SPILLOVERS AND TRAINING EFFECTS ON MENTAL HEALTH PRESCRIBING FOR CHILDREN *By* JANET CURRIE, W. BENTLEY MACLEOD, AND MENGSONG OUYANG *

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Variations in the costs and intensity of medical care across geographic regions are well documented, but their origins are not well understood (Skinner, 2012; Badinsky et al., 2023). One possible explanation is that there are spillovers in practice style between physicians practicing in the same area (Chandra and Staiger, 2007; Molitor, 2018). To the extent that such spillovers are important, it may be possible to reduce costs due to inappropriate treatment by, for example, using network structures to target physicians who are particularly influential (Jackson, 2008).

However, evidence for the spillovers hypothesis is mixed. For example, Chan (2021) studies variation in practice styles among physician trainees in a residency program. He finds remarkably little convergence in practice styles even in this setting of intensive training, although he does find that within teams, more junior residents defer to senior residents.

An alternative to the spillovers hypothesis is that physicians with similar practice styles happen to cluster in the same locations. For example, such clustering could occur because students from particular medical schools tend to set up practice near those schools.

In this paper, we examine variations in the way individual physicians prescribe mental health drugs to children who are being prescribed anti-anxiety or antidepressant drugs for the first time. This setting has several interesting features. First, much of the small-area-variations literature focuses on differences in treatment among the elderly and it is useful to look at other groups. Second, child mental health problems are very common, affecting as many as 20 percent of children at some point (Bethell et al., 2022). Third, there are relatively clear guidelines about what treatments are inappropriate in this setting. Hence, we can ask not only whether treatment varies, but whether it does so in ways that are likely to be harmful. Fourth, children may be treated by either more highly trained providers (psychiatrists) or, more often, by doctors who have much less training in child mental health. Most of these doctors are trained in pediatrics, family medicine, or internal medicine and are treating children in their roles as primary care physicians. One might expect spillover effects to be less important for physicians with stronger mental health training, a hypothesis that we investigate below.

I. Data and Methods

A. The IQVIA data

National data on prescriptions of psychiatric medications filled at retail pharmacies come from IQVIA's LRx data base from 2006-2018. IQVIA (formerly known as IMSQuintiles) is a public company specializing in pharmaceutical market intelligence.[1] We focus on the first prescription to a child less than 18 that appears in our data.[2] The state and 3-digit zip code of each physician in each year is approximated by the zip code that most of their patients come from. Non-physician providers are dropped.

Children being treated for depression or anxiety for the first time would normally be prescribed Selective Seratonin Reuptake Inhibitors (SSRIs) if they are prescribed any medications. The outcomes of interest include four types of concerning or "red-flag" alternative prescribing: 1) whether the child is less than the Food and Drug Administration's minimum age for the use of the drug; 2) whether the prescription is a benzodiazepine (addictive and dangerous in overdose);[3] 3) whether the prescription is for an older tricyclic antidepressant (worse side effects than SSRIs and limited efficacy in children); and 4) poly-pharmacy, i.e. multiple prescriptions on the same day.[4] We also look at whether any of these outcomes occurred (any red-flag).

The data can be used to define physician "cohorts" using their medical school's rank (from U.S. News and World Reports 2023) and their year of graduation from medical school. Graduation years before 1967 or after 2015 are excluded. The rest of the years are grouped into two-year bins so that there are 26 time bins in total. There are six school rank groups: 1-20, 21-50, 51-94, 95+, Canadian and Caribbean schools, and other foreign schools.

Table 1 provides an overview of the data at the zip code and cohort levels. The first four rows show that although we have large numbers of patients and physicians in each zip and cohort, the mean number of patients per physician is small, mainly because there are many physicians who only prescribe to a few children in any given year. As described below, our analysis will be at the patient level

[1] The IQVIA data is available for purchase to qualified researchers. For further information, contact Allen.Campbell@iqvia.com.

[2] In order to insure that it is the first, we use a six month lookback period in the first year of the data.

[3] Because very short courses of benzodiazepines are sometimes administered prior to surgery, we exclude prescriptions of less than seven days from consideration.

[4] There are 81 antidepressant drugs and 33 antianxiety drugs observed. Hydroxyzine is removed because it is often used to treat allergies.

and will leverage practice-style measures constructed at the zip and cohort levels rather than computing individual physician-year level measures of practice style.

