An analysis of the significant variation in psychostimulant use across the U.S.†

Farasat Bokhari PhD¹, Rick Mayes PhD²* and Richard M. Scheffler PhD³

¹Department of Economics, Florida State University, FL, USA
²Department of Political Science, University of Richmond, Richmond, VA, USA
³Department of Economics & Public Policy, Graduate School of Public Health, University of California, Berkeley, CA, USA

SUMMARY

Objective To provide a national profile of the area variation in per-capita psychostimulant consumption in the U.S.

Methods We separated 3030 U.S. counties into two categories of ‘low’ and ‘high’ per-capita use of attention deficit hyperactivity disorder (ADHD) drugs (based on data from the Drug Enforcement Administration), and then analyzed them on the basis of their socio-demographic, economic, educational and medical characteristics.

Results We found significant differences and similarities in the profile of counties in the U.S. that are above and below the national median rate of per-capita psychostimulant use (defined as g/per 100K population). Compared to counties below the median level, counties above the median level have: significantly greater population, higher per-capita income, lower unemployment rates, greater HMO penetration, more physicians per capita, a higher ratio of young-to-old physicians and a slightly higher students-to-teacher ratio.

Conclusions Our analysis of the DEA's ARCOS data shows that most of the significant variables correlated with ‘higher’ per-capita use of ADHD drugs serve as a proxy for county affluence. To provide a more complex, multivariate analysis of the area variation in psychostimulant use across the U.S.—which is the logical next step—requires obtaining price data to match the DEA's quantity data. Copyright © 2004 John Wiley & Sons, Ltd.

KEY WORDS — psychostimulants; attention deficit hyperactivity disorder (ADHD); methylphenidate; amphetamine; mental health; children; adolescents

BACKGROUND: PSYCHOSTIMULANT USE AS TREATMENT FOR ADHD

Psychostimulants (methylphenidate and amphetamines) are primarily used to treat attention deficit hyperactivity disorder (ADHD), which is the most commonly diagnosed behavioral disorder in children, making up more than 50% of all child psychiatric diagnoses.¹ Between 3 and 5% of U.S. school-age children are estimated to have ADHD. But individual community studies have reported prevalence rates ranging from as low as 1.7 to as high as 26%.²⁹,²⁰–²⁸ The core symptoms of ADHD include developmentally inappropriate levels of attention, concentration, activity, distractibility and impulsivity. According to the National Institutes of Health (NIH), children with ADHD have pronounced impairments and can experience long-term adverse effects on academic performance, vocational success and social-emotional development which have a profound impact on individuals, families, schools and society.³

ADHD is a major public health concern. Children with the disorder ‘consume a disproportionate share of resources and attention from the health care system, criminal justice system, schools and other social

Received 21 October 2003
Revised 24 March 2004
Accepted 5 May 2004

Copyright © 2004 John Wiley & Sons, Ltd.

*Correspondence to: Dr Rick Mayes, PhD. Assistant Professor of Public Policy, 28 Westhampton Way, University of Richmond, Richmond, VA 23173, USA. E-mail: bmayes@richmond.edu

†No conflict of interest was declared.
service agencies’. The direct costs of medical care for children and adolescents with the disorder are substantial for their families. Children with ADHD incur double the amount of out-of-pocket expenses compared to children without the disorder, as well as averaging 10 times more outpatient mental health visits, 3.4 times more pharmacy fills and 1.6 times more primary care visits.

Over the last decade and a half, psychostimulant use has increased dramatically (Figure 1), primarily among children and adolescents but also increasingly among adults. At the same time, there appears to be significant area variation in psychostimulant use (Table 1, Figure 2). In addition to our own findings, consumption rates have previously been reported to vary as much as 1:4 between states and as high as 1:10 between communities within states.

