Effect of New Psychotropic Pharmaceuticals on Disability Insurance Applications: Evidence from Matched SIPP/Administrative Data

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The research reported herein was performed pursuant to a grant from Policy Research, Inc. as part of the U.S. Social Security Administration's (SSA's) Improving Disability Determination Process Small Grant Program. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of Policy Research, Inc., SSA or any other agency of the Federal Government.

Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Support for this research at the Baruch and Cornell Research Data Centers from NSF(ITR-0427889) is also gratefully acknowledged.

Abstract

Considerable growth of U.S. Social Security Disability Insurance (DI) rolls during the last several decades has prompted research investigating various topics relating to DI applications. Medical innovation should hypothetically be contributing to the long-term decline in disability, but measuring this impact can be challenging. This paper focuses on the relationship between pharmaceutical innovation of mental health drugs and federal disability insurance applications.

Using data from the Survey of Income and Program Participation (SIPP) merged with administrative records from the Social Security Administration (SSA), I employ an econometric model of disability application behavior and examine the relationship between a measure of psychotropic pharmaceutical innovation and the decision to apply for DI benefits. I find a significant inverse relationship between the availability of psychotropic drugs and DI applications.

In the absence of any post-1995 increase in psychotropic pharmaceutical innovation, there would be a predicted 2.8% increase in applications for disability insurance. This translates to an estimated reduction of 950,000 DI applications, or approximately 380,000 DI awards over the period from 1996-2012; a relatively small impact on the over 33 million total applications during this time.

1. Introduction

The U.S. Social Security Administration's (SSA's) Disability Insurance program (DI) provides cash payments to individuals who are unable to work due to severe health impairments. In 2013, 8.9 million people received $140 billion in DI benefits. Over the past 5 years, the DI trust fund has experienced sharp decreases, which, if continued would render the program insolvent by 2016. Efficiency of the disability determination and review process is critical to the survival of the program.

The DI program insures nonelderly adults who are unable to work due to a physical or mental disability. To qualify, an individual must have worked for five out of the previous ten years in a job covered by Social Security, have a medically determinable impairment that is expected to result in death or last for at least a year, and be unable to engage in substantial gainful activity (SGA)[1].

Considerable growth of DI rolls during the last several decades has prompted research investigating various topics relating to DI applications. Not only has the number of applications and awards increased, but a distributional shift in disability type has occurred since the beginning of the program. In 1960, most disabilities included heart disease, stroke, neurological disorders, and other fatal disabilities. Recently, almost two-thirds of awards are going to those with mental impairments or musculoskeletal conditions such as back pain, diagnoses which impact workers at younger ages and are less fatal (Social Security Administration, 2006). The likely result is an increase in the average number of years beneficiaries are on disability rolls and an increase in lifetime award amounts.

Medical innovation should hypothetically be contributing to the long-term decline in disability, and likely has been for some diseases, but measuring this impact can be challenging. At the same time as the incidence of mental impairments has grown, the availability of new psychotropic drugs to treat these conditions has increased. More effective treatments should cause a proportion of DI applicants with mental disabilities to have reduced symptoms and enhanced functioning. This improvement would then be expected to be observed as fewer DI applications, a decrease in disability rolls, an increase in termination of benefits, and an increase in labor force participation.

This paper focuses on measuring the relationship between pharmaceutical innovation of mental health drugs and federal disability insurance applications. Using data from the Survey of Income and Program Participation (SIPP) merged with administrative records from the Social Security Administration (SSA), I employ an econometric model of disability application behavior and examine the relationship between a measure of psychotropic pharmaceutical innovation and the decision to apply for DI benefits.

[1] SGA is defined as a monthly earnings threshold. In 2015, a non-blind individual would need to earn more than $1090 monthly, net of impairment and work related expenses, to engage in substantial gainful activity.

Many studies have focused on the factors of DI program growth. Autor and Duggan (2006) review literature in the field and point to three major reasons for the increase in DI awards; changes in the eligibility rules, an increase in the earnings replacement rate, and an increase in the population of eligible workers. They find that an increase in aging and improvement in population health are comparatively minor factors, but improved health is significant in reducing the incidence of disabling disorders.

Lahiri, Song, and Wixon (2008) match SIPP data to SSA administrative records and estimate a model of DI application behavior. The authors use a carefully selected analytical sample and a number of meaningful explanatory variables from SIPP to estimate a probit model for the disability application decision, together with a recursive system of multiple equations for earnings and medical determination. They find a smaller work disincentive effect than previous studies; that no more than 37% of DI beneficiaries would return to sustained work if they did not receive benefits. In addition to several other findings, they discover a large significant effect of the expected value of Medicare for applicants; the availability of Medicare to DI beneficiaries boosts the average probability of application by 12%.

