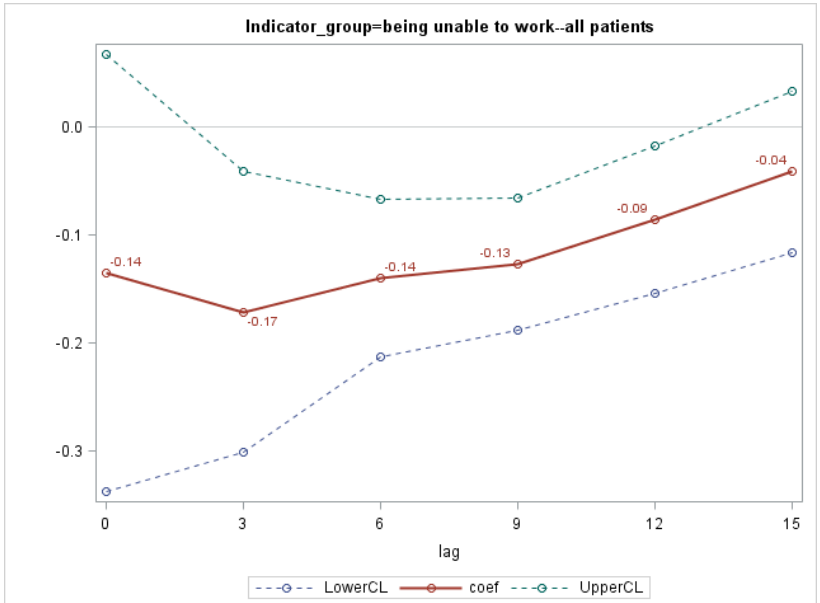
Figure 5

E. in fair or poor health





F. unable to work



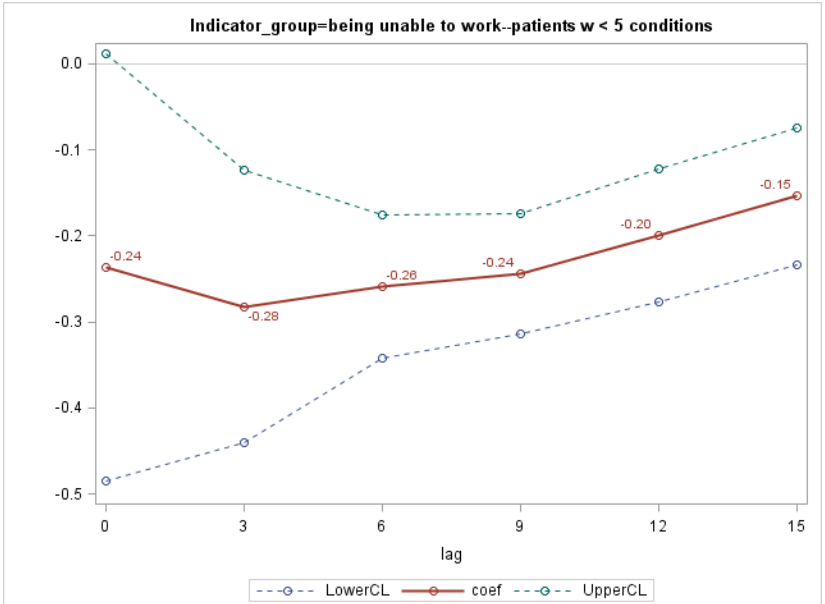
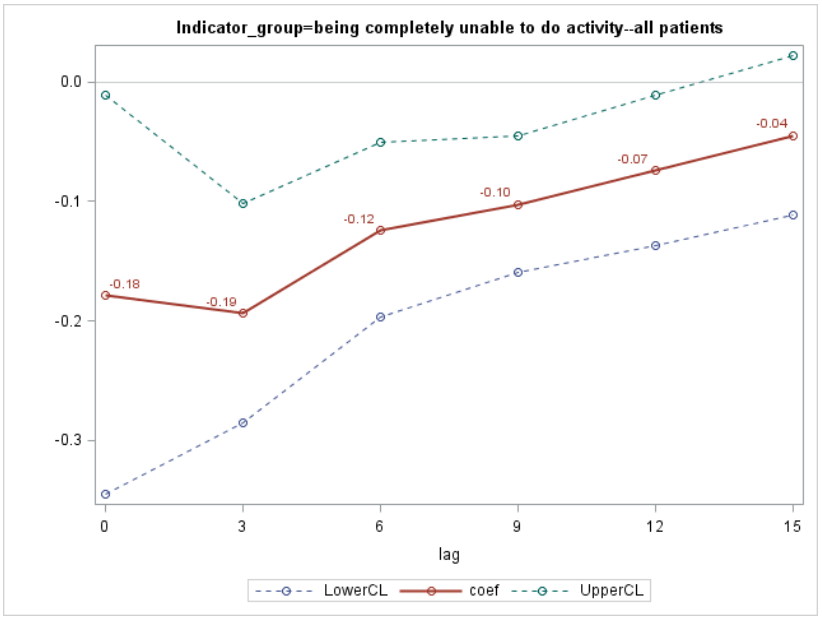
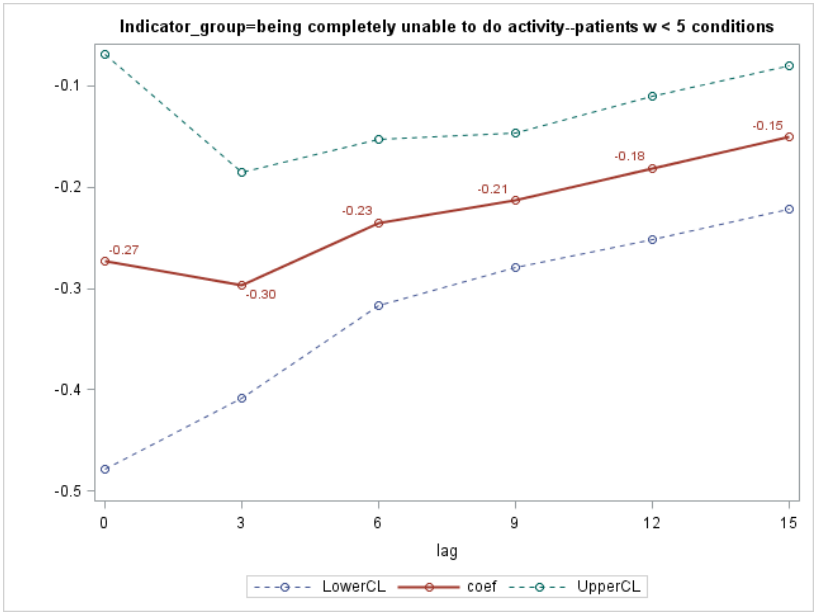