The significant growth in psychostimulant use began in the early 1990s (Figure 1), soon after major changes were enacted by policymakers in Washington, D.C., to

---

**Table 1. State psychostimulant distribution in kg/per 100,000 individuals, 2000**

<table>
<thead>
<tr>
<th>State</th>
<th>75th percentile</th>
<th>Above average quartile</th>
<th>Below average quartile</th>
<th>Low quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE (7.4)</td>
<td>NH (7.1)</td>
<td>ME (5.1)</td>
<td>MD (5.1)</td>
<td>LA (4.5)</td>
</tr>
<tr>
<td>RI* (6.2)</td>
<td>VT (6.2)</td>
<td>IN* (5.1)</td>
<td>MO (5.0)</td>
<td>WA (4.4)</td>
</tr>
<tr>
<td>MA* (6.0)</td>
<td>IA (5.9)</td>
<td>NC (4.9)</td>
<td>GA (4.9)</td>
<td>ID* (4.3)</td>
</tr>
<tr>
<td>MI (5.8)</td>
<td>SC (5.6)</td>
<td>AL (4.8)</td>
<td>KS (4.7)</td>
<td>WV* (4.3)</td>
</tr>
<tr>
<td>WI (5.5)</td>
<td>MT (5.4)</td>
<td>ND (4.6)</td>
<td>UT* (4.6)</td>
<td>KY* (4.1)</td>
</tr>
<tr>
<td>VA (5.4)</td>
<td>MN (5.3)</td>
<td>AR (4.6)</td>
<td>CT (4.6)</td>
<td>NE (4.0)</td>
</tr>
<tr>
<td>AK (4.6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Designates the 15 states with a Schedule II triplicate prescription monitoring program.
Designates the five states with monitoring programs in operation in 1981.

include ADHD as a protected disability under the supplemental security income (SSI) program and the individuals with disabilities education act (IDEA). These changes in federal disability policy may have led to an increased awareness of the disorder among some teachers, parents and clinicians. They may have also decreased the stigma associated with the diagnosis. But between 1990 and 1996, psychostimulant consumption increased 370% nationwide, while the number of patients diagnosed with the disorder grew from around 900,000 to approximately 3 million.

As Figure 1 illustrates, some states (Michigan, Georgia, Virginia) have had a tradition of using psychostimulants more than others (New York, California), while various states (Massachusetts, Texas and Pennsylvania) have oscillated above and below the national average from year to year. Viewed together with Figure 1, Table 1 shows the variation in distribution rates across states, which ranged from as high as 7.4 to as low as 1.7 kg/per 100,000 individuals in 2000.

Table 1 also shows that the 15 states with Schedule II triplicate prescription monitoring programs in 2000 had a combined psychostimulant distribution rate (3.3 kg/per 100,000 individuals) that was 36% lower than the combined distribution rate (4.5 kg/per 100,000 individuals) of the remaining 35 states, including D.C., which does not have a monitoring program. This statistically significant differential has existed every year, with minor fluctuations, from 1980 to 2000. Nevertheless, these same 15 states also used 36% less of the drugs back in 1981, when only five of them had monitoring programs in operation. So it is an open question as to how much, if at all, they dampen the aggregate use of psychostimulants. The programs could simply be the product of the states’ traditional predilection for lower use of these drugs.

Ultimately, the purpose of our study is to understand more about how psychostimulant use varies by socio-economic, demographic, educational and health system characteristics. For instance, we want to know if psychostimulant use is higher in more affluent areas, as well as areas with more: clinicians, children as a proportion of the total population; students-per-teacher; more white children as a proportion of the overall childhood population and HMO penetration.

