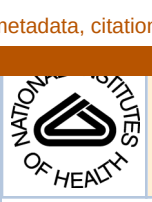

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Does managed care affect the diffusion of psychotropic medications?

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Abstract

Newer technologies to treat many mental illnesses have shown substantial heterogeneity in diffusion rates across states. In this paper, I investigate whether variation in the level of managed care penetration is associated with changes in state-level diffusion of three newer classes of psychotropic medications in fee-for-service Medicaid programs from 1991-2005. Three different types of managed care programs are examined: capitated managed care, any type of managed care and behavioral health carve-outs. A fourth order polynomial fixed effect regression model is used to model the diffusion path of newer antidepressant and antipsychotic medications controlling for time-varying state characteristics. Substantial differences are found in the diffusion paths by the degree of managed care use in each state Medicaid program. The largest effect is seen through spillover effects of capitated managed care programs; states with greater capitated managed care have greater initial shares of newer psychotropic medications. The influence of carve-outs and of all types of managed care combined on the diffusion path was modest.

Keywords

diffusion; managed care; psychotropic; medication; mental health

1. Introduction

Drug diffusion is an important marker of medical innovation and dissemination, describing the rate at which drugs are used in a defined population. In markets where under-use is thought to be an inefficient solution, such as most psychotropic drug markets, greater use of drug products may indicate gains at the external margin and thus a higher treated prevalence (Frank and Glied 2006) and more time under clinically improved conditions (Wells 1991; Kessler, Merikangas et al. 2007). Knowledge concerning the diffusion process would be of particular help to state Medicaid programs, for many are experimenting with components of behavioral health insurance without fully understanding consequences for spending and outcomes.

Psychotropic medications are a particularly interesting class of drugs to examine. Spending on psychotropic medications is growing rapidly and comprises a substantial portion of total behavioral health dollars. In 2003, psychotropic medications comprised an estimated 23 percent of total mental health care treatment expenditures (Mark, Levit et al. 2007). Psychotropic medications were the 4th largest class of outpatient medications sold in the U.S. in 2006 ranked by expenditure (Soni 2009).

Psychotropic medication diffusion has been inconsistent across patient populations and across regions. The reasons for differences in diffusion rates are complex (Drake, Skinner et al. 2008). State-level differences in diffusion may be motivated by a myriad of factors, including social capital, or state investments in its population, as well as relative wealth and degree of interaction among prescribers (Domino, Frank et al. 2009). State-level differences have been found to affect the diffusion of a wide array of technologies. Skinner and Staiger (2007) found that the same states that were early adopters of hybrid corn in Griliches' classic study (1957) were also likely to be early adopters of a diverse array of products including home computers and beta-blockers after hospitalizations for myocardial infarction. Differences in social capital measures and state educational investment measures such as 1928 graduation rates from high school among states were strongly predictive of these differences, but other state factors such as population density or per capita income were not. Managed care and other health care investments were not among the factors examined, but are potentially correlated with other investments made by states.

The goal of this manuscript is to contribute to a better understanding of the promoters and inhibitors of psychotropic drug diffusion in the Medicaid population by examining the association between managed care penetration and psychotropic drug use. Diffusion of psychotropic medications in a Medicaid population may in fact mirror diffusion in other populations; Goldman and Smith (2005), for example, found no difference in the diffusion of new pharmaceutical technologies for hypertension by socioeconomic status. I employ a novel econometric method for the estimation of diffusion curves that is in many ways superior to the widely-used logistic models. I use nationwide information on medication use in state Medicaid programs from 1991-2005 to characterize the diffusion of three new classes of psychotropic medications: selective serotonin reuptake inhibitors (SSRI) and selective serotonin-norepinephrine reuptake inhibitors (SNRI) antidepressants and atypical antipsychotic (also called second generation antipsychotics, or SGA) medications. Both SSRIs and SGAs were introduced in the late 1980s and have diffused quite rapidly. SNRIs were introduced in 1994 and have not diffused as quickly. The diffusion of all three product areas has been very uneven across different states in the U.S. It is unclear what factors may be correlated with these differences in diffusion rates.

2. Background

2.1 Psychotropic Drug Selection

What causes mental health providers to select one treatment option over another? Greater effectiveness from one product over others in the therapeutic class, the minimization of side effects and toxicity, marketing and other information, and lower costs of treatment are all reasons commonly cited in the literature on treatment selection for medical disorders (Berndt, Bui et al. 1995; Ellison, Cockburn et al. 1997; Berndt, Cockburn et al. 1998; Berndt, Bhattacharjya et al. 2002; Chintagunta, Jiang et al. 2008). Patient requests and characteristics, provider characteristics and familiarity with certain products can also play an important role ((Weiss, Charney et al. 1990; Peay and Peay 1994; Crystal 1995; Hellerstein 1998; Stern and Trajtenberg 1998); also see (Hemminki 1975; Christensen 1981; Bradley 1991) for literature reviews). Another source of variation is the relative contribution of the new product to the existing treatment class; new “breakthrough” drugs that are substantial improvements on existing technologies may enter the market more strongly than “me-too” or imitator products.

2.2 The Influence of Managed Care

It is likely that the insurance setting under which individual physicians practice may play an important role in explaining variations in prescribing. The strong proliferation of

pharmaceutical insurance either as a covered benefit in health insurance plans, or as a separate policy, as is the case with Medicare Part D prescription drug plans, has reduced the price sensitivity of consumers receiving prescription drugs (Leibowitz, Manning et al. 1985; Phelps 1997). The managed care era has ushered in a more generous pharmacy benefit for enrollees, but with it, a greater degree of restrictions on choices of treatment through formulary design, especially among expensive new products. These changes have likely led to very real changes in the selection of treatments for many disorders and thus changes in the diffusion patterns of new technologies. For example, Mas and Seinfeld found a negative association between HMO penetration and the adoption of 13 different hospital-based technologies (Mas and Seinfeld 2008).

While the tools of managed care may be declining in the private sector (Swartz 1999), they are still widely used in Medicaid programs. As of June 2008, more than 70% of Medicaid enrollees nationwide were in a health plan defined as managed care by the Centers for Medicare and Medicaid Services (CMS) and the percent of enrollees involved in managed care plans has continued to increase ((Centers for Medicare and Medicaid Services (CMS) 2009).

As the tools of managed care increasingly penetrate behavioral health insurance, the diffusion of new psychotropic products into existing treatment options is likely to be strongly affected. The direction of this effect is ambiguous due to the complexity and differing incentives inherent in these tools. Managed care plans vary considerably from strictly capitated models with clear incentives for cost reduction, to more loosely managed models, such as primary care case management. Mental health carve-outs have been shown to affect the patterns of care received, shifting care from more costly inpatient care to less expensive outpatient substitutes (Grazier 1999; Huskamp 1999).

It is not clear what impact, if any, managed care has on the use of newer drug products. Weiner and colleagues (1991) found no difference between managed care physicians and their fee-for-service counterparts in terms of the use of new drugs. Domino and Salkever (2003), however, found that managed care providers in a Medicaid program were more likely to use the new class of antidepressants, SSRIs, over their colleagues in a gate-keeper FFS model. Managed care enrollees were also found to be much less likely to receive a pharmaceutical treatment, indicating an overall negative association between managed care and newer antidepressant products. Berndt, Frank, and McGuire (1997) found that PPOs and mental health carve-outs have lower spending on SSRIs as a percentage of all antidepressant spending over fee-for-service indemnity plans.