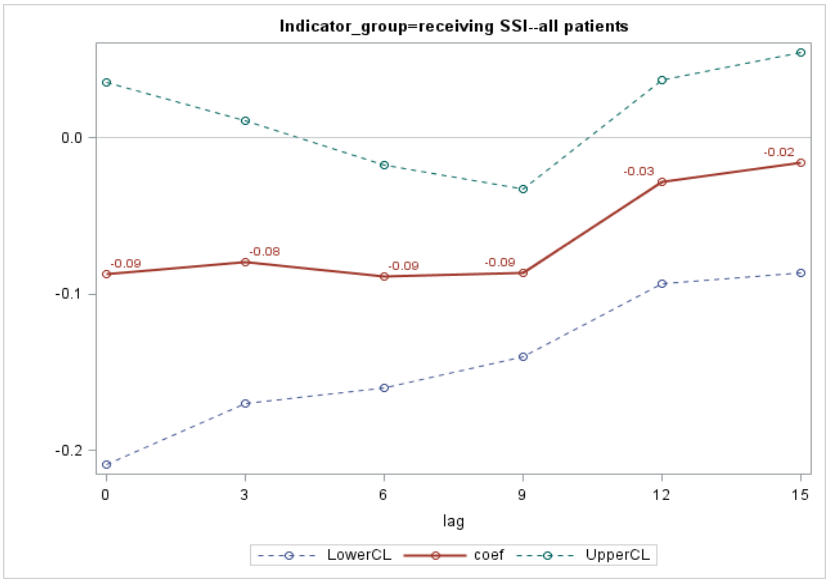
Figure 5

G. completely unable to do activity





H. receives SSI



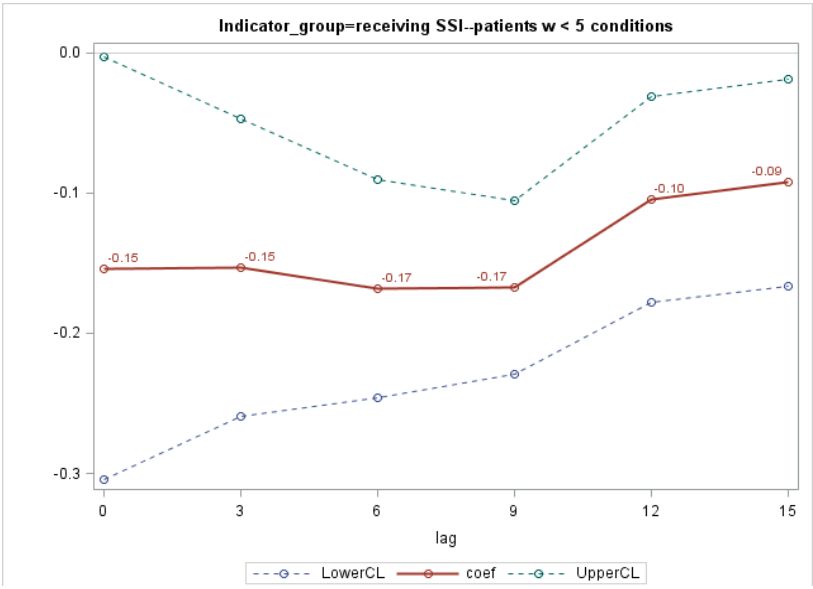
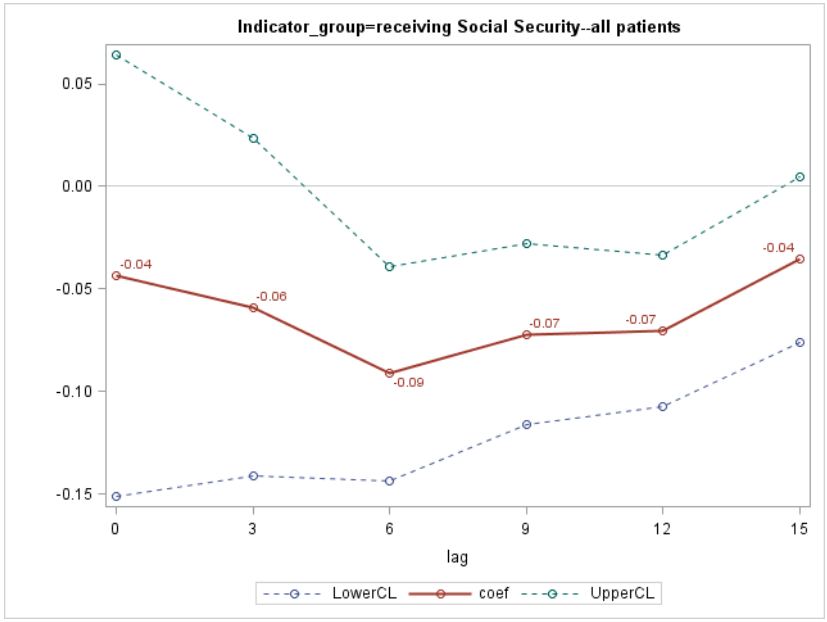
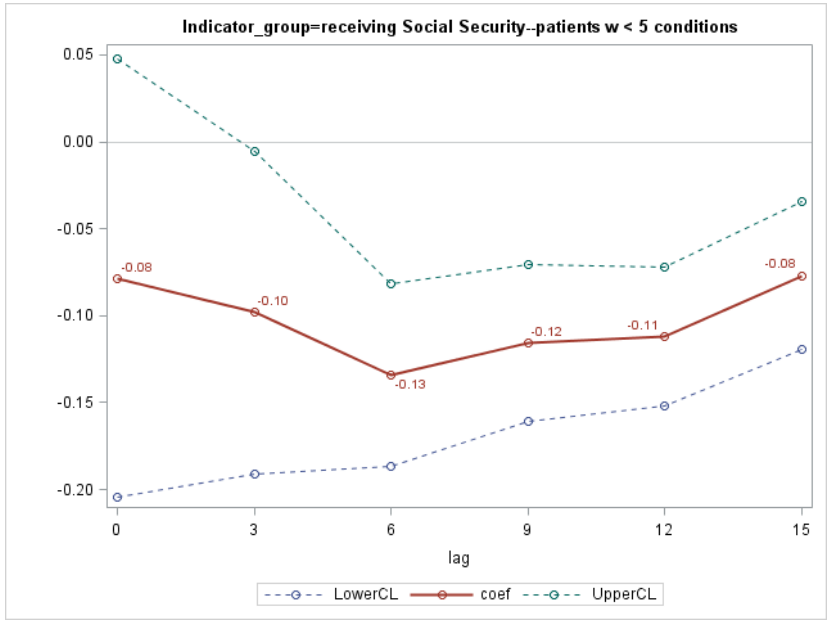