**RESEARCH DESIGN AND DATA SOURCES**

*Psychostimulants*

Our county-level data on psychostimulant distribution comes from the Drug Enforcement Administration’s
### Table 2. Characteristics of counties with high and low per capita use of psychostimulants, DEA’s ARCOS database differences in means for all U.S. counties for methylphenidate and amphetamine combined (2000)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean for all U.S. counties (standard error)</th>
<th>Low consumption ( n = 1515 ) counties (standard error)</th>
<th>High consumption ( n = 1515 ) counties (standard error)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socio-demographic and economic characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychostimulant distribution rate (g/per 100,000k) ( \dagger )</td>
<td>( 3359 , \text{g}^{**} ) (37.31)</td>
<td>( 1796 , \text{g}^{**} ) (20.72)</td>
<td>( 4923 , \text{g}^{**} ) (43.50)</td>
</tr>
<tr>
<td>Total population ( \dagger )</td>
<td>( 89 , 327 ) (52.22)</td>
<td>( 65 , 680 ) (86.25)</td>
<td>( 114 , 000 ) (59.34)</td>
</tr>
<tr>
<td>Per capita income ( \dagger )</td>
<td>( $21 , 397 ) (130.8)</td>
<td>( $20 , 118 ) (159.2)</td>
<td>( $22 , 760 ) (204.6)</td>
</tr>
<tr>
<td>Unemployment rate ( \dagger )</td>
<td>( 4.9% ) (0.049)</td>
<td>( 5.4% ) (0.079)</td>
<td>( 4.4% ) (0.055)</td>
</tr>
<tr>
<td>% of population with some form of health insurance ( \dagger )</td>
<td>( 82.9% ) (0.10)</td>
<td>( 82.1% ) (0.137)</td>
<td>( 83.7% ) (0.131)</td>
</tr>
<tr>
<td>White population as percentage of total population ( \ast )</td>
<td>( 81.9% ) (0.290)</td>
<td>( 81.1% ) (0.455)</td>
<td>( 82.6% ) (0.362)</td>
</tr>
<tr>
<td>Black population as percentage of total population</td>
<td>( 12.7% ) (0.280)</td>
<td>( 13.2% ) (0.438)</td>
<td>( 12.4% ) (0.352)</td>
</tr>
<tr>
<td>Asian population as percentage of the total population</td>
<td>( 4.5% ) (0.280)</td>
<td>( 5.5% ) (0.441)</td>
<td>( 3.4% ) (0.358)</td>
</tr>
<tr>
<td>State has schedule II Rx monitoring program ( \dagger )</td>
<td>( 30.7% ) (0.008)</td>
<td>( 34.3% ) (0.012)</td>
<td>( 27.0% ) (0.012)</td>
</tr>
<tr>
<td>Children/adolescents as a % of the population ( \dagger )</td>
<td>( 26.0% ) (0.061)</td>
<td>( 26.2% ) (0.10)</td>
<td>( 25.8% ) (0.075)</td>
</tr>
<tr>
<td><strong>Educational characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students-to-teacher ratio ( \dagger )</td>
<td>( 14.6 ) (0.048)</td>
<td>( 14.3 ) (0.070)</td>
<td>( 14.8 ) (0.066)</td>
</tr>
<tr>
<td>Private students-to-public students ratio ( \dagger )</td>
<td>( 0.058 ) (0.001)</td>
<td>( 0.043 ) (0.0018)</td>
<td>( 0.069 ) (0.002)</td>
</tr>
<tr>
<td>Private coed-to-private non-coed students ( \dagger )</td>
<td>( 58.0 ) (8.609)</td>
<td>( 38.0 ) (8.092)</td>
<td>( 68.3 ) (12.33)</td>
</tr>
<tr>
<td>Private sectarian-to-private non-sectarian students ( \dagger )</td>
<td>( 23.8 ) (2.755)</td>
<td>( 14.5 ) (2.072)</td>
<td>( 28.5 ) (3.990)</td>
</tr>
<tr>
<td><strong>Health system characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HMO penetration (% of individuals enrolled in HMOs) ( \dagger )</td>
<td>( 12.1% ) (0.048)</td>
<td>( 10.2% ) (0.070)</td>
<td>( 14.1% ) (0.066)</td>
</tr>
<tr>
<td>Number of HMOs operating in a county ( \dagger )</td>
<td>( 3.9 ) (0.069)</td>
<td>( 3.4 ) (0.092)</td>
<td>( 4.5 ) (0.101)</td>
</tr>
<tr>
<td>MDs/per 100,000 individuals ( \dagger )</td>
<td>( 112 ) (2.690)</td>
<td>( 86 ) (3.50)</td>
<td>( 139 ) (4.00)</td>
</tr>
<tr>
<td>Child psychiatrists as percentage of total MDs ( \dagger )</td>
<td>( 0.4% ) (0.026)</td>
<td>( 0.3% ) (0.038)</td>
<td>( 0.5% ) (0.036)</td>
</tr>
<tr>
<td>Psychiatrists as percentage of total MDs ( \dagger )</td>
<td>( 3.0% ) (0.099)</td>
<td>( 2.5% ) (0.149)</td>
<td>( 3.4% ) (0.119)</td>
</tr>
<tr>
<td>GPs, FPs as percentage of total MDs ( \dagger )</td>
<td>( 41.1% ) (0.515)</td>
<td>( 47.7% ) (0.757)</td>
<td>( 34.7% ) (0.662)</td>
</tr>
<tr>
<td>Pediatricians as percentage of total MDs ( \dagger )</td>
<td>( 5.5% ) (0.129)</td>
<td>( 4.9% ) (0.200)</td>
<td>( 6.1% ) (0.160)</td>
</tr>
<tr>
<td>Neurologists as percentage of total MDs ( \dagger )</td>
<td>( 0.9% ) (0.046)</td>
<td>( 0.7% ) (0.085)</td>
<td>( 1.1% ) (0.039)</td>
</tr>
<tr>
<td>Any psychiatrists present? ( \dagger )</td>
<td>( 0.544 ) (0.099)</td>
<td>( 0.684 ) (0.012)</td>
<td>( 0.401 ) (0.013)</td>
</tr>
<tr>
<td>Any child psychiatrists present? ( \dagger )</td>
<td>( 0.777 ) (0.007)</td>
<td>( 0.882 ) (0.008)</td>
<td>( 0.671 ) (0.012)</td>
</tr>
<tr>
<td>Any neurologists present? ( \dagger )</td>
<td>( 0.691 ) (0.008)</td>
<td>( 0.820 ) (0.009)</td>
<td>( 0.559 ) (0.012)</td>
</tr>
<tr>
<td>Any pediatricians present? ( \dagger )</td>
<td>( 0.434 ) (0.009)</td>
<td>( 0.554 ) (0.013)</td>
<td>( 0.307 ) (0.012)</td>
</tr>
</tbody>
</table>