TABLE 1— SUMMARY STATISTICS

	Zip level	Cohort level
Panel A: Psychiatrists		
Avg. # physicians per year	28.87 (46.31)	171.14 (107.33)
Avg. # patients<18 per year	945.51 (1288.60)	5456.23 (4792.62)
Avg. # prescriptions per year	4074.06 (5555.21)	23383.25 (20494.48)
Patients/physician per year	36.31 (21.33)	27.07 (11.52)
Share any red flag	0.485(0.118)	0.416(0.074)
Share violating age limits	0.468 (0.117)	0.400 (0.071)
Share tricyclics	0.086 (0.068)	0.062 (0.021)
Share benzodiazepines	0.023 (0.022)	0.023 (0.012)
Share poly-pharmacy	0.067 (0.043)	0.058 (0.009)
Panel B: Non-psychiatrists		
Avg. # physicians per year	192.31 (200.17)	1150.48 (805.64)
Avg. # patients<18 per year	939.69 (1059.76)	5512.92 (4347.01)
Avg. # prescriptions per year	3268.46 (3815.42)	19024.48 (15912.23)
Patients/physician per year	4.84 (1.76)	4.38 (1.23)
Share any red flag	0.515(0.091)	0.506(0.074)
Share violating age limits	0.418 (0.083)	0.395 (0.070)
Share tricyclics	0.158 (0.062)	0.166 (0.040)
Share benzodiazepines	0.081 (0.052)	0.081 (0.035)
Share poly-pharmacy	0.026 (0.012)	0.024 (0.004)

Notes: Standard deviations in parentheses. There are 880 and 889 3-digit zip codes clusters for psychiatrists and non-psychiatrists repectively and 156 cohort clusters.

The next several rows show that almost half of the children receiving antidepressant or anti-anxiety prescriptions for the first time, receive a prescription that raises a red flag. The majority of these children are getting drugs that are not approved for their age. Over ten percent are receiving tricyclics, and about five percent receive a benzodiazepine prescription lasting longer than seven days. Over four percent also receive prescriptions for two or more of these drugs from the same provider on the same day.

In previous research using these data, Currie and MacLeod (2018) and Cuddy and Currie (2020, forthcoming) document a great deal of small area variation in treatment for depression in terms of the probability that drugs are prescribed, the variety of drugs prescribed, and the doctor's favorite drugs. They also show that doctors who are outliers, in the sense that they violate treatment guidelines, generate real costs in terms of increasing a given patient's future costs for both drug and non-drug treatment including visits to the Emergency Room for mental health crises. Hence, it is important to understand sources of this variation.

B. The Model

Suppose that the true model is:

(1) $y_{ijt} = a_j + \beta_1 t_{jt} + \beta_2 z_{jt} + \beta_3 x_{ijt} + \epsilon_{ijt}$,

where $y_{ijt} \in \{0,1\}$ is the treatment of patient i by doctor j at time t, a_j is a constant doctor-specific treatment style, t_{jt} reflects the time-varying impact of doctor $j's$ training (e.g. some doctors may be trained in a way that makes it more likely for them to stay abreast of current research), x_{ijt} are child-specific variables including the patients age, sex, and residential zip code, and ϵ_{ijt} is an iid error term.

The z_{jt} is a zip code effect denoting either zip-code level determinants of care or spillovers from all of the other physicians in j's zip code and is defined as:

$z_{jt} = \frac{\sum_{i(k\in Z, k\neq j)} y_{ikt}}{\sum_{i(k\in Z,k\neq j)} 1}$, a "leave-one-out" average of the practice styles of all of the other physicians in the zip code, omitting doctor *j*.

However, local spillovers can be difficult to identify due to what Manski (1993) calls the "reflection effect." That is, the observed behavior is an equilibrium phenomena in which z_{jt} influences y_{ijt} and vice-versa. Bramoulla, Djebbari, and Fortin (2009) observe that the network structure of the environment can be used to solve the reflection problem.

In our case, data on physician training can be used to predict both doctor *j*'s behavior and the behavior of other doctors in the same zip code who belong to other cohorts. Specifically, suppose that,

(2) $t_{jt} = \bar{y}^{c}_{jt} + v_{ijt}$,

where $\bar{y}^{c}_{jt}$ is a measure of the average behavior of doctors in *j*'s cohort who practice outside of *j*'s zip code in year *t*:

$\bar{y}^{C}_{jt} = \frac{\sum_{i(k\in C\cap Z')} y_{ikt}}{\sum_{i(k\in C\cap Z')} 1}$. That is, this variable is constructed as a simple average of the prescribing received by all children treated by doctors from cohort *C* who practice outside of zip code *Z* in year *t*. Because we expect the practice styles of psychiatrists and non-psychiatrists to evolve differently over time, the measure of psychiatrists includes only psychiatrists, while the measure of non-psychiatrists includes only non-psychiatrists.