Behavioral Health Carve-outs—One type of managed behavioral health care is a mental health/substance abuse carve-out, found both in the public and private sectors. Insurers taking a carve-out approach contract all mental health and frequently substance abuse services to a secondary insurer, which arranges a provider network to provide care. Nineteen states had waivers for mental health and/or substance abuse carve-outs in their Medicaid programs by 1998. The carve-out approach is also common among private insurers, with 72% of individuals with health insurance enrolled in specialty behavioral health insurance plans (U.S. Department of Health and Human Services 1999).

Mental health carve-outs have been shown to have strong effects on the patterns of care received, shifting care from more costly inpatient care to less expensive outpatient substitutes (Grazier and Eselius 1999). In most cases prescription drugs are not included in carve-out arrangements and are covered instead under the primary (general) insurance policy (Huskamp 2003). New psychotropic medications may be adopted much more readily under

carve-out arrangements, as providers shift patients onto pharmaceutical care for which the carve-out vendor is not at risk (Frank, Conti et al. 2005).

The extent to which individuals are shifted onto medications may vary by disease. Ling, Berndt and Frank (2008) hypothesized that the shift towards pharmaceutical care will be larger for antidepressant medications than for antipsychotic medications, because of the improved side effect profile of newer antidepressants has increased the feasibility of use in general medication settings. They examined the effect of carve-outs on both the total number of antidepressant and antipsychotic prescriptions and on the shares of particular classes of these medications and found that carve-outs are associated with more antidepressant, but fewer antipsychotic prescriptions. They also found lower shares of older tricyclic antidepressants and greater shares of SSRIs. No significant differences in the shares of SGAs were found. Busch and colleagues also did not observe differences in the rate of medication use among persons with schizophrenia after a Medicaid carve-out in one state (Busch, Frank et al. 2004).

In summary, it is likely that penetration of managed care plans is one of the major influences on drug diffusion, through increased use of formularies and increased access to outpatient services, but the direction of the effect is not obvious and may differ across types of managed care and across drug classes.

3. Conceptual model

The epidemic model is often used to motivate diffusion processes (Stoneman 2002) and leads to an S-shape. In this model, the world of potential adopters of a durable good or technology is partitioned into two sets of individuals (or firms), based on whether or not they have adopted the technology. In the initial period, the set of users is non-zero to avoid a trivial time path of diffusion. In subsequent time periods, non-users *infect* or contact users at a certain rate, generally specified as a linear function of the percent of the total potential adopters who have already adopted. This contact promotes the conversion of non-users to users with some fixed probability.

Formally, the standard epidemic model has a population of N potential adopters of a good, of which $M(t)$ are adopters at any time t (notation follows (Stoneman 2002). The rate at which non-users contact users is proportional to the current rate of use, specified as $\delta\frac{M(t)}{N}$; the probability that this contact leads to conversion is specified as γ. Therefore, the rate at which the user population increases over time is

$$\frac{dM(t)}{dt}=\phi\frac{M(t)}{N}\left(N-M(t)\right) \quad (1)$$

where $\phi=\delta\gamma$.

Several extensions to this model lead to ambiguities in the diffusion path. First, users may also convert to non-users. This can be specified as the infection of users by non-users in the population and can be modeled as a function of the proportion non-users. This can be labeled as reverse contagion, information sharing, product failure, or fads that vary according to a critical mass of users or non-users. For simplicity, I specify that some fraction, α, of users convert back to non-users by ceasing to purchase the good in a subsequent period. Therefore, the change in the level of use over time is

$$\frac{dM(t)}{dt} = \phi \frac{M(t)}{N} (N - M(t)) - \alpha M(t). \quad (2)$$

If $\alpha > \phi$, then the diffusion rate is negative; $\alpha < \phi$ leads to an ambiguous result.

Second, under the classic model, if the entry of a competing product leads both users and non-users of the earlier entrant to convert to the use of the new product, the first and second derivatives of the diffusion curve similarly become ambiguous. The basic epidemic model can easily be transformed to allow for the use (or non-use) of two products, assuming exclusivity in use, according to

$$\frac{dM_2(t)}{dt} = \phi_2 \frac{M_2(t)}{N} (N - M_1(t) - M_2(t)). \quad (3)$$

Further, suppose that users of product 1 can switch to product 2 according to

$$\phi_2 \frac{M_2(t)}{N} M_1(t), \quad (4)$$

leaving the total change in users of product 1 as

$$\frac{dM_1(t)}{dt} = \phi_1 M_1(t) \left(1 - \frac{M_1(t)}{N}\right) - \frac{(\phi_1 + \phi_2) M_1(t) M_2(t)}{N}. \quad (5)$$

The sign of this expression is ambiguous without further information on the relative rate of adoption and conversion between the two products. Since variation in these rates varies among products and markets, more complex empirical diffusion models should allow for increasing as well as decreasing rates of diffusion, and probably both over different stages in the product lifecycle.

These models lead not only to an ambiguous first derivative, but to ambiguous higher order derivatives as well. Similar extensions can lead to similar results from other theoretical models often used to motivate diffusion. Models of Bayesian updating (Phelps 2000), for example, may also explain changes in use, both positive and negative, as individuals' posterior beliefs change as they gain information from experience or other users or non-users.

Finally, it is worth noting that the classical diffusion model considers primarily durable goods or goods which require a substantial commitment to use such that users do not switch easily among competing goods. For non-durable goods, such as pharmaceuticals or apples, the cumulative proportion of individuals or firms who have ever used a product is less important than the *current* proportion of potential users purchasing a good. This means that empirical work will generally focus on estimating a time-varying market share, which is even less likely to resemble an S-shape.

The monotonically increasing S-shaped curve, then, becomes an empirical question, one that should be determined by, not required of, empirical evidence. In practice, diffusion curves may be seen theoretically to take on many shapes (Hahn, Park et al. 1994; Andersen 1999; Comin, Hobijn et al. 2006; Comin, Hobijn et al. 2008), which means that empirical models such as the logistic may not provide the flexibility needed to model the diffusion of many products or technologies.

4. Methods

4.1 Data

The data used for these analyses are the total prescriptions paid by fee-for-service Medicaid programs in 49 states and the District of Columbia from 1991 – 20051. 1991 is the earliest year of this data available and data were not used after 2005 because the introduction of Medicare Part D has substantially affected the level and possibly mix of psychotropic medication paid for by the Medicaid program. The Medicaid drug utilization data are reported quarterly and are available from the Center for Medicare and Medicaid Services (CMS) as the Medicaid Drug Utilization Files. They contain no personal identifiers or individual characteristics.

4.2 Measures of Drug Use

Prescription lengths vary across individuals and dosage varies across medications, so all medications used were converted into the World Health Organization's Defined Daily Dose units (World Health Organization Collaborating Center for Drug Statistics Methodology 2006). DDD units express drug use in standard person-day doses; recommended dosing of some drug products changed over time and levels contemporaneous to each year are used2. Thus 10 DDD units indicate the amount of medication that would be prescribed on average to one person for 10 days or to 10 people for one day. I convert all medication usage into DDD units and then aggregate into the relevant classes at the state-quarter level. The dependent variables for each medication class (SSRIs, SNRIs, and SGAs) were expressed as the percentage of the total DDDs in each quarter for each class of medications (antidepressants and antipsychotics). Several brand name drugs in these classes lost patent protecting during the study period (e.g., Prozac the first SSRI, lost protection in 2001); both generic and brand name drug doses are included in the DDD market share. Observations with reported shares of 0 or 100% were set to missing as visual inspection confirmed that these were substantial departures from adjacent observations within states. Robustness analyses using share of prescriptions were conducted and results are similar to those reported here.