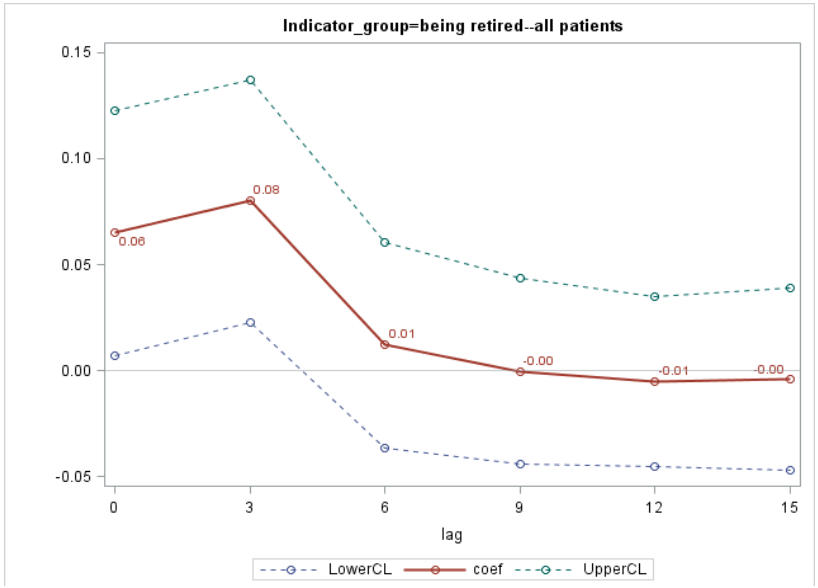
Figure 5

I. receives Social Security





J. is retired



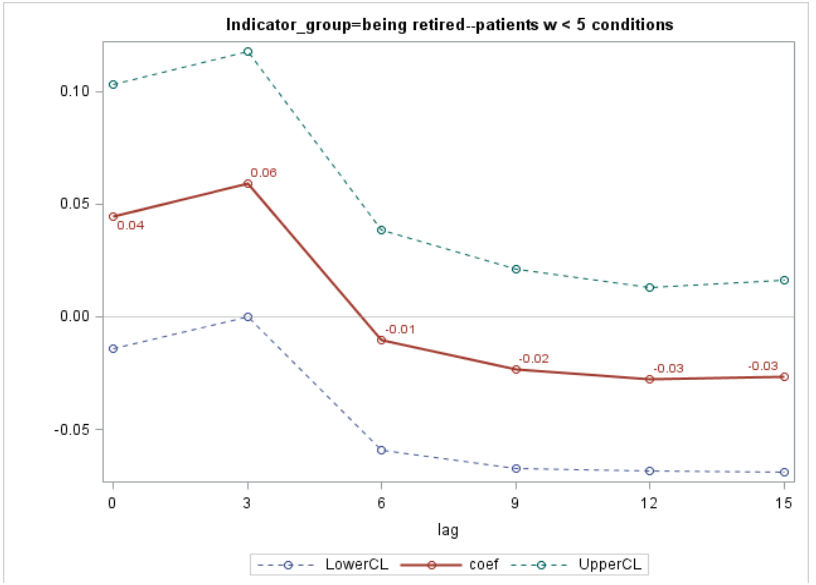
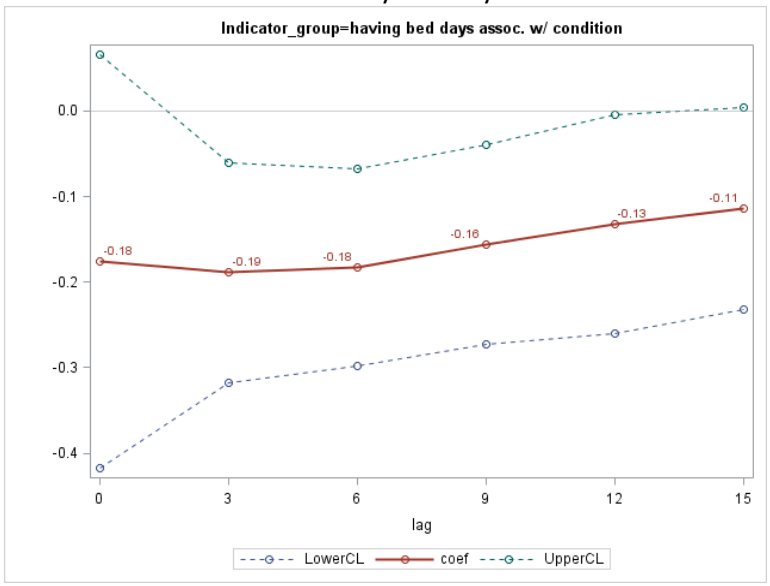
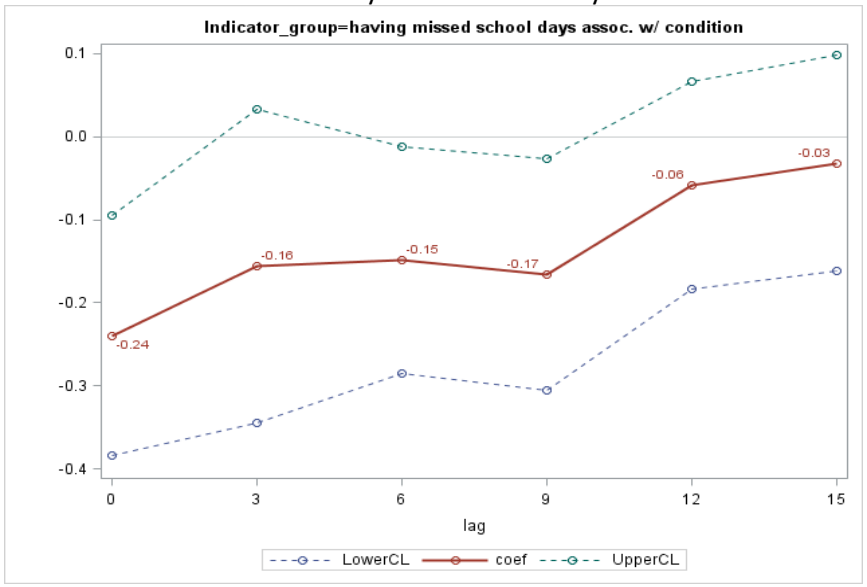