(Continues)
Automation of Reports and Consolidated Orders System (ARCOS) database, which monitors the flow of controlled substances from their point of manufacture through commercial distribution channels to points of sale or distribution at the dispensing/retail level: hospitals, retail pharmacies, practitioners and teaching institutions. Each year ARCOS reports more than 30,000,000 transactions.

Based on the DEA’s description of the ARCOS database, distribution is highly related to consumption. The DEA’s psychostimulant data that we analyzed includes the most commonly used drugs to treat ADHD: methylphenidate, amphetamines and dextroamphetamine sulfate. For our area variation analysis in Table 2, we aggregated the DEA’s 2000 ARCOS data on psychostimulant distribution from the five-digit zip code level to the county level (dependent variable) and then linked it with numerous county characteristics (independent variables) based on data from: area resource files (ARF), Census Estimates, InterStudy Publications on HMOs and the Department of Education’s Common Core of Data. Approximately 70% of psychostimulants is prescribed for children and adolescents with attention deficit disorder (ADD). Thus, the majority of these drugs prescribed in any area are for persons younger than 19 years old and diagnosed with at least ADHD, as the diagnosis has high rates of comorbidity.

In order to test the reliability and validity of the DEA’s ARCOS data for measuring the area variability in psychostimulant use (not just distribution), we cross-checked it with auxiliary datasets that measure actual prescription amounts at the state level. For example, for the state of California we obtained prescription data from the state’s Schedule II prescription drug monitoring program (run by the state’s Department of Justice), which records information on every Schedule II prescription written within each of the state’s 3-digit zip codes. The prescription claims data from California’s monitoring program lists the number of pills dispensed in each 3-digit zip code, and their various strengths, for a limited number of drugs containing methylphenidate (e.g. Concerta, Ritalin, methylphenidate hydrochloride etc.). Using this data, we classified each of the 57 3-digit zip codes in California as either ‘high’ (28 areas) or ‘low’ (29 areas) users of psychostimulants, depending on whether they were above or below the median level of consumption for these drugs in the state. We then took the DEA’s ARCOS data for methylphenidate distribution to 5-digit zip codes in CA and aggregated it up to 3-digit level to match California’s data.