Equation (2) implies that doctor *j*'s prescribing reflects a time varying component which can be predicted by the behavior of other doctors from the same cohort, i.e. that doctors with similar training will have practice styles that evolve similarly over time, other things being equal. By construction, $\bar{y}^{c}_{jt}$ is not affected by factors specific to *j's* zip code.

Similarly, the zip code effect z_{jt} can be decomposed into the predicted behavior of other doctors in *j*'s zip code who are from cohorts *C' ≠ C,* and a residual component that may reflect other zip code specific factors such as the availability of health care facilities.

We wish to find a predictor for the year *t* practice style of doctors in *j*'s zip code who are from other cohorts. The behavior of these doctors can be predicted using the behavior of doctors for whom *C' ≠ C* and *Z' ≠* Z, that is, doctors from cohorts *C'* who practice outside the zip code *Z*. This quantity, $\bar{y}^{z'c'}_{jt}$, can be computed for every doctor by first defining $\bar{y}^{c}_{kt}$ for each doctor *k* in the sample, and then taking the average over the relevant $\bar{y}^{c}_{kt}$ for all of the other doctors in doctor *j*'s zip code for whom (*C' ≠ C)* and (*Z' ≠* Z): $\bar{y}^{Z'C'}_{jt} = \frac{\sum_{(k\neq j,k\in Z)} \bar{y}^{C}_{kt}}{\sum_{(k\neq j,k\in Z)} 1}$. This variable is mechanically independent of both the practice style and the cohort of doctor j. Hence, we can write:

(3) $z_{jt} = \bar{y}_{jt}^{z'c'} + zipres_{jt}$.

Substituting (2) and (3) into (1) yields the following estimating equation:

(4) $y_{ijt} = a_j + \beta_1 \bar{y}_{jt}^{c} + \beta_2 \bar{y}_{jt}^{z'c'} + \beta_3 x_{ijt} + \beta_4 zipres_{jt} + w_{ijt},$

where standard errors are clustered at the level of the physician's zip code.

The variable $zipres_{jt}$ is constructed by regressing a leave-one-out measure of z_{jt} on $\bar{y}_{jt}^{c}$ and $\bar{y}_{jt}^{z'c'}$. As shown in Table 2, these variables explain about 15 percent of the variation in z_{jt} for psychiatrists, and 41 percent of the variation in z_{jt} for non-psychiatrists. While both measures are highly statistically significant predictors of z_{jt}, $\bar{y}_{jt}^{z'c'}$, the predicted practice style of the other doctors in j's zip, is a much more important than the own-cohort effect.

TABLE 2— REGRESSION OF Z_{JT} ON $\bar{y}_{jt}^{c}$ AND $\bar{y}_{jt}^{z'c'}$

	(1) Psychiatrists	(2) Non-psychiatrists
Training ($\bar{y}_{it}^{c}$)	0.098**	0.040**
	(0.001)	(0.001)
Spillovers ($\bar{y}_{it}^{z'c'}$)	0.860**	0.985**
	(0.002)	(0.001)
Adj. R-squared	0.150	0.413
Mean of dep. Var.	0.444	0.513
# Observations	2997881	4015856

Notes: Standard errors in parentheses and clustered at the level of the physician's zip code.
** Significant at the 5 percent level.

In equation (4), if $\beta_1 > 0$ we interpret this as evidence of a training effect since the behavior of similarly trained physicians outside of doctor j's zip code predicts their behavior. If $\beta_2 > 0$, then there is evidence of a spillover effect since the training of the other physicians in doctor j's zip code predicts doctor j's behavior. If $\beta_4 > 0$, then zip code specific factors other than those captured by own training and spillover effects also matter. Lastly, it is worth considering the relative importance of the doctor-specific fixed effects vs. the training and spillover effects which are allowed to be time varying. If fixed effects are very important, then is an indication that physician practice style is difficult to change.

II. Results

Estimates of (4) are shown in Table 3 separately for patients of psychiatrists (Panel A) and non-psychiatrists (Panel B). Non-psychiatrists engage in more red-flag prescribing than the psychiatrists, consistent with having less training in the use of these medications.