Figure 6

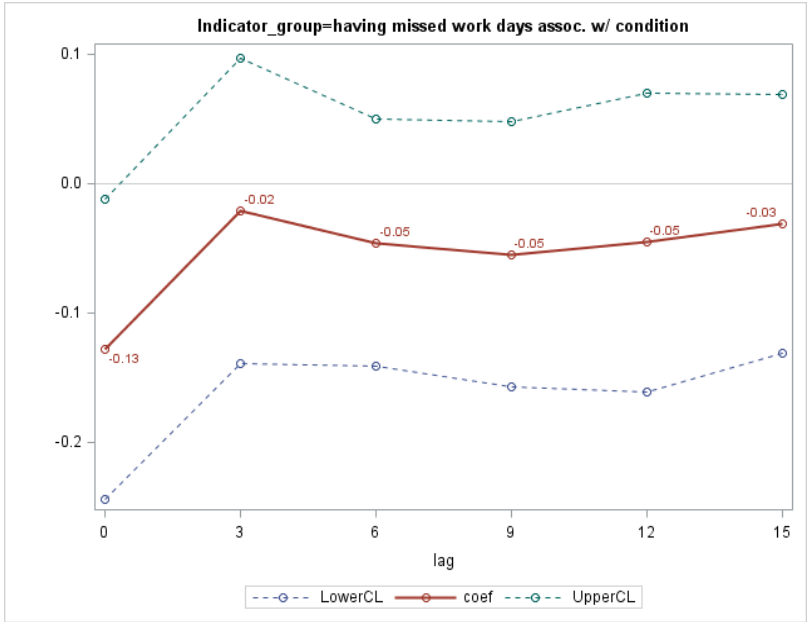
A. any bed days?



B. any missed school days?



C. any missed work days?



D. any prescribed medicines?

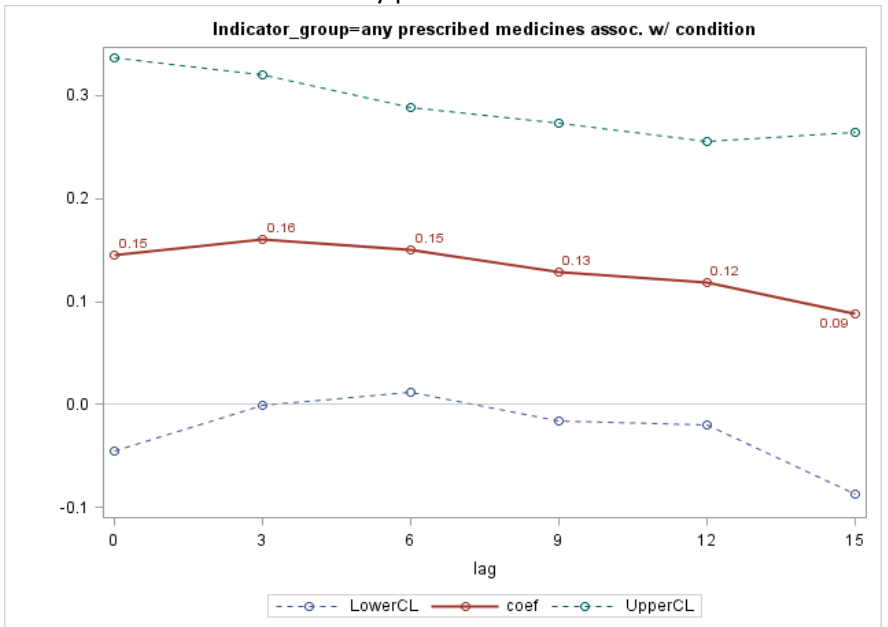
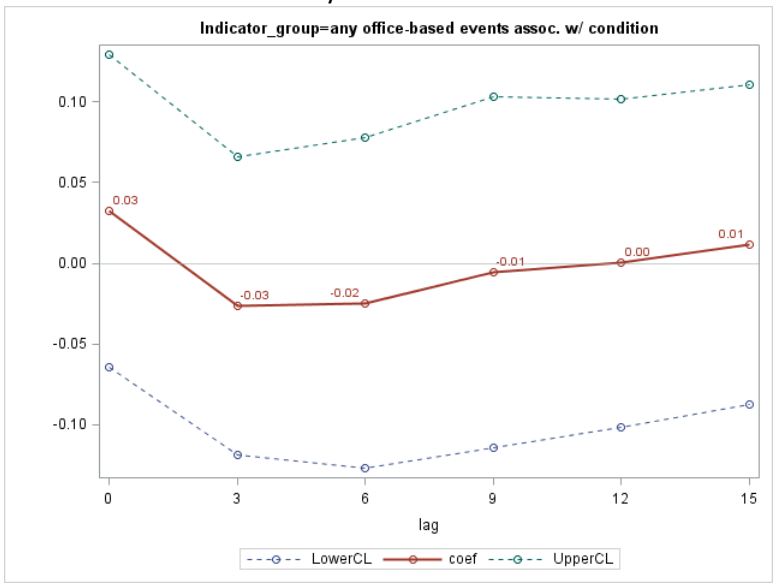
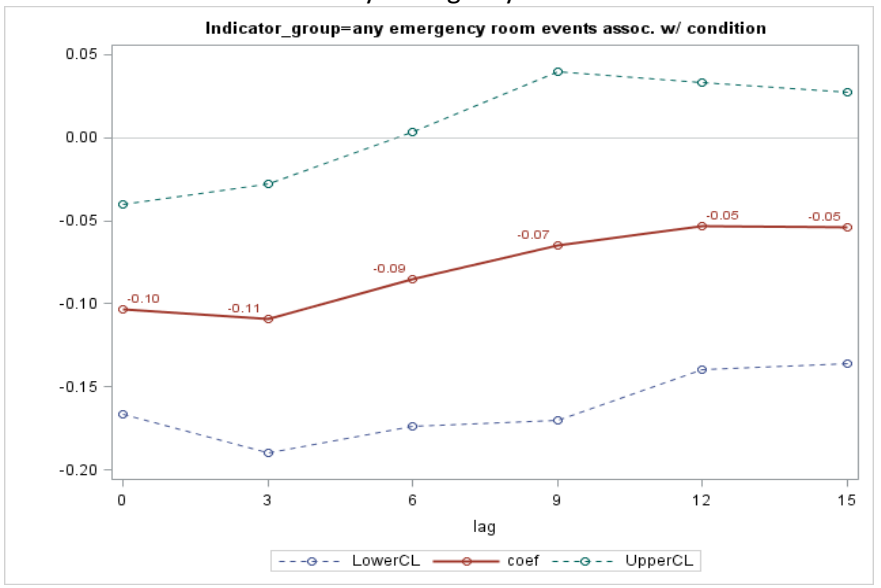