A handful of studies have attempted to measure pharmaceutical innovation. Most recently, Lichtenberg (2011) finds a state-level inverse relationship between disability award rates and the availability of newer prescription drugs. The author quantifies pharmaceutical innovation by calculating a measure of drug vintage: a category average approval date for a drug's active ingredient weighted by its utilization. When added to models explaining DI awards, the availability of newer drugs explains a decrease in the predicted disability award rate; from what would be 3.65% to 3.42% between 1995 and 2004, or approximately 418,000 DI beneficiaries over ten years. Two other Lichtenberg papers (2005, 2012) explore the effects of newer prescription drugs using self-reported measures of health from the National Health Interview Survey (NHIS), and the Medical Expenditure Panel Survey (MEPS). These studies find that newer drugs result in improved health and ability to work.

In this study, I construct a measure of the availability of new psychotropic prescription drugs and examine how it relates to the DI application decision of different at-risk populations. Using micro-data from the SIPP matched to SSA administrative records on DI applicants, I construct a population at-risk of applying for DI, and a subset of this group identified as mentally impaired. I find a significant inverse relationship between the availability of new psychotropic pharmaceuticals and individual DI applications in both populations, however this decrease is relatively small. This paper adds to the literature by incorporating a measure of mental health drug vintage into a micro-data analysis of the disability application decision, focusing on a sub-population of those self-reported as mentally impaired.

The rest of the paper is structured as follows: Section 2a describes the disability data, the matching process, and explains the derivation of the analytical samples. Section 2b gives details on the pharmaceutical data sources, and describes the process for creating the psychotropic drug vintage measure. Section 3 lays out the econometric model, followed by results in section 4. Discussion of the results and a conclusion are in sections 5 and 6 respectively.

2. Data

Two categories of data are used in this study, disability data and pharmaceutical data. Disability data, including demographics, disability characteristics, application information, and earnings history, were obtained from the U.S. Census Bureau's Survey of Income and Program Participation (SIPP) linked with administrative files from the Social Security Administration (SSA) and the Internal Revenue Service (IRS). For the scope of this research only, I was granted special sworn status by the Census Bureau to access confidential micro-data onsite at a physically secure Research Data Center (RDC)[2]. While at the RDC I was permitted to match individuals surveyed in SIPP to SSA's 831 disability file and Summary Earnings Records (SER) from the IRS. No personally identifiable information was accessed or compromised according to Census Title 13 and Title 26 authority. Prior to being reported, output for this project was subject to rigorous disclosure avoidance review by the Census Bureau. Table 1 gives a detailed list of datasets used and their origin.

Pharmaceutical data on mental health drugs and their usage comes from three publically available sources: the National Institute of Mental Health (NIMH), the Federal Drug Administration (FDA), and the Centers for Medicare and Medicaid Services (CMS).

Table 1: Data Sources

Dataset	Years	Source	Use
SIPP	1996 – 2008	Public Use (Census)	• Demographic information • Disability characteristics • Mental health conditions
831 File	1988 – 2011	Confidential (SSA)	• DI application, allowance, denial • Filing date
Summary Earnings Records	1978 – 2010	Confidential (IRS)	• Earnings history for individuals in SIPP
Mental Health Medications	1975 – 2013	Public Use (NIMH)	• Psychotropic Rx names • Psychotropic Rx categories
National Drug Code Directory	1975 – 2013	Public Use (FDA)	• Rx NDC codes • Initial approval dates
Medicaid Drug Use	1991 – 2013	Public Use (CMS)	• Rx utilization by year and state for weighting purposes

a. Disability Data

An analytical sample was created by combining the four most recent panels from the SIPP: 1996, 2001, 2004, and 2008. In each national panel of SIPP, a set of households is selected and interviewed every four months. Each interview event constitutes a wave in the panel. Certain topical modules are assigned to selected waves where additional interview questions are included. Detailed questions regarding adult disability were asked in the topical modules for wave 6 of the 2008 panel, and wave 5 of the 2004, 2001, and 1996 panels. The interview month

[2] This research was performed at multiple locations of the New York Census Research Data Center, both at Cornell University in Ithaca and Baruch College in New York City.

from these four disability topical module waves form the basis of the sample and include a rich set of details on functional and work limitations as well as health conditions.

This set of individuals from SIPP were then matched to SSA's disability application database known as the 831 file. Each record in the 831 file is an occurrence of a disability application, and multiple applications may be submitted by an individual. SIPP records are organized by individual over months. The first observable application for each individual was selected if more than one disability application was found. In the entire 831 file, approximately 30% of applicants are categorized as applying for the primary reason of mental impairment.

To form the analytical sample, individuals were selected if they were between the ages of 18 and 64 and disability insured[3]. The sample was then further restricted to individuals who filed for DI within 36 months of the disability topical wave interview month. Since non-applicants do not have a filing date, one was randomly assigned based on the distribution of applicants, according to Kreider (1999). These parameters resulted in a full analytical sample of 101,500 which can be categorized into three mutually exclusive groups: 88,450 non-applicants, 5,010 allowed applicants, and 8,040 denied applicants.