4.3 Managed Care measures

I examine the association between managed care and psychotropic medication diffusion using three different measures of managed care. Managed care rates for all three variables are derived from CMS reports (Centers for Medicare and Medicaid Services (CMS) 2009). The first definition includes only capitated managed care plans, such as HMOs. It is expected that more heavily managed plans have greater control over prescribing practices of providers through tighter formulary design or contractual arrangements with medical professionals as is the case with staff-model HMOs. The second definition of managed care is a broader definition, which includes both capitated models as well as more loosely managed models such as PPOs and primary care case management or gatekeeper models. While capitated models are a subset of all managed models, the degree to which individuals may be in both plans cannot be determined in these data, therefore I do not examine non-capitated managed care models separately. These models are hypothesized to have a lower

[1]Arizona is the only state that is entirely exempted from the Federal Medicaid program, thus its drug utilization data is not captured. For simplicity, the 49 states and the District of Columbia are subsequently referred to as “states.” Drug utilization information is not available for Medicaid enrollees in capitated managed care programs which are at risk for medication expenses, since these claims are generally paid directly by the capitated health plan, rather than by the Medicaid program.

[2]Three psychotropic drug products experienced changes in DDDs during our study period: the DDD for two SSRIs, sertraline and fluvoxamine, changed from 75 MG/day to 50MG/day in 1996 and in 1991, the DDD for risperidone changed from 6MG/day to 5MG/day). I am grateful to the staff at WHO Collaborating Centre for Drug Statistics Methodology for providing historic data on drug dosing.

average level of influence on drug diffusion, given the weaker incentives to manage all health care costs.

The third definition examines the use of behavioral health carve-outs and is expressed as a binary variable, indicating whether the state used a carve-out for at least some of its Medicaid population during the year. The carve-out indicator was derived from annual Medicaid managed care reports (Centers for Medicare and Medicaid Services (CMS) 2009) for 1995-2005. Earlier years were taken from Ling, Berndt, and Frank (Ling, Berndt et al. 2008). It is unclear what effect the use of behavioral health carve-outs has on psychotropic diffusion. States with carve-outs may put greater emphasis on controlling behavioral health care costs, in which case the diffusion of newer drug products may be more restrictive. These states, however, may also seek to better manage adverse selection from having health plans compete to avoid costlier mental health treatment users (Frank, Huskamp et al. 1996) and therefore may be more concerned with quality of care and access to evidence-based practices.

The interpretation of the managed care effects vary according to the measure used. The data cover all prescription medications purchased via fee-for-service in state Medicaid programs and do not include those medications covered in capitated contracts. Therefore, the effects of capitated managed care are on fee-for-service medication use and are assumed to indicate spillover effects, which have been observed in other settings (Baker 1997; Baker 1999; Domino and Salkever 2003). The broader measure of managed care includes capitated as well as primary care case management programs, which are largely fee-for-service, and thus these effects are assumed to be a mix of spillover and direct effects. Mental health carve-outs are generally not risk-bearing arrangements (Frank, Huskamp et al. 1996) and even if capitated, do not tend to cover prescription medications. These effects are therefore assumed to be direct in the sense that prescriptions written by carve-out providers are likely to be filled in the fee-for-service setting.

4.4 Other explanatory variables

A variety of state characteristics are used as explanatory variables to control for time variant factors that may be correlated with both the diffusion of psychotropic medication and with managed care status. These annual measures and their sources are: the state median income, the percent of the state population with income less than 100% and 200% of the federal poverty level, the state population (U.S. Census), the state unemployement rate (Bureau of Labor Statistics), the total state government expenditures, total state Medicaid expenditures as percent of total general fund expenditures during the state fiscal year (the National Association of State Budget Offices), and the Federal matching percentage (CMS), expressing the percentage of total Medicaid expenditures paid for by the Federal government each year. Expenditure variables are expressed in 2005 dollars and were deflated by the GDP index. The percent of Medicaid enrollees classified as children or elderly and the number of physicians in each state were originally considered as explanatory variables, but contributed little explanatory power and substantially restricted the sample due to missing observations for some states and years. State-fixed effects are included to control for remaining state differences that are constant over time.

Absent from these models is the inclusion of other factors that may affect drug diffusion, such as physician detailing by drug company representatives or other forms of advertising, either in technical journals or direct to consumers. There are several reasons for this. Nationwide information sources such as advertising, FDA updates, or scientific publications will not promote state-level differences, and are thus factored into the overall time trends. Advertising efforts, especially detailing, that are likely to vary across states may be correlated with managed care. Drug detailing efforts, for example, may be lower in areas

with greater managed care since drug decisions are likely to be more tightly controlled by formulary design, over which individual physicians have little control. In addition, physician time for drug detailing visits may be more constrained in managed care settings. Finally, local direct-to-consumer advertising efforts for antidepressants have been shown to be a small fraction of national advertising campaigns for prescription medications (Meyerhoefer and Zuvekas 2008), and therefore will likely not contribute much to the state-level differences explored here. In addition, some states had changes in prescribing authority given to nurse practitioners during the study period; these effects may again be part of the managed care effect. Therefore, I do not separately control for levels of marketing efforts or changes in prescribing authority, although I certainly acknowledge the important effect on drug diffusion these efforts have (Berndt, Bhattacharjya et al. 2002; Kravitz, Epstein et al. 2005).

4.5 Model Specification

Dependent variables reflecting the proportion of the FFS Medicaid market accounted for by new psychotropic technologies are analyzed with fourth-order polynomial regression models with state fixed effects. This modeling approach does not impose an S-shape as do standard logistic models and has marginal effects that are easier to interpret (Domino 2009). I pool data across states and use state fixed-effects models to examine diffusion models on quarterly data, with managed care penetration over time as the key explanatory variable. Managed care penetration is interacted with the fourth order time polynomial to determine how managed care has affected not only the level of use, but the path of diffusion. The final model specification is:

$$y_{it}=\beta_0+\beta_1 t+\beta_2 t^2+\beta_3 t^3+\beta_4 t^4+\beta_5 MC_{it}+\sum_{j=1}^{4}\beta_{j+5} MC_{it} * t^j+\gamma Z_{it}+\mu_i+\varepsilon_{it},$$

Where t indexes quarters from 1991-2005, MC is specified as one of the three managed care definitions described above, Z are other time-varying state characteristics, μ are state fixed effects, and ε are independently distributed disturbances. Robust standard errors are reported.

The decision to use a 4th order polynomial instead of other higher or lower terms is somewhat arbitrary. I ran a Wald test on the significance of the 4th order terms in all models and rejected the null that these terms are jointly zero in seven out of nine models. In 5th order models, I also rejected the null hypothesis that the 5th order terms were jointly zero in all nine models. The improvement in the mean square prediction error, one measure of the loss function, between the 4th and 5th order models was small (4.0E-04 to 2.0E-06, representing between a 0.6% and 11.1% improvement) as was the improvement from the 3rd to 4th order models (1.0E-07 to 3.9E-04 or 0.06% to 10.4%). However, plots of diffusion curves from 5th order models showed considerably greater out-of-range predictions (e.g., at time=1, the SSRI shares ranged from 0.02 to 0.59. Predictions from the 4th order capitated model ranged from 0.22 to 0.52 whereas predictions from the 5th ordered capitated model ranged from 0.25 to 0.86). Only results from the slightly more parsimonious 4th order model are reported.