Figure 6

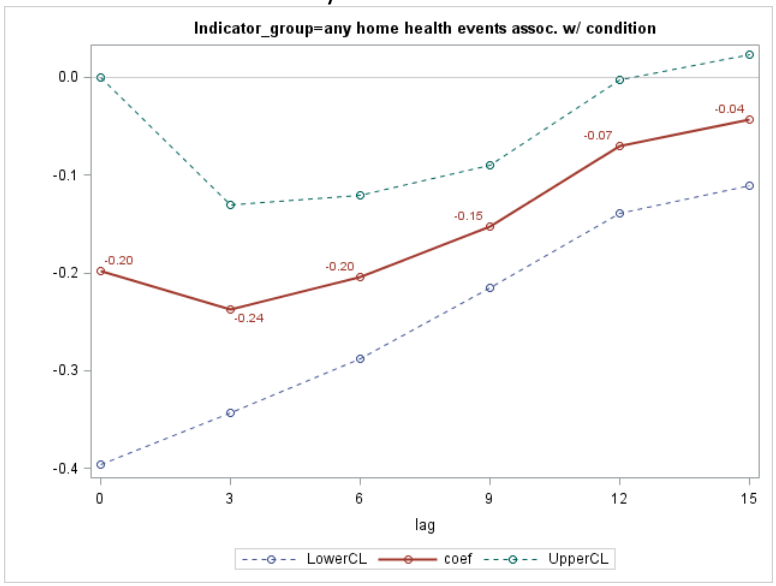
E. any office-based visits?