Selected descriptive statistics for the full analytical sample, categorized as non-applicants, denied applicants, and allowed applicants, are presented in Table 2. All demographic variables included in the descriptive statistics were obtained from SIPP, except for information regarding individual earnings (earnings, earnings variance, and labor force attachment), which were calculated using restricted Summary Earnings Records from the IRS. *Earnings* is calculated as an average of the two years prior to the application year, in an attempt to exclude the effect of reduced earnings from disability or in anticipation of disability application. *Earnings variance* is a measure of an individual's variability of income in the one to six years prior to application. *Labor force attachment* is a count of the number of years out of the ten years prior to the filing year with positive earnings.

Table 2: Sample Means

	Non-applicants	Denied	Allowed
Sample Size	88,450	8,040	5,010
Age	46.2	43.4	46.7
Male	0.401	0.434	0.514
White	0.441	0.338	0.347
Married	0.573	0.443	0.476
Family Size	2.80	2.85	2.66
High School Grad	0.310	0.372	0.368
Some College	0.346	0.324	0.311
College Grad	0.201	0.068	0.104
Family Income (monthly)	3,982	2,188	2,529
Health Insured	0.304	0.577	0.485

[3] To be DI insured, workers must have 20 quarters of positive earnings out of the previous 40 quarters if over age 30.

Southern Region	0.319	0.414	0.360
Western Region	0.223	0.169	0.187
Midwest Region	0.252	0.236	0.232
Difficulty Lifting	0.352	0.353	0.364
Difficulty Walking	0.292	0.357	0.384
Difficulty with IADL	0.109	0.178	0.234
Use Aids	0.087	0.117	0.163
Mental Condition	0.048	0.078	0.101
Earnings[4] (annual)	16,236	9,919	14,969
Earnings Variance[3]	471.9	442.8	586.2
Labor Force Attachment[3]	6.38	6.84	7.18

Compared to non-applicants, disability applicants have a higher proportion of unmarried, minority males, and tend to have lower earnings, less education, and higher incidence of reported mental conditions. Of those who apply, the denied group has much lower earnings than the allowed group and less attachment to the labor force. These descriptive statistics are consistent with the expectation that an individual's decision to apply for DI benefits is made up of more than just medical considerations. An individual's earnings, specifically, are often determined jointly with the decision to apply for DI, and must be given special treatment in the model.

An examination of applicants in the sample reveals the large number of applications which are filed due to a mental health condition. See Table 3. Of the 5,010 allowed applicants in the sample, 33.1% are for mental health conditions, compared to 20.0% for musculoskeletal disabilities, and 46.9% for every other type of impairment. Of the 8,040 denied applicants, 22.4% submitted for mental health.

Table 3: Applicants by Disability Type

	Mental Health Condition	**Musculoskeletal Condition**	**All Other Disabilities**
All Applicants	3,460 (26.5%)	4,210 (32.3%)	5,380 (41.2%)
Allowed	1,660 (33.1%)	1,000 (20.0%)	2,350 (46.9%)
Denied	1,800 (22.4%)	3,210 (39.9%)	3,030 (37.7%)

b. Measurement of Drug Vintage

To calculate a measure of new pharmaceutical drug availability, I use a method similar to Lichtenberg's design of drug vintage. A product's usage in a given state and year is used to weight the date the product was approved as a new molecular entity. This results in an indication of the availability of new mental health pharmaceuticals in an individual's state during the year of disability filing.

[4] Calculated using confidential data from SER.

The National Institute of Mental Health (NIMH) maintains a list of Mental Health Medications[5] and groups them into categories: Antipsychotic, Antidepressant, Mood Stabilizing, and Anti-anxiety[6]. I considered this NIMH list of 66 psychotropic drugs and their generic counterparts a comprehensive source for mental health pharmaceuticals. Each product and its generic was referenced to a set of NDC (National Drug Code) numbers from the NDC Directory published by the Federal Drug Administration (FDA), resulting in a dataset with over 2,000 NDC codes.

Each NDC code uniquely identifies a product application by a manufacturer or labeler, and each product typically has several FDA applications varying by dosage, package size, or other classifying information. All NDC codes with a common proprietary or generic name were included in the set for a particular product. The earliest new molecular entity date provided by the FDA approval history within the set was assigned to the entire set. For example, Prozac is the proprietary name for the antidepressant medication generically known as fluoxetine. All NDC codes for Prozac and fluoxetine were then assigned the date of 12/29/1987, the date the molecular entity in Prozac first became available. Any future FDA approvals for variations on a proprietary product or its generic—such as the introduction of a time-release alternative a decade later—would still be assigned the initial new molecular entity date of the drug.

Each drug start date was then weighted by its usage. Obtaining national usage data is prohibitive, so publicly available Medicaid usage data was substituted. Lichtenberg shows that Medicaid drug utilization data is an appropriate proxy for the national distribution of prescriptions filled, and pays for approximately 15% of all U.S. outpatient prescriptions (Lichtenberg 2011). Given that this utilization measure is for weighting the FDA approval dates, a similar distribution to national prescribing habits is adequate to justify the use of Medicaid data.