Using the DEA’s data, we again classified each of the 57 3-digit zip codes as either ‘high’ (again 28 areas) or ‘low’ (29 areas) use areas based on the median value. Of the 28 areas classified as ‘high’ use by data from California’s prescription monitoring program, 27 were also correctly classified as ‘high’ use by the DEA data, while only 1 area was incorrectly classified as low use. Similarly, of the 29 areas classified by California’s data as ‘low’ use areas, 28 were also classified as ‘low’ use by DEA, while one area was incorrectly classified as high use. Thus, the sensitivity and specificity of using DEA data is 96.4 and 96.6%, respectively. Because the incidence of high/low counties (using median values) is 0.5, this implies that the probability of false positives is only 0.0346 (or 3.5%). With this extremely low probability of false positives, we can safely use DEA data on distribution of psychostimulant drugs to classify all U.S. counties as having either ‘high’ or ‘low’ per-capita rates of psychostimulant consumption.

RESULTS
The county-level analysis of per-capita psychostimulant use reveals significant differences and similarities between ‘low’ and ‘high’ use areas. Counties with

higher per-capita consumption rates have, on average, greater population density, higher per capita income, lower unemployment rates, a greater proportion of their population with health insurance coverage, greater HMO penetration, more HMOs operating in each county and more physicians (including specialists) per capita. They do not, however, have more children as a proportion of the population.

Expressed as a percentage of total physicians, counties above the median rate of psychostimulant consumption have a greater percentage of pediatricians, psychiatrists, child psychiatrists and neurologists, but a lower percentage of general and family practitioners. While there appears to be no significant difference in the male-to-female ratio among physicians, counties with higher consumption rates have a higher young-to-old physician ratio.

There are also differences in the educational environment across the two sets of counties. Counties with higher rates of psychostimulant use have slightly higher students-to-teacher ratios in public schools, but significantly higher ratios of private school students-to-public schools students, private coed-to-private non-coed students and private sectarian (religious)-to-private non-sectarian students.

DISCUSSION

In general, the results in Table 2 suggest a positive relationship between county affluence and higher per-capita use of psychostimulant drugs. For instance areas with ‘high’ use of psychostimulants have, on average, about $2650 greater per-capita income and a 1% lower unemployment rate than areas with ‘low’ use. These findings are consistent with the findings of a recent study on the geographic variation in the prevalence of psychostimulant medication use among children. They also suggest a positive relationship between higher use of the drugs and areas with greater population density and greater access to medical care (more physicians, more specialists and higher levels of health insurance). To receive psychostimulants, one needs access to a prescribing physician. So it is not surprising that areas with greater affluence and health system resources also have higher use of psychostimulants.

What is surprising in our findings is the difference in the composition of medical professionals between areas of ‘high’ and ‘low’ psychostimulant use. While greater numbers of physicians per capita would be correlated with affluence, the areas with ‘high’ use of psychostimulants also have a higher ratio of younger-to-older physicians: areas with ‘high’ use have 1.9 younger (<55 years old) physicians for every 1 older (≥55 years old) physician, whereas in areas with ‘low’ use the ratio is only 1.6 to 1. Two plausible explanations for this difference are that: (1) younger physicians are systematically self-locating in more affluent areas (which are correlated with high use of psychostimulants), and/or (2) that the medical training of younger physicians is inherently different and that, on average, they are more likely than their older colleagues to prescribe psychostimulants. While the first explanation is certainly plausible, we believe that in recent years—with ADHD being more widely recognized and accepted as a legitimate mental disorder—the second explanation probably explains a greater proportion of the variance. If this is the case, then it behooves us to further investigate if older physicians are more likely to be ‘under’ prescribing or if younger physicians are more likely to be ‘over’ prescribing. Similar differences can be seen across various medical specialties. Areas with ‘high’ use have a greater percentage of psychiatrists, child psychiatrists and pediatricians as a percentage of total physicians in the area.