F. any emergency room visits?



G. any home health visits?



H. any inpatient events?

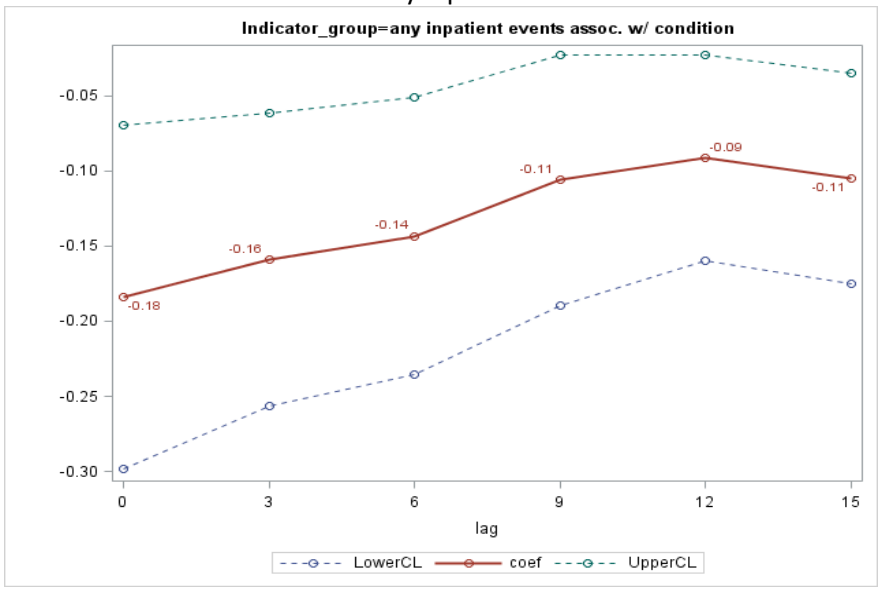
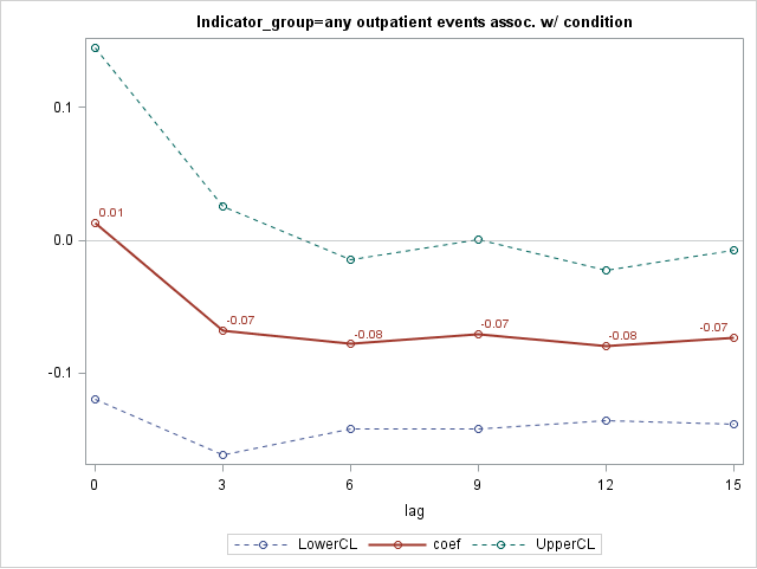


Figure 6

I. any outpatient events?



Appendix Table 1

Estimates of $\beta_{mid,k}$ and $\beta_{high,k}$ (from eq. (3)) from models of 10 person-level disability and Social Security recipiency measures

		$\beta_{mid,k}$					$\beta_{high,k}$			
row	lag (k)	Coef.	Std. Err.	z	P>|z|		Coef.	Std. Err.	z	P>|z|
	A. has any limitation									
1	0	-0.072	0.096	-0.75	0.46		-0.076	0.096	-0.79	0.43
2	3	-0.073	0.076	-0.97	0.33		-0.077	0.076	-1.01	0.31
3	6	**-0.089**	**0.044**	**-2.03**	**0.04**		**-0.092**	**0.044**	**-2.11**	**0.04**
4	9	**-0.079**	**0.037**	**-2.14**	**0.03**		**-0.082**	**0.036**	**-2.27**	**0.02**
5	12	-0.047	0.039	-1.21	0.23		-0.051	0.039	-1.32	0.19
6	15	0.000	0.040	0.01	1.00		-0.004	0.040	-0.11	0.92
	B. has any limitation work/housework/school									
7	0	-0.102	0.102	-1.00	0.32		-0.060	0.100	-0.60	0.55
8	3	**-0.127**	**0.066**	**-1.93**	**0.05**		-0.085	0.064	-1.32	0.19
9	6	**-0.094**	**0.041**	**-2.30**	**0.02**		-0.051	0.040	-1.29	0.20
10	9	**-0.074**	**0.031**	**-2.40**	**0.02**		-0.031	0.030	-1.03	0.30
11	12	-0.044	0.035	-1.26	0.21		-0.001	0.035	-0.04	0.97