As part of the Medicaid Drug Utilization Review (DUR) program, each state is required to annually report drug prescription details. Data on the number of prescriptions, number of product units, and total reimbursements are publicly available from Medicaid[7]. I compiled over 1100 data files for each state between years 1991 and 2013 to create a utilization dataset. NDC codes and start dates were then cross referenced to this utilization data for each state and year. Product units were chosen as the best weight for calculating psychotropic drug vintage, while the sum of all reimbursements is used as a control variable later in the regression analysis. A certain number (less than 4%) of year-states are not reported in the DUR files, so these weighted measures were imputed using information from available states in the same year[8].

[5] http://www.nimh.nih.gov/health/publications/mental-health-medications/nimh-mental-health-medications.pdf

[6] There is also a combination antipsychotic and antidepressant category consisting of one drug, Symbyax, which, for this analysis, was absorbed into the antipsychotic category. Medications for ADHD were not considered for this study.

[7] http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Benefits/Prescription-Drugs/Medicaid-Drug-Programs-Data-and-Resources.html

[8] Medicaid State Utilization data was not reported for Arizona from 1991-2009, Arkansas from 2001-2013, Indiana in 2008, Kentucky in 1994, Maryland in 2003, Michigan in 2005, Montana in 2013, Tennessee from 1995-1998, and West Virginia in 1999.

Two measures of psychotropic drug vintage were calculated. The first weights the FDA approval date by product units for each state, in every year from 1991-2013, for each of the four selected NIMH categories.

$$psych\_vintage_{gst} = \frac{\sum_p Rx_{pgst} FDA\_date_p}{Rx_{pgst}} \quad (1)$$

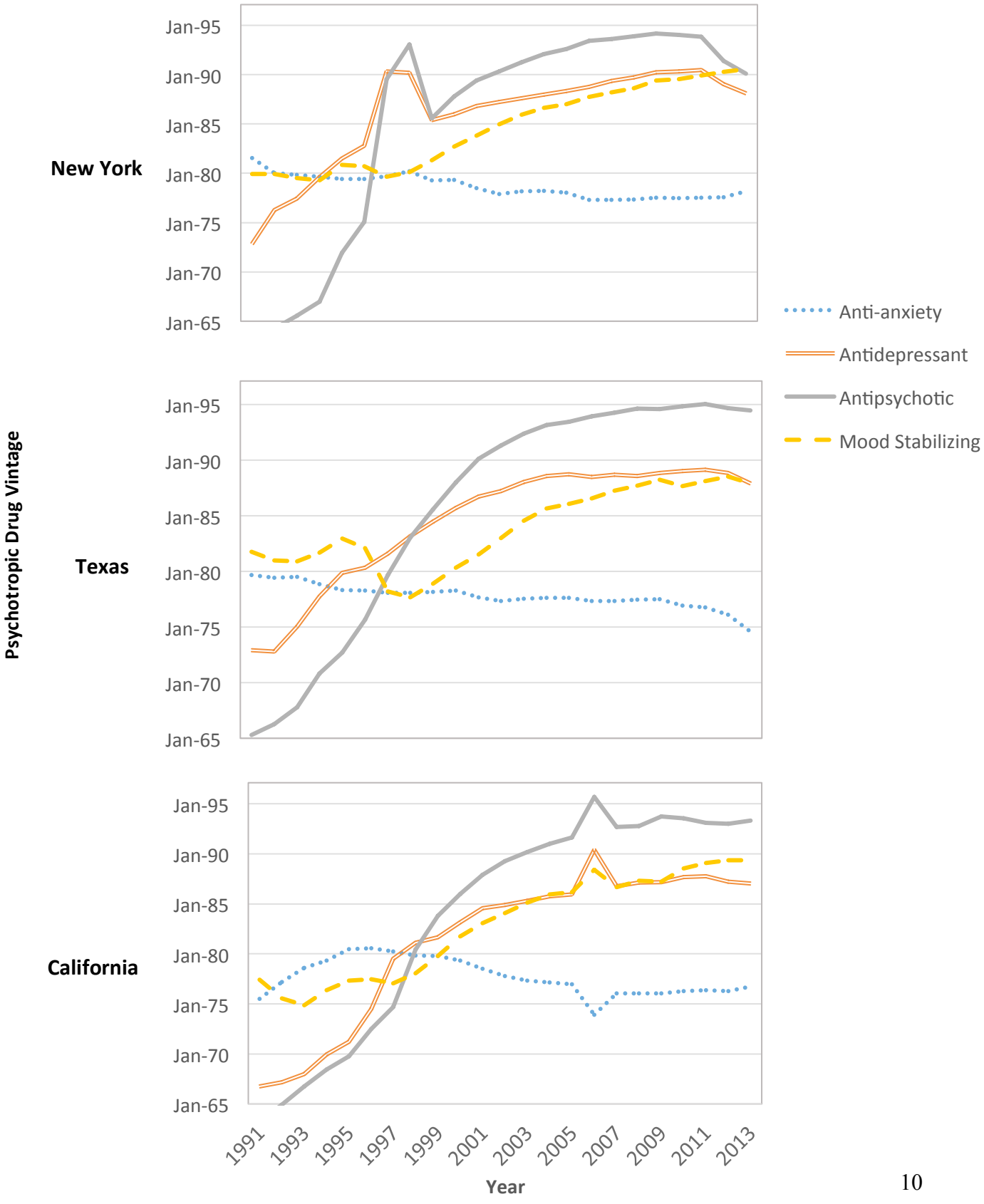
$psych\_vintage_{gst}$ = the utilization-weighted average FDA approval date for psychotropic drugs in category g in state s in year t