Table 3 shows that physician fixed effects are very important: Comparing columns (1) and (2) shows that including them increases the explanatory power of the model by two to four times and greatly reduces the coefficient on the proxy for training, $\bar{y}_{jt}^{c}$. Hence, most of the doctor's own cohort effect is captured by a doctor fixed effect, although there is still some evolution in cohort behavior over time.

TABLE 3— EFFECTS OF PROXIES FOR TRAINING, SPILLOVERS, AND ZIP CODES ON THE PROBABILITY A CHILD RECEIVED A RED-FLAG DRUG

	(1)	(2)	(3)
Panel A. Psychiatrists' patients, N=2,997,881			
Zip residual (*zipres*)	0.181**	0.142**	…
	(0.021)	(0.013)	
Training ($\bar{y}_{jt}^{c}$)	0.844**	0.121**	0.106**
	(0.045)	(0.037)	(0.037)
Spillovers ($\bar{y}_{jt}^{z'c'}$)	0.471**	0.200**	0.180**
	(0.094)	(0.067)	(0.071)
Patient age, years	-0.023**	-0.023**	-0.023**
	(0.000)	(0.000)	(0.000)
Female patient	-0.057**	-0.050**	-0.050**
	(0.001)	(0.001)	(0.001)
Mean of Dep. Var.	0.440	0.440	0.440
Adj. R-squared	0.080	0.181	0.181
Panel B. Non-psychiatrist patients, N=4,015,856			
Zip residual (*zipres*)	0.157**	0.130**	…
	(0.022)	(0.012)	
Training ($\bar{y}_{jt}^{c}$)	0.804**	0.177**	0.176**
	(0.029)	(0.026)	(0.026)
Spillovers ($\bar{y}_{jt}^{z'c'}$)	0.108	0.386**	0.486**
	(0.144)	(0.095)	(0.099)
Patient age, years	-0.025**	-0.023**	-0.023**
	(0.000)	(0.000)	(0.000)
Female patient	-0.005**	-0.007**	-0.007**
	(0.001)	(0.001)	(0.001)
Mean of Dep. Var.	0.525	0.525	0.525
Adj. R-squared	0.075	0.281	0.281
Doctor fixed effects?	No	Yes	Yes

Notes: Standard errors in parentheses. All models also control for patient zip code fixed effects and year of service fixed effects. Standard errors are clustered at the level of the physician's zip code. ** Significant at the 5 percent level.

The coefficient on the proxy for spillovers, $\bar{y}_{jt}^{z'c'}$, is also reduced by the inclusion of doctor fixed effects, suggesting that some of what a leave-one-out zip-level measure captures is a clustering of doctors with similar practice styles within an area.

Still, changes in $\bar{y}_{jt}^{z'c'}$ remain highly statistically significant, indicating that within zip code spillovers from other doctors are an important determinant of practice styles. Comparing estimates for psychiatrists and non-psychiatrists suggests that spillover effects are larger for the latter, perhaps consistent with having less specific training.

While column (2) shows our preferred specification, column (3) shows something analogous to a reduced form regression that includes only the exogenous variables $\bar{y}_{jt}^{c}$ and $\bar{y}_{jt}^{z'c'}$ and not $zipres_{jt}$. One reason to omit $zipres_{jt}$ is that unlike $\bar{y}_{jt}^{c}$ and $\bar{y}_{jt}^{z'c'}$ it may still reflect a combination of local determinants of practice style. Not surprisingly, given the variables' construction, the estimated coefficients on $\bar{y}_{jt}^{c}$ and $\bar{y}_{jt}^{z'c'}$ are very similar. What is more informative is that the R-squared is the same in columns (2) and (3) indicating that $zipres_{jt}$ adds little to the explanatory power of the model.

Table 4 shows estimates from separate models for each type of red-flag prescribing. The dependent variable measures indicate that non-psychiatrists are three times more likely to prescribe tricyclics, and more than twice as likely to prescribe benzodiazepines. However, psychiatrists are more likely to prescribe multiple drugs on the same day, and slightly more likely to prescribe a drug to a child who is too young.

The estimates suggest that spillover effects are particularly large for non-psychiatrists in the case of prescribing drugs to patients who are too young, prescribing benzodiazepines, and prescribing more than two drugs on the same day. At the opposite extreme, variation in prescribing of benzodiazepines by psychiatrists is mainly captured by physician fixed effects. Similarly, prescribing of tricyclics by non-psychiatrists is also captured by physician fixed effects.