Another important difference between areas with ‘high’ and ‘low’ use is both the number of HMOs and total HMO penetration (where penetration is measured as the percentage of the population enrolled in HMOs). Given the cost-minimizing objectives of HMOs, one would expect the consumption of psychostimulants to be lower in areas with higher HMO penetration. However, the results show that areas with ‘high’ consumption have greater HMO penetration. Once again, this could be simply a manifestation of spurious correlations with other variables (e.g. HMOs systematically entering more affluent markets). Yet this finding is also consistent with the cost minimization objectives if we consider that the alternative treatment—counseling and/or psychiatric therapy that focuses on cognitive and behavioral adjustments—is far more costly. Thus, HMOs could be systematically substituting cheaper drug therapy for the more expensive counseling options. (Note that HMOs advocate the use of one product over another via the formularies; however, this does not affect our finding because our results are not for a specific psychostimulant drug such as Ritalin or Adderall, but rather for all psychostimulants combined.)

In addition, we find that ‘high’ use counties have, on average, slightly fewer children as a proportion of the population. One would expect that areas with a higher proportion of children would have higher per-capita rates of psychostimulant use, given that ADHD is primarily diagnosed among children. A possible explanation for this counterintuitive result is provided...
by a recent research finding that children in families with four or more children were 26% less likely than
children in smaller families to consume a psychostimulant medication. In other words, areas that have
smaller families are more likely to have fewer children as a proportion of the total population, but the children
are more likely to be using these drugs.

Finally, we find that areas with ‘high’ use have a
slightly higher students-to-teacher ratio than areas with ‘low’ use. This finding is in sharp contrast to the
affluence explanation given above, since more affluent areas typically have lower students-to-

teacher ratios. Again, there are two competing explanations for this finding: (1) areas where stu-
dents-to-teacher ratios are higher place a greater burden on teachers; hence, misbehavior could lead to
more children being sent to the school psychologist for screening, resulting in higher detection rates of
ADHD and ultimately of psychostimulant consumption; (2) that the observed correlation is just that, a
(spurious) correlation—controlling for other factors
will make this finding insignificant. Given that
population is greater in ‘high’ use counties, we tend
to favor the second explanation.

LIMITATIONS

One limitation of this study, as previously mentioned,
is that the ARCOS data measures distribution of drugs
(not actual consumption). For example, the shipment
may be sent to one location, but used in another. Our
use of other auxiliary datasets, however, which do
measure psychostimulant consumption at the state
level, confirms that the DEA data is a sufficiently
accurate measure of the variability in the use of these
drugs (albeit not an ideal one).

A second limitation of this study, also previously
mentioned, is that it is merely descriptive with bivariate

correlates. Because we do not have price data that
would show how much the price of these drugs varies
geographically, we concluded that we could not
perform a multivariate analysis without undue concern
over potential omitted variable bias. In other words, we
assume that the price of psychostimulant drugs has
some measure of impact on its consumption. And not
being able to account for it, therefore, casts doubt on
the results of any multivariate analysis. In addition to
our own efforts, we encourage others to try to obtain
compatible price data that can be used to determine
which factors (socio-demographic, educational or
health system) are the most significant, when others
are controlled, in predicting counties’ per-capita
psychostimulant use.

DIRECTIONS FOR FUTURE RESEARCH

While there is significant variation in the use of psy-
chostimulant drugs across the country, there is also
considerable variation in other variables as well. An
important and necessary direction for future research
is to test if any of these covariates are causally related
to consumption rates and, if so, the direction and
strength of causality should be estimated. A starting
point is to specify a structural model for the equili-

brium quantity and price of the psychostimulant drugs
in each market and then test hypotheses regarding the
effects of these covariates on the consumption rates.
The difficulty, however, lies in obtaining price data
on psychostimulant drugs at the county level to match
the DEA’s quantity data. As previously explained, this
is why we restricted our study to a bivariate analysis.