Rx_{pgst} = quantity of drug product p in category g in state s in year t

FDA_date_p = the FDA approval date of the active ingredient of product p

Figure 1 shows the psychotropic drug vintage for a few representative states by mental health drug category. An increasing drug vintage measure indicates the growing utilization of newer drugs in that category over time. Note that in most states, there is more usage of pharmaceutical innovation in the categories including antidepressants, mood stabilizers, and antipsychotics. The anti-anxiety drug category tends to have a lower drug vintage compared with other categories. And while there looks to be sufficient variation between states, there is strong positive correlation of drug vintage measures between categories. To avoid the problem of multicollinearity, it is best to use a single drug vintage for modeling by collapsing categories into a weighted mean of all mental health drugs.

Figure 1: Psychotropic Drug Vintage by Category, Selected States



The second measure of psychotropic drug vintage is calculated without categories and results in a weighted approval date for each state and year included in the reference period.

$$psych\_vintage_{st} = \frac{\sum_p Rx_{pst} FDA\_date_p}{Rx_{pst}} \quad (2)$$

Figure 2 shows the mean psychotropic drug vintage for a few representative states. This is the measure of mental health drug innovation used in the model explaining the DI application decision. This utilization weighted mean of the approval date of psychotropic drugs was merged into the SIPP/831 dataset by state and filing year, assigning each individual observation a measure of the availability of new drugs in their geographical location during the time of disability onset.

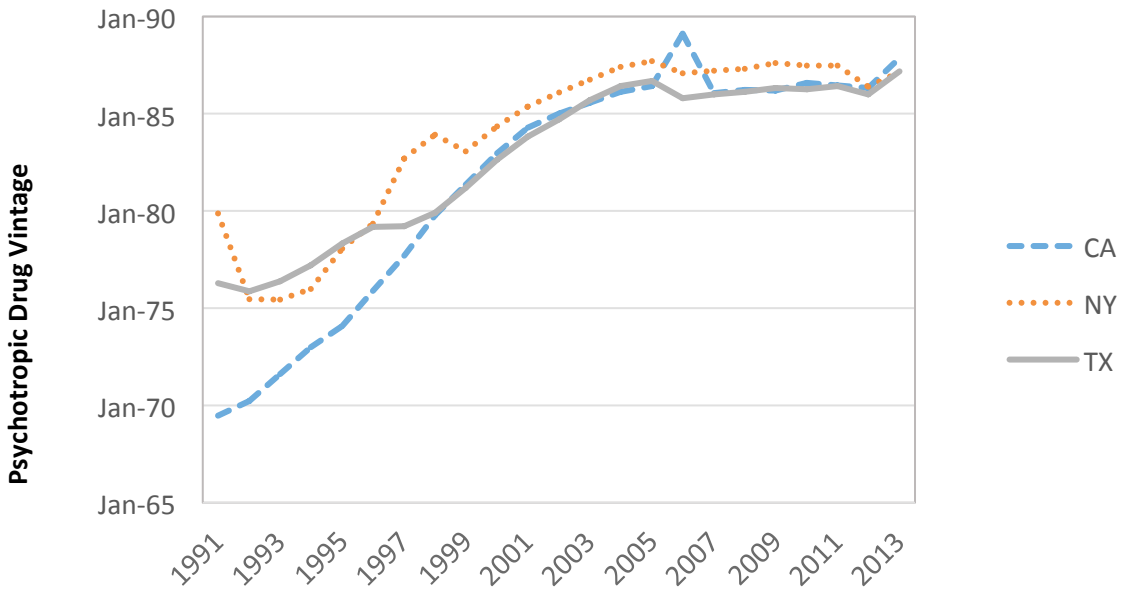


Figure 2: Mean Psychotropic Drug Vintage, Selected States

3. Methods

In order to estimate the DI application choice I use two equations to explain the decision process, an application equation and an earnings equation. An individual's decision to apply for DI benefits is influenced by many demographic and health characteristics. Earnings are of particular importance not only because non-applicants have higher earnings than applicants, but because earnings are a determinant in the award decision and individuals may restrict earnings in order to qualify for benefits. This model accounts for the endogeneity of earnings and allows earnings to influence the application decision, while also allowing the application decision to

influence earnings. The measure of psychotropic drug vintage is included in the application equation, along with a control for total drug usage, and a vector of calendar year dummy variables.