12	15	-0.008	0.037	-0.22	0.83		0.034	0.037	0.93	0.35
	C. has limitation in physical functioning									
13	0	-0.092	0.096	-0.96	0.34		-0.064	0.095	-0.68	0.50
14	3	-0.093	0.062	-1.49	0.14		-0.064	0.061	-1.05	0.29
15	6	**-0.089**	**0.033**	**-2.70**	**0.01**		-0.060	0.033	-1.84	0.07
16	9	**-0.052**	**0.025**	**-2.04**	**0.04**		-0.024	0.025	-0.93	0.35
17	12	-0.033	0.029	-1.14	0.26		-0.005	0.029	-0.19	0.85
18	15	0.008	0.035	0.22	0.83		0.035	0.035	1.01	0.31
	D. has cognitive limitations									
19	0	-0.125	0.099	-1.26	0.21		-0.089	0.098	-0.91	0.36
20	3	**-0.127**	**0.063**	**-2.02**	**0.04**		-0.090	0.061	-1.48	0.14
21	6	**-0.113**	**0.041**	**-2.73**	**0.01**		-0.076	0.040	-1.88	0.06
22	9	**-0.096**	**0.035**	**-2.71**	**0.01**		-0.058	0.035	-1.67	0.09
23	12	-0.070	0.038	-1.85	0.07		-0.033	0.037	-0.88	0.38
24	15	-0.044	0.032	-1.37	0.17		-0.006	0.031	-0.20	0.84
	E. in fair or poor health									
25	0	-0.127	0.105	-1.21	0.23		-0.107	0.103	-1.04	0.30
26	3	**-0.135**	**0.065**	**-2.07**	**0.04**		-0.115	0.063	-1.83	0.07
27	6	**-0.104**	**0.053**	**-1.95**	**0.05**		-0.084	0.052	-1.61	0.11
28	9	-0.080	0.052	-1.55	0.12		-0.061	0.051	-1.19	0.24
29	12	-0.044	0.052	-0.84	0.40		-0.024	0.051	-0.47	0.64
30	15	-0.034	0.039	-0.87	0.39		-0.015	0.039	-0.37	0.71