Ultimately, differences in psychostimulant consump-
tion rates across the country could arise for three basic
reasons: a greater proportion of people are diagnosed
with ADHD in some areas than in others;14,17–20 a
greater proportion of people are prescribed psychosti-

mulants in some areas than in others, even though
the same proportion of people may be diagnosed with
ADHD;8 and the same proportion of people are
diagnosed with ADHD and prescribed psychostimu-

lants, but patients in some areas are systematically
given larger dosages than in other areas.14,16

Given these reasons and our preliminary findings, we
have identified two areas ripe for additional research.
First, market level, multivariate analyses (which
control for price differentials) are needed to tease out
how—and to what extent—economic, demographic,
educational, regulatory and health system factors
affect regional rates of psychostimulant consumption.
Second, researchers should examine physicians’
practice styles in diagnosing and treating ADHD to
see how much they vary, and whether they vary
systematically by patients’ and/or physicians’ personal
characteristics (e.g. age, race, gender, ethnicity, type of
health insurance, professional experience, type of
practice—group/solo etc.).

ACKNOWLEDGEMENTS

We wish to thank Doug Schwalm, Ph.D., James Bosco,
Ph.D., Patricia Pastor, Ph.D., and Jennifer Mayes for
their helpful critiques of this paper at various stages
of its development. We also want to express our grati-
tude to the Nicholas C. Petris Center on Healthcare
Markets & Consumer Welfare and the Center for Child
& Youth Policy at the University of California, Berkeley for their financial support of our research.
REFERENCES


10. State prescription monitoring programs track the quantity of the drug and the identity of the physician and patient for every individual psychostimulant prescription filled by a pharmacy. Control begins with the establishment of production limits (quotas) for Schedule I & II substances. Schedule I substances have the highest potential for abuse and addiction and have no accepted medical use in the United States. Schedule II includes such drugs as methadone, meperidine (Demerol), cocaine, oxycodone (Percodan) and methylphenidate (Ritalin). Because of their high abuse potential, the use of Schedule II drugs is the most restricted and greater controls are placed on them.

11. Zito J, Safer D, dosReis S, Gardener J, Bolese M. decreased prescription for a Schedule II (and in a few states, certain Schedule I) substance. A multiple copy prescription monitoring program or electronic tracking systems, which can be used alone or with distribution limits (quotas) for Schedule I & II substances. Schedule I substances have the highest potential for abuse and addiction and have no accepted medical use in the United States. Schedule II includes such drugs as methadone, meperidine (Demerol), cocaine, oxycodone (Percodan) and methylphenidate (Ritalin). Because of their high abuse potential, the use of Schedule II drugs is the most restricted and greater controls are placed on them.


31. State prescription monitoring programs track the quantity of the drug and the identity of the physician and patient for every individual psychostimulant prescription filled by a pharmacy. Control begins with the establishment of production limits (quotas) for Schedule I & II substances. Schedule I substances have the highest potential for abuse and addiction and have no accepted medical use in the United States. Schedule II includes such drugs as methadone, meperidine (Demerol), cocaine, oxycodone (Percodan) and methylphenidate (Ritalin). Because of their high abuse potential, the use of Schedule II drugs is the most restricted and greater controls are placed on them.


Copyright © 2004 John Wiley & Sons, Ltd.

Pharmacoepidemiology and Drug Safety, (in press)
Schedule III and IV) controlled substance on a state issued, preprinted, serialized duplicate or triplicate form; (2) The prescriber writes and the dispenser maintains file copies of the prescription for a period of two to five years (for triplicate programs). Duplicate prescription programs do not require the prescriber to maintain copies; (3) The dispenser forwards a copy of the prescription to the mandated state authority; With an electronic data transmission system, however: (1) The prescriber writes an original prescription for a Schedule II (and in some states, Schedules III, IV and V) controlled substance on a prescription form; (2) The dispenser maintains the original prescription for a period of two to five years; (3) The dispenser transmits the prescription information either electronically (via modem, disk, tape, black box) or by universal claim form to the mandated state authority. This system allows prescription information to be submitted electronically. In most states, if the dispenser lacks the requisite computer equipment and/or fills less than 20-25 Schedule II prescriptions per month, information is submitted on a Universal Claim Form.