There is the potential for the endogeneity of managed care with the diffusion variables measured here. That is, managed care firms may strategically enter markets according to levels of health care use and competition (Baker 1997; Ellis and Gurol 2002). Using the same data, Ling, Berndt and Frank examined the endogeneity of mental health carve-outs

with the number of psychotropic prescriptions and did not find strong evidence of endogeneity (Ling, Berndt et al. 2008). In this manuscript, our dependent variables focus on the composition rather than the size of the psychotropic drug markets and therefore the exogeneity of managed care may be a reasonable assumption.

5. Results

The rates of drug adoption showed significant variation across states and time periods (Table 1). The mean SSRI use was 23% of all antidepressants in 1991, four years after their introduction, ranging across states from almost none to 71%. The SSRI use rate in 2005 was 74%, ranging from 64% to 82%. SNRIs had a much lower level of use; in 1995 just under 3% of all DDD units were for this class of antidepressants, growing to 9% by 2005. Atypical antipsychotics demonstrated an even more remarkable diffusion rate, comprising only 4% of daily dose antipsychotic units in 1991, but reaching 92% by 2005. Managed care rates also varied considerably across states and over time. In 1991, states only had an average of 2.9% of Medicaid enrollees in capitated plans and only 2% of states (that is, one state) had mental health carve-outs. By 1995, 11% of enrollees were in capitated plans, 29% of enrollees were in any type of managed care plan, and 14% of states had carve-outs. A decade later, in 2005, 30% of Medicaid enrollees were in capitated plans, 64% were in any type of managed care program, and 33% of states had carve-outs.

Results from the polynomial models show that capitated managed care was consistently associated with a large increase in the share of new psychotropic medications in the initial time period, controlling for time trends (Table 2); this effect was not significant for SSRIs. The uninteracted managed care variable indicates that a ten percentage point increase in the use of capitated managed care is associated with between a 2.7 (SNRIs) and 10.1 (SGAs) percentage point increase in the use of these newer classes of psychotropic medications in the initial period.

Figure 1 plots the predicted diffusion path for these three classes during the study period at five different levels of capitated managed care[3]. Early in the diffusion process, states with greater use of capitated payments in their Medicaid programs had higher levels of new psychotropic medication use in contrast to states with no capitation, indicating a strong spillover effect in innovation from these programs. By the mid 1990s, the levels of use across states converged and have stayed fairly similar. In exploratory analyses to further investigate this finding, I ran models on drug-specific shares for three of the atypical products, separately by time periods prior to 2000 and those from 2000-2005 (results available by request). The Wald test on the capitated managed care terms was significant in models prior to 2000, but not after this time period, consistent with the finding that capitated managed care was associated with more rapid diffusion early in the study period.

Including non-capitated models in the definition of managed care lowers the association between managed care and drug diffusion. This broader uninteracted managed care term was significant only in SGA model. The managed-care – time interactions were largely individually insignificant, although the Wald test of joint significance is significant at the 0.05 level for both the SSRI and SGA models. The predicted diffusion curve for SGAs at varying levels of managed care (Figure 2) again confirms a path largely independent of this broader measure of managed care involvement (as well as a fairly sigmoidal shape).

[3]It should be noted that only 2 states had 100% capitated Medicaid programs at any point, although 4 states had capitation rates of 95% or greater. Figure 1c demonstrates the downside of the 4th order polynomial model: overfitting of the model resulted in too large an estimated spread in the initial time periods.

The use of behavioral health carve-outs was associated with much smaller increases in the level of newer psychotropic medication use and the uninteracted carve-out term was only significant in the SGA model (Table 2 & Figure 3). Although I reject the hypothesis that the diffusion paths are the same between carve-out and non-carve-out states, the magnitude of the difference in diffusion paths is small. SGAs are seen to have an initially higher level of use in carve-out states, followed by a substantial decline in use, until the diffusion paths converge in 1997.

4. Discussion

I found evidence of differences in diffusion paths of newer psychotropic medications using three different definitions of managed care used by state Medicaid programs. In particular, capitated managed care programs strongly increased the initial rate of diffusion of all three medication classes examined here and changed the shape of the diffusion curve.

These results may indicate that the spread of capitated managed care plans in state Medicaid programs may have been partially responsible for the strong early launches of newer classes of psychotropic medications, especially SSRIs and SGAs. While much remains to be learned about the diffusion of medical technologies, the greater level of initial use likely serves as a catalyst for further diffusion as prescribers learn about new medications from their patients and their colleagues (Coscelli and Shum 2004; Domino, Frank et al. 2009) and develop norms for further use (Frank and Zeckhauser 2007).

These results expand on the Ling, Berndt, and Frank (Ling, Berndt et al. 2008) findings in several ways. First, I examine three different types of managed care programs. Second, if I remove the managed care-time interactions and many of the state covariates from our SSRI and SGA carve-out models, I replicate their results. However, these interactions point to significant differences in the time path of diffusion, not just the level of use. In particular, I find that carve-outs have statistically significant different diffusion paths (Table 2) with slightly lower initial levels of use of SSRIs and greater initial shares of SGAs. Figure 3 makes it clear that the rate of use of these newer classes of psychotropic medications are not unambiguously higher (or lower) throughout the study period.

A number of limitations should be noted. The aggregate data used here do not allow for examination of subpopulations which may be more likely to have demonstrable effects of managed care on drug diffusion. The DDD conversion assumes a constant dosing level, which may not reflect the actual patient doses. Off-label uses of psychotropic medications, particularly present in psychotropic medications (Radley, Finkelstein et al. 2006; Domino and Swartz 2008), may be more likely to be curtailed under managed care, but cannot be examined with these data since accompanying diagnostic information is not available. Aggregate level data also do not allow for models of diffusion at the extensive versus intensive margins. That is, I cannot tell whether the diffusion curves modeled here are motivated by increases in the number of users, or increases in the dosing or compliance rate for existing users. Other authors have found that increases in medication use translated to a greater treated population (Berndt, Bhattacharjya et al. 2002; Frank and Glied 2006). Domino and Swartz (2008) found that the diffusion of atypical antipsychotics was accomplished not through greater compliance or dosing, but because of substantial growth in the number of off-label users and antipsychotic users with newer on-label conditions. In addition, I cannot determine the level of polypharmacy, nor whether increases in the rate of polypharmacy have contributed to changes in the diffusion path. Factors such as drug characteristics, marketing effects, FDA updates, scientific publications, and other sources of information, as well as individual and physician characteristics may also have important effects but because of their association with managed care are not the focus of this paper.

Finally, I also cannot place a value on greater diffusion since our data do not contain information on clinical outcomes nor on the prevalence of disease by state. Skinner and Staiger (2009), for example, found a large association between the diffusion of innovations in heart attack treatments and productivity outcomes and patient survival.

Given the recent controversy over whether SNRIs and SGAs really have delivered on early promises of cost-effectiveness and the greater incentives to manage health care expenditures in capitated health insurance plans (Barrett, Byford et al. 2005; Rosenheck, Leslie et al. 2006), it is somewhat surprising that the greater use of these plans are seen to be associated with greater use of these costlier medication classes. The fact that the rates of use quickly converged to that of non-managed plans may indicate the greater efficiency with which capitated plans affect change by providers, with a substantial showing in the early years of these medications and a stronger cooling off period as more information was available on these newer psychotropic agents.