Application: $$I_i = Y_i + X_{iA}\beta_A + C\gamma + \mu \cdot psych\_vintage_i + \delta \cdot Rx\_total_i + \varepsilon_{iA} \quad (3)$$

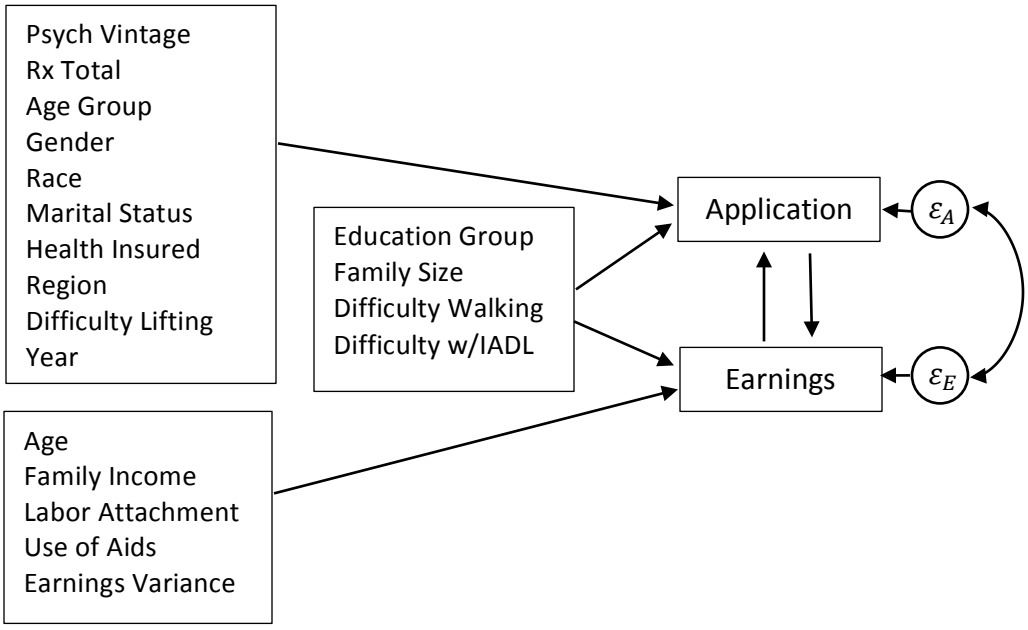
Earnings: $$Y_i = I_i + X_{iE}\beta_E + \varepsilon_{iE} \quad (4)$$

I_i = individual i's decision to apply for DI benefits (1=apply, 0=otherwise)
Y_i = two year average earnings prior to filing year for individual i
X_{iA} = vector of demographic and health variables included in application decision
X_{iE} = vector of demographic and health variables included in earnings equation
C = vector of calendar year dummy variables
$psych\_vintage_i$ = weighted mean psychotropic drug vintage in i's state and filing year
Rx_total_i = total drug usage in i's state and filing year

The primary coefficient of interest is μ, which measures the effect of new psychotropic drug availability on the decision to apply for DI benefits. By adding controls for the total drug usage and calendar year dummies, the coefficient on psychotropic drug vintage is not affected by trends of increasing general drug use or by macro influences from business cycles.

The model is then estimated using a full information maximum likelihood method (FIML), with application affecting earnings, earnings affecting application, and allowing for correlated error terms ε_{iA} and ε_{iE}. For identification of this model I assume normality in errors and use a set of explanatory variables such that the number of dependent variables in the application equation which are not in the earnings equation are greater than the number of dependent variables in the earnings equation but not in the application equation. The path diagram of the model may be depicted as in Figure 3.

Figure 3: FIML Model Diagram



I apply this model to the full analytical sample, and two additional sample subsets. A second sample is constructed by restricting the full sample to include only those individuals who were at-risk of applying for DI based on their reported health conditions in SIPP. By restricting the sample to those at-risk of applying for disability, the population of non-applicants is more accurately represented by individuals who have some disability characteristic, but did not choose to apply for DI benefits. A complete list of the 67 variables used to select this disabled population can be found in the Appendix. The disabled sample is a subset of the full sample and includes 13,100 non-applicants, 4,100 allowed applicants, and 5,600 denied applicants.

A third sample was constructed to include those individuals at-risk of applying for DI based on their self-reported mental health conditions in SIPP. This third sample is a subset of the second disabled sample. SIPP questions specifically relating to mental health impairments is restricted to four questions about the top reasons causing an individual's work limitations, fair or poor health, and difficulty with certain activities. Due to this limitation in the survey, the third sample is much smaller and ill-suited for in-depth interpretation, with 520 non-applicants, 620 allowed applicants, and 690 denied applicants. See Table 4 for details.

Table 4: Sample Tabulations[9]

	Full Sample	At-Risk of Disability	At-Risk of Mental Condition
Total SIPP Sample	101,500	22,800	1,830
Non-Applicants	88,450 (87%)	13,100 (57%)	520 (28%)
Allowed	5,010 (5%)	4,100 (18%)	620 (34%)
Denied	8.040 (8%)	5,600 (25%)	690 (38%)

4. Results

The full information maximum likelihood (FIML) estimates of the model outlined in equations (3) and (4) are presented in Table 5 and Table 6 below. Table 5 reports estimates for the application equation, and Table 6 reports estimates for the earnings equation. The first column of each table reports estimates for FIML on the full sample, and the second and third columns report estimates on the two sample subsets: individuals at-risk of disability and individuals at-risk of a mental condition. Sample sizes and log likelihood reported at the end of Table 6.