Appendix Table 1

Estimates of $\beta_{mid,k}$ and $\beta_{high,k}$ (from eq. (3)) from models of 10 person-level disability and Social Security recipiency measures

		$\beta_{mid,k}$					$\beta_{high,k}$			
row	lag (k)	Coef.	Std. Err.	z	P>|z|		Coef.	Std. Err.	z	P>|z|
	F. unable to work									
31	0	-0.113	0.125	-0.90	0.37		-0.052	0.123	-0.42	0.67
32	3	**-0.158**	**0.079**	**-2.00**	**0.05**		-0.096	0.077	-1.25	0.21
33	6	**-0.133**	**0.041**	**-3.28**	**0.00**		-0.071	0.040	-1.79	0.07
34	9	**-0.118**	**0.035**	**-3.36**	**0.00**		-0.056	0.035	-1.61	0.11
35	12	-0.071	0.039	-1.83	0.07		-0.009	0.038	-0.24	0.81
36	15	-0.025	0.041	-0.61	0.54		0.037	0.040	0.93	0.35
	G. completely unable to do activity									
37	0	-0.155	0.103	-1.51	0.13		-0.110	0.101	-1.09	0.27
38	3	**-0.178**	**0.055**	**-3.24**	**0.00**		**-0.133**	**0.053**	**-2.49**	**0.01**
39	6	**-0.114**	**0.040**	**-2.85**	**0.00**		-0.069	0.040	-1.75	0.08
40	9	**-0.092**	**0.033**	**-2.79**	**0.01**		-0.046	0.032	-1.43	0.15
41	12	-0.059	0.035	-1.65	0.10		-0.013	0.035	-0.38	0.71
42	15	-0.027	0.036	-0.75	0.45		0.018	0.036	0.51	0.61
	H. receives SSI									
43	0	-0.063	0.075	-0.84	0.40		-0.032	0.073	-0.43	0.67
44	3	-0.061	0.052	-1.17	0.24		-0.030	0.051	-0.59	0.56
45	6	**-0.076**	**0.039**	**-1.95**	**0.05**		-0.044	0.039	-1.15	0.25
46	9	**-0.074**	**0.031**	**-2.40**	**0.02**		-0.042	0.030	-1.40	0.16
47	12	-0.011	0.036	-0.30	0.77		0.021	0.036	0.59	0.56
48	15	0.002	0.037	0.06	0.95		0.034	0.037	0.92	0.36
	I. receives Social Security									
49	0	-0.025	0.063	-0.40	0.69		-0.006	0.061	-0.09	0.93
50	3	-0.045	0.046	-0.98	0.33		-0.025	0.044	-0.56	0.58
51	6	**-0.080**	**0.026**	**-3.06**	**0.00**		**-0.060**	**0.026**	**-2.35**	**0.02**
52	9	**-0.062**	**0.022**	**-2.74**	**0.01**		-0.041	0.022	-1.85	0.06
53	12	**-0.057**	**0.020**	**-2.91**	**0.00**		-0.037	0.020	-1.89	0.06
54	15	-0.022	0.021	-1.03	0.30		-0.001	0.021	-0.07	0.94
	J. is retired									
55	0	**0.072**	**0.030**	**2.41**	**0.02**		**0.073**	**0.030**	**2.45**	**0.01**
56	3	**0.087**	**0.030**	**2.90**	**0.00**		**0.088**	**0.030**	**2.95**	**0.00**
57	6	0.018	0.025	0.73	0.46		0.019	0.025	0.76	0.45
58	9	0.006	0.022	0.25	0.80		0.006	0.022	0.27	0.78
59	12	0.001	0.020	0.05	0.96		0.002	0.020	0.08	0.94
60	15	0.003	0.022	0.13	0.90		0.003	0.022	0.15	0.88