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Reviewer Appendix: Models on other antidepressants and antipsychotics

Table 3

Coefficients (robust standard errors) from 4th order polynomial fixed effect regression models of diffusion of older antidepressant and antipsychotic medication

Managed Care measure	Drug Class	Managed care measure	Managed care – Time interaction	Managed care – Time^2 interaction	Managed care – Time^3 interaction	Manag Time^4
Narrow (capitated only)	Older Antidepressants	-0.38* (0.17)	0.010 (0.018)	0.00233** (0.00084)	-6.81e-05** (1.67e-05)	5.70e-0 (1.18e-
	Older Antipsychotics	-1.01** (0.25)	0.153** (0.031)	-0.0076** (0.0014)	1.51e04** (2.82e-05)	-1.04e- (1.97e-
Broad (capitated plus PCCM)	Older Antidepressants	-0.28 (0.33)	0.020 (0.041)	-0.005 (0.0018)	3.85e-06 (3.25e-05)	-5.22e- (2.12e-
	Older Antipsychotics	-2.29** (0.73)	0.281** (0.090)	-0.0122*** (0.0039)	2.20e-05** (7.05e-05)	-1.42e- (4.58e-
Behavioral Health Carve-out	Older Antidepressants	0.07 (0.06)	-0.0270** (0.0084)	0.00185** (0.00043)	-4.27e-05** (8.93e-06)	3.22e-0 (6.54e-
	Older Antipsychotics	-0.231** (0.042)	0.0456** (0.0064)	-0.00259** (0.00368)	5.63e-05** (8.80e-06)	-4.13e- (7.13e-

Older antidepressants are defined as all those not in the SSRI and SNRI classes;

** p<0.01;

* p<0.05

Figure 4a

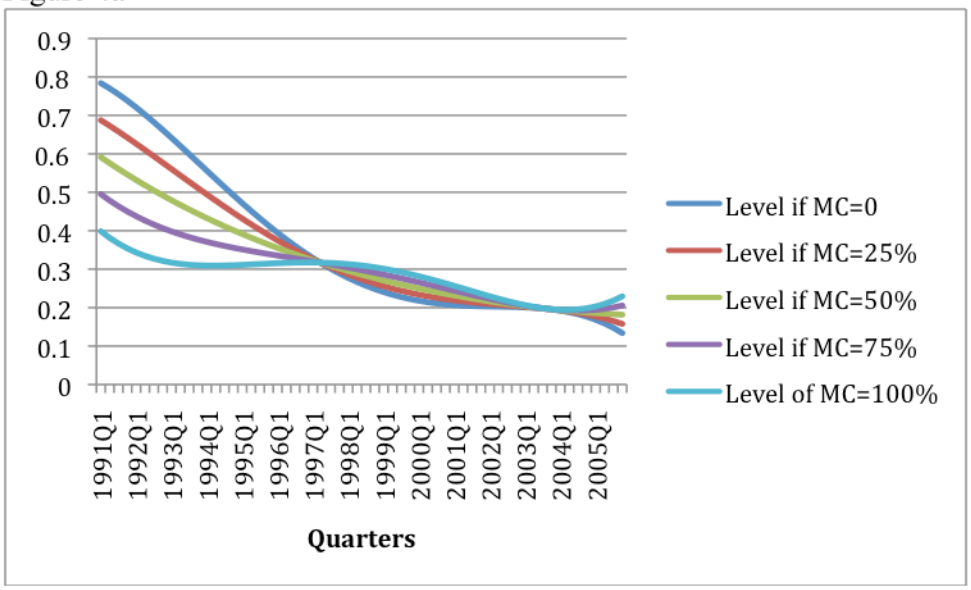


Figure 4b

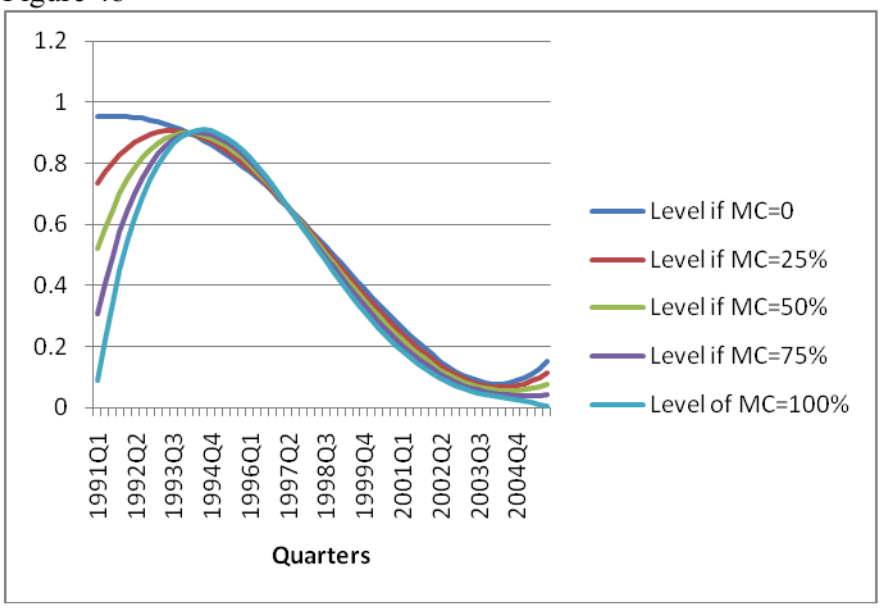


Figure 4. The Predicted Retraction Path of Older Psychotropic by Level of Capitated Managed Care Enrollment in State

Figure 4a: Non-SSRI or SNRI Antidepressants

Figure 4b: First generation antipsychotics

References

Andersen B. The Hunt for S-shaped Growth Paths in Technological Innovation: a Patent Study. Journal of Evolutionary Economics. 1999; 9:487–526.

Baker LC. The Effect of HMOs on Fee-for-Service Health Care Expenditures: Evidence from Medicare. Journal of Health Economics. 1997; 16(4):453–481. [PubMed: 10169101]

Baker LC. Association of Managed Care Market Share and Health Expenditures for Fee-for-Service Medicare Patients. JAMA. 1999; 281(5):432–437. [PubMed: 9952203]

Barrett B, Byford S, et al. Evidence of cost-effective treatments for depression:a systematic review. Journal of Affective Disorders. 2005; 84(1):1–13. [PubMed: 15620380]

Berndt ER, Bhattacharjya A, et al. An Analysis of the Diffusion of New Antidepressants: Variety, Quality, and Marketing Efforts. The Journal of Mental Health Policy and Economics. 2002; 5:3–19. [PubMed: 12529566]

Berndt ER, Bui L, et al. Information, Marketing and Pricing in the U.S. Anti-Ulcer Drug Market. American Economic Review. 1995; 85(2):100–105. [PubMed: 10160519]

Berndt, ER.; Cockburn, IM., et al. Is Price Inflation Different for the Elderly? An Empirical Analysis of Perscription Drugs. In: Garber, A., editor. Frontiers in Health Policy Research. Vol. 1. Cambridge, Massachusets: MIT Press; 1998. p. 33-75.