In each sample variation, the coefficient on psychotropic drug vintage is negative and significant, meaning that the availability of newer mental health drugs reduces DI applications. The impact of psychotropic pharmaceutical innovation is over 1.5 times greater for those reporting some disabling condition compared to the full sample, and nearly 3.5 times greater than the full sample for those reporting a mental condition.

[9] Counts are rounded in accordance with U.S. Census Bureau requirements on restricted data disclosure.

Table 5: Application Equation FIML Results

	Full Sample	At-Risk of Disability	At-Risk of Mental Condition
Earnings	-0.00391***	-0.00715***	0.00860
	(0.0002)	(0.0007)	(0.0046)
Psychotropic Drug Vintage	-0.01911***	-0.03017***	-0.06628***
	(0.0014)	(0.0041)	(0.0168)
Drug Total (Medicaid Reimb.)	-0.00004	-0.00039	-0.00644
	(0.0007)	(0.0023)	(0.0086)
Age 55+	0.13459***	0.20104***	-0.01319
	(0.0042)	(0.0126)	(0.0597)
Age 45-54	0.11989***	0.19104***	0.01607
	(0.0039)	(0.0118)	(0.0508)
Age 35-44	0.08163***	0.13384***	0.02401
	(0.0035)	(0.0114)	(0.0419)
Male	0.04604***	0.10260***	0.00776
	(0.0023)	(0.0073)	(0.0259)
White	-0.03582***	-0.06015***	-0.07884***
	(0.0019)	(0.0059)	(0.0225)
Married	-0.02612***	-0.02526***	0.01027
	(0.0027)	(0.0075)	(0.0307)
Never Married	-0.02756***	-0.00762	0.03079
	(0.0032)	(0.0092)	(0.0328)
Family Size	-0.00577***	-0.01369***	-0.02480**
	(0.0006)	(0.0021)	(0.0077)
High School Grad	-0.04113***	-0.02356**	0.00034
	(0.0034)	(0.0090)	(0.0307)
Some College	-0.05861***	-0.05223***	-0.02672
	(0.0035)	(0.0095)	(0.0328)
College Grad	-0.05808***	-0.09319***	-0.15386**
	(0.0044)	(0.0137)	(0.0549)
Health Insured	0.08852***	0.17649***	0.20226***
	(0.0026)	(0.0085)	(0.0371)
Difficulty Lifting	0.17239***	0.08594***	0.05006
	(0.0040)	(0.0066)	(0.0288)
Difficulty Walking	0.25274***	0.16129***	0.10446***
	(0.0042)	(0.0068)	(0.0285)
Difficulty with IADL	0.26360***	0.22186***	0.10060***
	(0.0052)	(0.0080)	(0.0250)
South Region	-0.00109	0.00778	-0.06123*
	(0.0025)	(0.0081)	(0.0301)
West Region	-0.02836***	-0.05449***	-0.04586
	(0.0028)	(0.0091)	(0.0345)
Midwest Region	-0.00448	-0.01350	-0.05931
	(0.0026)	(0.0084)	(0.0330)
Constant	0.46948***	0.63661***	0.97920***
	(0.0150)	(0.0397)	(0.1364)

* p<0.05, ** p<0.01, *** p<0.001

Table 6: Earnings Equation FIML Results

	Full Sample	At-Risk of Disability	At-Risk of Mental Condition
Applicant	7.35863***	4.04674***	-9.99374**
	(0.6504)	(0.8943)	(3.0910)
Age	0.09123***	0.06827***	0.08279**
	(0.0060)	(0.0109)	(0.0316)
Family Size	0.06022	-0.07780	-0.12585
	(0.0346)	(0.0706)	(0.1901)
High School Grad	1.95203***	2.44822***	0.47895
	(0.2035)	(0.3281)	(0.7756)
Some College	3.36557***	4.04116***	-0.03923
	(0.2078)	(0.3432)	(0.8360)
College Grad	9.98595***	11.01002***	4.99053***
	(0.2334)	(0.4444)	(1.1898)
Difficulty Walking	-7.41511***	-2.84996***	0.98192
	(0.3180)	(0.2892)	(0.7624)
Difficulty with IADL	-3.63745***	-2.06872***	0.58539
	(0.3665)	(0.3625)	(0.7182)
Use of Aids	-1.00294**	0.57127	1.73123
	(0.3520)	(0.3346)	(1.0166)
Family Income	0.00078***	0.00100***	0.00028**
	(0.0000)	(0.0000)	(0.0001)
Labor Force Attachment	2.71715***	2.41135***	1.58889***
	(0.0200)	(0.0442)	(0.1119)
Earnings Variance	0.00195***	0.00096***	0.00109***
	(0.0000)	(0.0001)	(0.0003)
Constant	-12.96286***	-12.72947***	1.06552
	(0.2951)	(0.6700)	(2.5456)
Log Likelihood	-3199002.345	-789952.590	-61843.982
N	101,510	22,810	1,830

* p<0.05, ** p<0.01, *** p<0.001

5. Discussion

The above results imply a significant inverse relationship between an individual's decision to apply for DI benefits and the availability of new pharmaceuticals for mental health. To determine the size of this impact, estimates from the full sample model were used to predict a counterfactual measure of psychotropic vintage assuming no pharmaceutical innovation after 1995. Had no new mental health drugs become available after 1995, the full sample model predicts there would have been 2.8% more DI applications between 1996 and 2012. This translates to approximately 950,000 additional applications over 16 years.