TABLE 4 — EFFECTS OF PROXIES FOR TRAINING, SPILLOVERS, AND ZIP CODES ON THE TYPE OF INAPPROPRIATE PRESCRIBING

	(1) Too young	(2) Tricyclics	(3) Benzo-diazepines	(4) 2+ drugs same day
Panel A. Psychiatrists' patients, N=2,997,881				
Zip residual (*zipres*)	0.144**	0.082**	0.030**	0.107**
	(0.012)	(0.018)	(0.008)	(0.018)
Training ($\bar{y}_{jt}^{c}$)	0.111**	0.118**	0.033	0.096*
	(0.038)	(0.045)	(0.027)	(0.054)
Spillovers ($\bar{y}_{it}^{z'c'}$)	0.216**	0.247**	-0.036	0.116
	(0.069)	(0.083)	(0.051)	(0.127)
Patient age, years	-0.025**	-0.010**	-0.000**	0.006**
	(0.000)	(0.000)	(0.000)	(0.000)
Female patient	-0.049**	-0.027**	0.001**	0.016**
	(0.001)	(0.001)	(0.000)	(0.001)
Mean of Dep. Var.	0.430	0.068	0.020	0.052
Adj. R-squared	0.184	0.154	0.106	0.066
Panel B. Non-psychiatrist patients, N=4,015,856				
Zip residual (*zipres*)	0.126**	0.087**	0.129**	0.041**
	(0.012)	(0.012)	(0.010)	(0.014)
Training ($\bar{y}_{it}^{c}$)	0.155**	0.014	0.207**	0.033
	(0.031)	(0.025)	(0.025)	(0.034)
Spillovers ($\bar{y}_{it}^{z'c'}$)	0.623**	0.107	0.408**	0.389*
	(0.114)	(0.095)	(0.083)	(0.210)
Patient age, years	-0.036**	-0.003**	-0.006**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Female patient	-0.026**	0.009**	0.001**	0.002**
	(0.001)	(0.001)	(0.000)	(0.000)
Mean of Dep. Var.	0.397	0.204	0.081	0.017
Adj. R-squared	0.276	0.396	0.271	0.047
Doctor fixed effects?	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. All models also control for patient zip code fixed effects and year of service fixed effects. Standard errors are clustered at the level of the physician's zip code. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Age and female gender, which were both negatively associated with overall red-flag prescribing in Table 3, are shown to have varying effects for different types of prescribing. Mechanically, older children are less likely to be prescribed a drug for which they are too young. They are also slightly less likely to be prescribed tricyclics or benzodiazepines, but more likely to be prescribed multiple drugs on the same day. Girls are less likely to be prescribed drugs for which they are too young, but more likely to be prescribed benzodiazepines and more than one drug on the same day.

III. Discussion and Conclusions

One significant limitation of our work is that we do not observe the condition of the children who are being treated. Yet, if prescribing were determined only by the child's medical needs, we would not expect to see the large, regular, and persistent effects of our proxies for physician training and spillovers. A second limitation is that we only see children who are prescribed medications; hence what we are measuring is deviations from prescribing guidelines among children who received any prescription for an antidepressant or anti-anxiety drug. A third limitation is that our proxies for cohort-specific training effects, and for the behavior of other physicians within a zip code are imperfect, although they do capture a significant share of the within-zip code variation in practice style.

Estimates using these proxies suggest that a 20 percent increase in a psychiatrist's cohort's use of red-flag drugs outside of the zip code is associated with a 2.4 percent increase in red-flag prescribing. Among non-psychiatrists a 20 percent increase would lead to a 3.5 percent increase in red-flag prescribing. A 20 percent increase in the predicted red-flag prescribing of physicians from the other cohorts who are represented in a given physician's zip code would have larger effects: It would increase red-flag prescribing among the psychiatrists in a zip code by 4.0 percent and would increase such prescribing among non-psychiatrists by 7.7 percent.

The estimates by type of red-flag prescribing confirm that spillover effects are consistently larger for non-psychiatrists than for psychiatrists, suggesting that specific training in the use of mental health drugs mitigates the extent to which harmful prescribing practices spread. An exception is the variation in prescribing of tricyclics by non-psychiatrists which is explained mostly by physician fixed effects.

In summary, we provide new evidence about the importance of spillovers in practice style in models that also demonstrate the importance of fixed doctor-specific idiosyncracies in practice style, and of cohort-level evolution in practice style. The results suggest that finding influential doctors within provider networks could be an important way to improve medical practice.

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