Berndt ER, Frank G Richard, et al. Alternative Insurance Arrangements and the Treatment of Depression: What are the Facts? American Journal of Managed Care. 1997; 3(2):135–143. [PubMed: 10169245]

Bradley CP. Decision Making and Prescribing Patterns- a Literature Review. Family Practice- an International Journal. 1991; 8(3):276–287.

Busch AB, Frank RG, et al. The Effect of a Managed Behavioral Health Carve-out on Quality of Care for Medicaid Patients Diagnosed as Having Schizophrenia. Archives of General Psychiatry. 2004; 61:442–448. [PubMed: 15123488]

Centers for Medicare and Medicaid Services (CMS). Medicaid Managed Care Enrollent Reports, various years. 2009. Retrieved October 28, 2009, from http://www.cms.hhs.gov/MedicaidDataSourcesGenInfo/04_MdManCrEnrllRep.asp

Chintagunta, P.; Jiang, R., et al. NBER Working Paper Series. Cambridge, MA: NBER; 2008. Information, Learning, and Drug Diffusion: The Case of Cox-2 Inhibitors.

Christensen DB, B Patricia J. Drug Prescribing: Patterns, Problems, and Proposals. Social Science and Medicine. 1981; 15A:343–355.

Comin, D.; Hobijn, B., et al. NBER Working Paper Series. Cambridge, MA: 2006. Five Facts You Need to Know about Technology Diffusion.

Comin D, Hobijn B, et al. A new approach to measuring technology with an application to the shape of the diffusion curves. Journal of Technology Transfer. 2008; 33(2):187–207.

Coscelli A, Shum M. An empirical model of learning and patient spillovers in new drug entry. Journal of Econometrics. 2004; 122(2):213–246.

Crystal S, Sambamoorthi U, Merzel C. The Diffusion of Innovation in AIDS Treatment--Zidovudine Use in Two New Jersey Cohorts. Health Services Research. 1995; 30(4):593–614. [PubMed: 7591783]

Domino, ME. A Flexible Functional Form for Diffusion Research. Chapel Hill, NC: UNC; 2009.

Domino, ME.; Frank, RG., et al. The Diffusion of Antipsychotic Medications: Does the Close-Knittedness of Provider Networks Matter?. Chapel Hill, NC: UNC; 2009.

Domino ME, Salkever DS. Price Elasticity and Pharmaceutical Selection: the Influence of Managed Care. Health Economics. 2003; 12(7):565–586. [PubMed: 12825209]

Domino ME, Swartz MS. Who are the New Users of Antipsychotic Medications? Psychiatric Services. 2008; 59(5):507–514. [PubMed: 18451006]

Drake R, Skinner J, et al. What Explains the Diffusion of Treatments for Mental Illness? American Journal of Psychiatry. 2008; 165(11):1385–1392. [PubMed: 18981070]

Ellis RP, Gurol I. Health Plan Entry and Exit in the Medicare Managed Care Market. 2002

Ellison SF, Cockburn I, et al. Characteristics of demand for pharmaceutical products: an examination of four cephalosporins. RAND Journal of Economics. 1997; 28(3):426–446. [PubMed: 11794359]

Frank RG, Conti RM, et al. Mental Health Policy and Psychotropic Drugs. The Milbank Quarterly. 2005; 83(2):271–98. [PubMed: 15960772]

Frank, RG.; Glied, SA. Better But Not Well: Mental Health Policy in the United States since 1950. Baltimore, MD: The Johns Hopkins University Press; 2006.

Frank RG, Huskamp HA, et al. Some economics of mental health carve-outs. Archives of General Psychiatry. 1996; 53(10):933–937. [PubMed: 8857870]

Frank RG, Zeckhauser RJ. Custom-made versus ready-to-wear treatments: Behavioral propensities in physicians' choices. Journal of Health Economics. 2007; 26:1101–1127. [PubMed: 18031852]

Goldman D, Smith JP. Socioeconomic Differences in the Adoption of New Medical Technologies. American Economic Review. 2005; 95(2):234–237.

Grazier K, Eselius LL, Hu TW, Shore KK, G'Sell WA. Effects of a Mental Health Carve-out on Use, Costs and Payers; a Four-year Study. Journal of Behavioral Health Services and Research. 1999; 26(4):381–389. [PubMed: 10565099]

Grazier KL, Eselius LL. Mental Health Carve-Outs: Effects and Implications. Medical Care Research and Review. 1999; 56(Supplement 2):37–59. [PubMed: 10327823]

Griliches Z. Hybrid Corn: an Exploration in the Economics of Technological Change. Econometrica. 1957; 25(4):501–522.

Hahn M, Park S, et al. Analysis of New Product Diffusion Using a Four-Segment Trial Repeat Model. Marketing Science. 1994; 13(3):224–247.

Hellerstein JK. The importance of the physician in the generic versus trade-name prescription decision. RAND Journal of Economics. 1998; 29(1):108–136. [PubMed: 10182437]

Hemminki E. Review of Literature on the Factors Affecting Drug Prescribing. Social Science and Medicine. 1975; 9:111–115.

Huskamp HA. Episodes of Mental Health and Substance Abuse Treatment Under a Managed Behavioral Health Care Carve-out. Inquiry. 1999; 36:147–161. [PubMed: 10459370]

Huskamp HA. Managing Psychotropic Drug Costs: Will Formularies Work? Health Affairs. 2003; 22(5):84–96. [PubMed: 14515884]

Kessler R, Merikangas K, et al. Prevalence, comorbidity, and service utilization for mood disorders in the United States at the beginning of the twenty-first century. Annual Review of Clinical Psychology. 2007; 3:137–58.

Kravitz RL, Epstein RM, et al. Influence of Patients' Requests for Direct-to-Consumer Advertised Antidepressants: A Randomized Controlled Trial. JAMA. 2005; 293(16):1995–2002. [PubMed: 15855433]

Leibowitz, A.; Manning, WG., et al. A RAND Note N-2278-HHS. 1985. The Demand for Prescription Drugs as a Function of Cost-Sharing.

Ling DC, Berndt ER, et al. Economic Incentives and Contracts: The Use of Psychotropic Medications. Contemporary Economic Policy. 2008; 26(1):49–72.

Mark TL, Levit KR, et al. Mental Health Treatment Expenditure Trends, 1986–2003. Psychiatric Services. 2007; 58(8):1041–1048. [PubMed: 17664514]

Mas N, Seinfeld J. Is Managed Care Restraining the Adoption of Technology by Hospitals? Journal of Health Economics. 2008; 27:1026–1045. [PubMed: 18417230]

Meyerhoefer CD, Zuvekas SH. The Shape of Demand: What Does It Tell Us about Direct-to-Consumer Marketing of Antidepressants? The BE Journal of Economic Analysis & Policy. 2008; 8(2):1–32.

Peay MY, Peay ER. Innovation in High Risk Drug Therapy. Social Science and Medicine. 1994; 39(1):39–52. [PubMed: 8066486]

Phelps, CE. Health Economics. Reading, Massachusetts: Addison-Wesley; 1997.

Phelps, CE. Information Diffusion and Best Practice Adoption. In: Culyer, AJ.; Newhouse, JP., editors. Handbook of Health Economics. Vol. 1A. Amsterdam: Elsevier; 2000. p. 223-264.