The actual allowance rate calculated using SSA Applications and Awards data over the entire 1996-2012 time period was 40.1% (Social Security Administration, 2013). By incorporating this allowance rate, an estimated 380,000 fewer beneficiaries are on disability rolls due to mental health pharmaceutical innovation. Within the sample of individuals at-risk of disability, this

reduction in applications is predicted to be 4.4%; and within the sample at-risk of a mental condition, the reduction in applications could be as high as 9.5%.

Because these application reductions are cumulative over the entire time period, this result translates to an average 4,700 fewer applications per month, with the SSA reporting 164,700 applications received in a typical month. Given that mental health conditions are receiving over one-third of awards, and Medicaid spending for mental health drugs is nearly $9 billion annually, the impact from these new pharmaceuticals is smaller than expected.

From a policy perspective, recognizing and incorporating the positive effects of pharmaceutical innovation is valuable. I have shown a significant impact of newer psychotropic drugs on disability applications, but it is small. This result implies a potential greater impact if the disability determination process incorporates the availability and use of new drugs for mental health applications.

An extension of this research would be to explore the mechanisms by which pharmaceutical innovation is impacting disability outcomes. It would be straightforward to apply this model to categorical psychotropic drug vintages to identify which, if any, groups of mental health drugs are driving the reduction in disability applications. Relating this measure of psychotropic drug vintage to other disability outcomes, including labor force participation rates is also a natural sequel to this study. A deeper analysis of the concept would be to create a model identifying which DI beneficiaries to target for review and potential termination from benefits based on individual diagnoses and the specific mental health treatments available.

6. Conclusion

Given the substantial growth and impending insolvency of the disability insurance program, policymakers are examining the best ways to potentially restructure the determination process. Consideration of the impact of new pharmaceuticals would be one way to strengthen disability criteria.

In this study I compute a measure of innovation for mental health drugs and show using micro-level data that it is significant at reducing the number of disability applications. During the period of study from 1996-2012, I estimate that psychotropic drugs developed since 1996 contributed to a 2.8% decrease in DI applications, leading to approximately 380,000 fewer beneficiaries. While this impact of psychotropic drug vintage is significant, it is relatively small compared to the substantial number of mental health applications, over 33.5 million during the time period.

Future SSA research may be able to improve the Continuing Disability Review (CDR) process by focusing CDR funds more efficiently towards beneficiaries whose conditions may be improved by new mental health drugs.

Appendix: Disability variables from SIPP used in sample selection

SIPP Variable Indicating Risk of Disability	Description
EDISABL	Work-limiting physical or mental condition
EDISPREV	Work-preventing physical/mental/health condition
EJOBDIF	Long-lasting physical or mental condition which makes finding a job difficult
EJOBCANT	Health or condition preventing working
EHSTAT	Quality of health (4=fair, 5=poor)
ECOND1, ECOND2, ECOND3	Conditions causing difficulty with certain activities (19=mental or emotional problem or disorder)
ECONDPH1, ECONDPH2, ECONDPH3	Condition causing fair/poor health (19=mental or emotional problem or disorder)
ECONDW1, ECONDW2, ECONDW3	Condition causing work limitation (19=mental or emotional problem or disorder)
EMAIN1 EMAIN2	Main reason for difficulties (19=mental or emotional problem or disorder)
ECANE, EWCHAIR, EHEARAID	Use of assistive aids
ESEEDIF, ESEENOT, EHEARDIF, EEHARNOT, ESPEECHD, ESPEECHC	Limitations in sight, hearing, or speech
ECANT10, EDIF10, ECANT25, EDIF25, EPUSHD, EPUSHC, EGRASPD, EGRASPC	Difficulty or unable to lift, push, or grasp
ESTANDD, ESITD, ESTOOPD, EREACHD	Difficulty in types of physical movement
EWALKD, EWALK2D, EWALK2H, EWALKC, ESTAIRSD, ESTAIRSC	Difficulty or needs help in walking or climbing stairs
EINDIF, EINHELP, ETELED, ETELEC, EHWORKH, EHWORKD	Difficulty or needs help in getting around inside the house
EBEDDIF, EBEDHELP, EBATHDIF, EBATHH, EDRESSD, EDRESSH, EEATDIF, EEATHELP, ETOILETD, ETOILETH, EMEALSD, EMEALSH, EMEDD, EMEDH, EMONEYD, EMONEYH, EOUTDIF, EOUTHELP	Difficulty or needs help in activities of daily living (IADL)

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