Radley DC, Finkelstein SN, et al. Off-label Prescribing Among Office-based Physicians. Archives of Internal Medicine. 2006; 166(9):1021–1026. [PubMed: 16682577]

Rosenheck RA, Leslie DL, et al. Cost-effectiveness of second-generation antipsychotics and perphenazine in a randomized trial of treatment for chronic schizophrenia. American Journal of Psychiatry. 2006; 163(12):2080–2089. [PubMed: 17151158]

Skinner, J.; Staiger, D. NBER Working Paper Series. Cambridge: NBER; 2009. Technology Diffusion and Productivity Growth in Health Care.

Skinner, JS.; Staiger, D. Technology Adoption from Hybrid Corn to Beta Blockers. In: Berndt, ER.; Hulten, CR., editors. Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches. Chicago: University of Chicago Press; 2007.

Soni, A. The Top Five Therapeutic Classes of Outpatient Prescription Drugs Ranked by Total Expense for Adults Age 18 and Older in the U.S. Civilian Noninstitutionalized Population, 2006. Statistical Brief #232. January. 2009 Retrieved July 20, 2009, from http://www.meps.ahrq.gov/mepsweb/data_files/publications/st232/stat232.pdf

Stern S, Trajtenberg M. Empirical Implications of Physician Authority in Pharmaceutical Decisionmaking. draft. 1998

Stoneman, P. The Economics of Technological Diffusion. Oxford: Blackwell Publishers; 2002.

Swartz K. The Death of Managed Care as We Know It. Journal of Health Politics, Policy and Law. 1999; 24(5):1201–1205.

U.S. Department of Health and Human Services. Mental Health: A Report of the Surgeon General. Rockville, Maryland: U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services, National Institutes of Health, National Institute of Mental Health; 1999.

Weiner JP, Lyles A, et al. Impact of Managed Care on Prescription Drug Use. Health Affairs. Spring; 1991 :140–154. [PubMed: 2045046]

Weiss R, Charney E, et al. Changing Patient Managment: What Influences the Practicing Pediatrician? Pediatrics. 1990; 85(5):791–795. [PubMed: 2330241]

Wells KB. Caring for Depression in America: Lessons Learned from Early Findings of the Medical Outcomes Study. Psychiatric Medicine. 1991; 9(4):503–519. [PubMed: 1749834]

World Health Organization Collaborating Center for Drug Statistics Methodology. The ATC/DDD System. 2006. Retrieved September 15, 2006, from http://www.whocc.no/atcddd/

Figure 1a

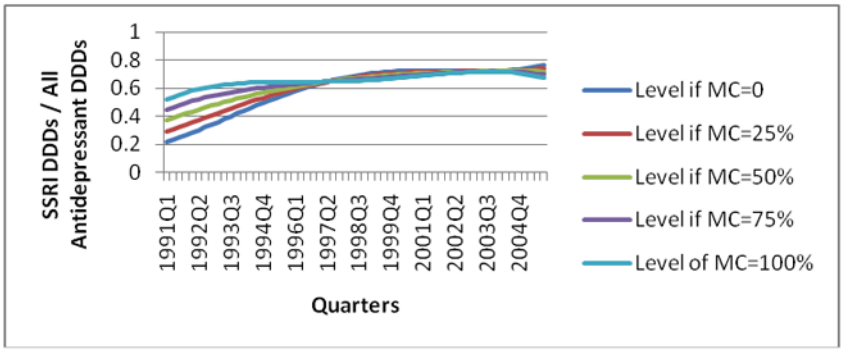


Figure 1b

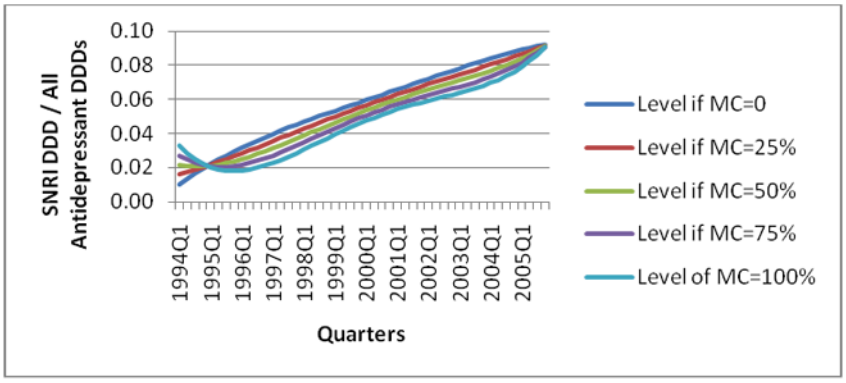


Figure 1c

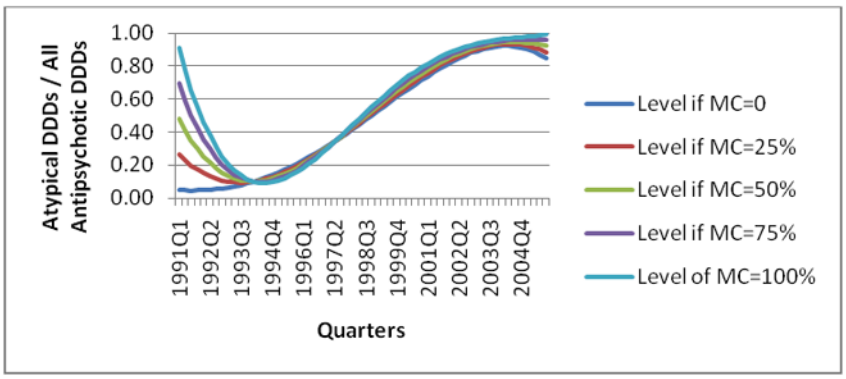


Figure 1. The Predicted Diffusion Path of New Psychotropic by Level of Capitated Managed Care Enrollment in State

Figure 1a: SSRI diffusion

Figure 1b: SNRI Diffusion

Figure 1c: SGA Diffusion

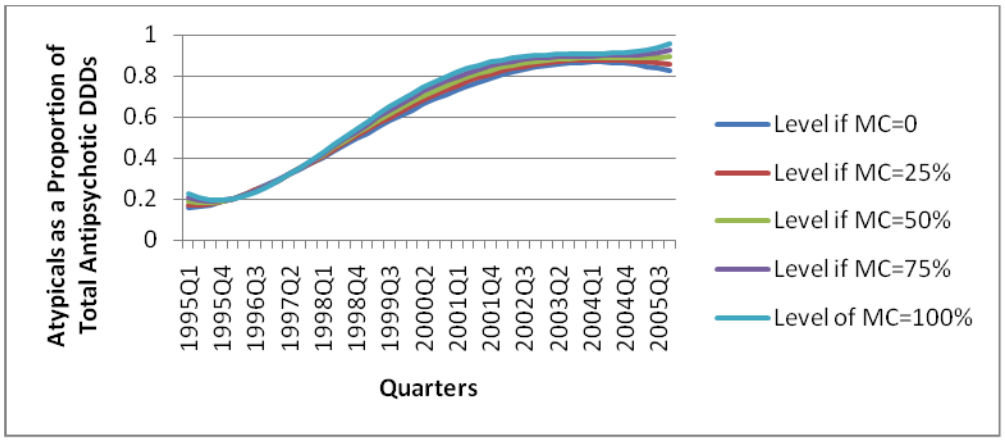
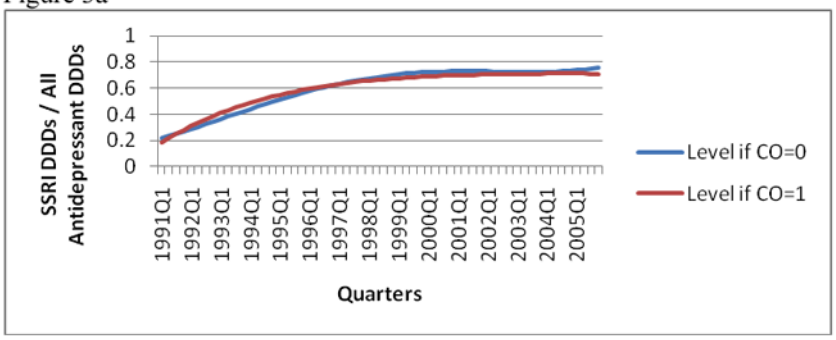


Figure 2. The Predicted Diffusion Path of Second Generation antipsychotics by enrollment in any type of Managed Care

Figure 3a



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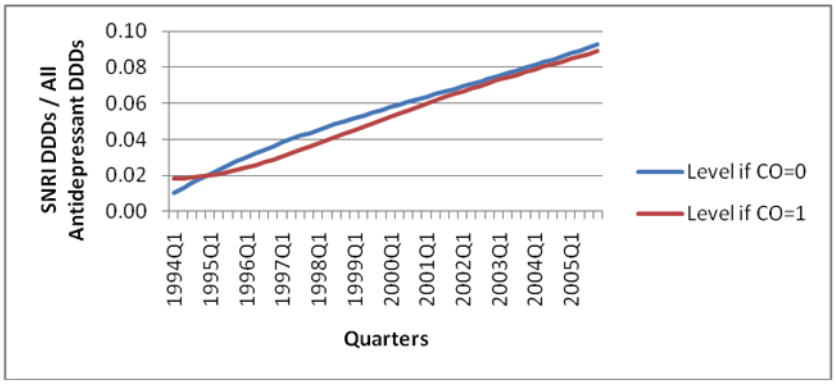

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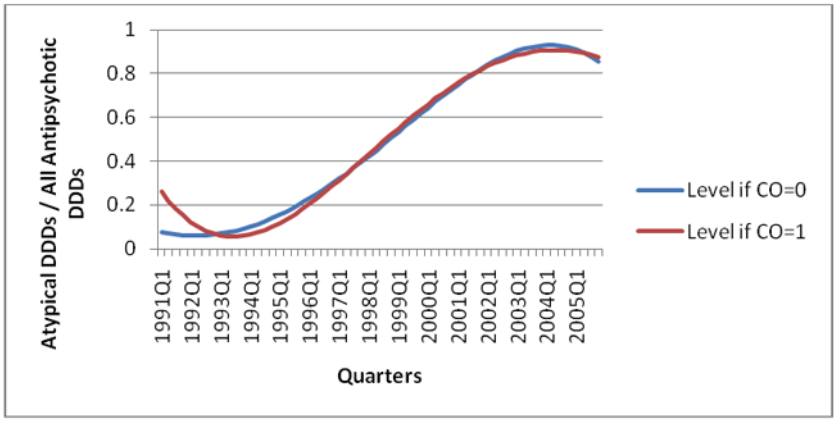

Figure 3. The Predicted Diffusion Path of New Psychotropic Medications by Carve-out status
Figure 3a: SSRI diffusion
Figure 3b: SNRI Diffusion
Figure 3c: SGA Diffusion

Table 1

Summary statistics and years available

Variable	Mean	Standard Deviation	Min	Max	Years available
Dependent variables					
SSRIs / all antidepressants	0.60	0.18	0.00	0.99	1991 - 2005
SNRIs / all antidepressants	0.05	0.03	0.0	0.27	1994 - 2005
Second generation antipsychotics / all antipsychotics	0.49	0.35	0.0	1.00	1991 - 2005
Medicaid managed care measures					
All types of managed care	0.54	0.29	0.0	1.0	1995 - 2005
Capitated managed care	0.22	0.26	0.0	1.0	1991 - 2005
Mental health carve-outs	0.24	0.43	0.0	1.0	1991 - 2005
State characteristics					
Median income (thousands)	43.9	7.3	26.1	63.5	1991 - 2005
Percent of population at 100% federal poverty level	0.13		0.05	0.26	1991 - 2005
Percent of population at 200% federal poverty level	0.32		0.18	0.51	1991 - 2005
Total state expenditures (millions)	20.4	23.1	1.7	171.5	1991 - 2005
Percent of state expenditures on Medicaid	.13	0.06	0.03	0.41	1991 - 2005
Unemployment rate	0.05	0.01	0.02	0.11	1991 - 2005
Federal Medicaid matching rate	60.7	8.8	50.0	80.0	1991 - 2005
State population (millions)	5.5	6.1	0.5	36.1	1991 - 2005

Table 2

Coefficients (robust standard errors) from 4th order polynomial fixed effect regression models of diffusion

Managed Care measure	Drug Class	Managed care measure	Managed care – Time interaction	Managed care – Time^2 interaction	Managed care – Time^3 interaction	Managed care – Time^4 interaction	F-statistic on joint probability of no managed care effect$^+$	n
Narrow (capitated only)	SSRI	0.286 (0.212)	0.011 (0.022)	-2.02e-03 * (9.26e-05)	5.79e-05** (1.67e-05)	-4.84e-07** (1.08e-07)	15.37**	2741
	SNRI	0.269* (0.120)	-0.033* (0.015)	1.38e-03* (6.65e-04)	2.46e-05 (1.27e-05)	1.58e-07 (8.65e-08)	3.58**	2150
	SGA	1.01** (0.25)	-0.153** (0.031)	0.0076** (0.0014)	-1.51e-04** (2.82e-05)	1.04e-06** (1.97e-07)	6.40**	2738
Broad (capitated plus PCCM)	SSRI	0.24 (0.31)	-0.013 (0.037)	9.27e-05 (0.0016)	4.93e-06 (2.79e-05)	-6.37e-08 (1.77e-07)	3.37*	2018
	SNRI	0.10 (0.10)	-0.013 (0.013)	5.79e-04 (5.85e-04)	-1.13e-05 (1.11e-05)	7.94e-08 (7.94e-08)	0.76	2010
	SGA	2.29** (0.79)	-0.281** (0.090)	0.0122** (0.0039)	-2.20e-04** (7.05e-05)	1.42e-06** (4.58e-07)	4.00**	2015
Behavioral Health Carve-out	SSRI	-0.060 (0.052)	0.0229** (0.0074)	-1.54e-03** (3.76e-04)	3.53e-05** (7.94e-06)	-2.65e-07** (5.84e-08)	11.84**	2760
	SNRI	0.082 (0.056)	-0.0092 (0.0072)	3.35e-04 (3.23e-04)	-5.02e-06 (6.10e-06)	2.67e-08 (4.10e-08)	3.09*	2157
	SGA	0.231** (0.042)	-0.0456** (0.0064)	2.59e-03** (3.68e-04)	-5.63e-05** (8.80e-06)	4.13e-07** (7.13e-08)	12.16**	2757

SSRI=selective serotonin reupdate inhibitor antidepressants; SNRI= selective Serotonin-norepinephrine reuptake inhibitor; SGA=second generation antipsychotics. All models control for state fixed effects, time in a 4th order polynomial and all state characteristics reported in Table I.

** p<0.01;

* p<0.05;

$^{+}$Wald tests of the joint significance of all five managed care terms: managed care alone and managed care interactions with the 4th order polynomial time terms significant at p<0.05.