Online Appendix to

Provider effects in antibiotic prescribing: Evidence from physician exits

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A Model of prescribing and practice style differences – Details

We characterize antibiotic prescribing in a stylized model that follows Finkelstein et al. (2016). We assume that patient i's utility from consuming an amount of antibiotics y at point t is determined as follows:

$$u(y|\alpha_i, h_{it}) = \alpha_i y - \frac{1}{2}(y - h_{it})^2,$$

where α_i denotes individual time-invariant factors and h_{it} denotes patient health, and patient utility is additively separable in patient-specific factors and time-varying health. The optimal level of care patients would choose under full information is given by $y^*_{ijt} = \text{argmax}_y \, \tilde{u}_j(y|\alpha_i, h_{it}) = \alpha_i + h_{it}$. The individual time-invariant factors α_i absorb patient-level drivers of antibiotic consumption that remain fixed over time including, for example, preferences for higher antibiotic consumption or location-specific effects. A higher demand for antibiotics due to time-invariant patient-level drivers is represented by a higher value of α_i. A higher demand for antibiotics due to time-varying patient health is represented by a higher value of h_{it}, which implies worse health.

Each patient i in each year t is matched to a provider, which we denote by a set of physicians j. Physicians j make antibiotic prescribing decisions on account of their patients such that the utility from treating patients is maximized, but also taking into account physicians' personal preferences and costs. We operationalize the physicians' utility as follows:

$$\tilde{u}_j(y|\alpha_i, h_{it}) = u(y|\alpha_i, h_{it}) + (\delta_j - c_{jt})y,$$

where δ_j denotes j's prescribing practice style and c_{jt} denotes time-varying clinic characteristics. Physicians' utility $\tilde{u}_j(y|\alpha_i, h_{it})$ thus captures differences between prescribing decisions that

arise due to heterogeneity in the time-invariant provider practice styles (differences in δ_j) and time-varying clinic characteristics that affect the cost of antibiotic prescribing (differences in c_{jt}). We assume that time-varying and time-invariant factors are additively separable.

Finally, Equation (1) is obtained by maximizing physicians' utility:

$$\tilde{u}_j(y|\alpha_i, h_{it}) = \alpha_i y - \frac{1}{2}(y - h_{it})^2 + (\delta_j - c_{jt})y.$$

In denoting Equation (1), we subsume time-varying patient health h_{it} and time-varying clinic characteristics c_{jt} into a vector of time-varying characteristics x_{it}.

B Number of observations

Table A.1 provides an overview over the number of clinics, patients, and observations on the patient-year level in our sample by clinic treatment status.

Our sample includes patients at 563 never-treated clinics, as well as patients at 242 clinics that are exposed to any type of physician exit within the period of 2005 to 2012. The majority of physician exits leads to the closure of a clinic.

Note that never-treated patients can be assigned to a treated clinic, for example if they are assigned to that clinic strictly after the physician exit has already occurred.

Table A.1: Number of observations

	Clinics	**Patients assigned to clinics**	**Observations**
Never-treated	563	1,103,672	6,263,693
Treated	242	329,414	1,526,215
Clinic closure	211	221,045	882,718
No clinic closure	31	108,369	643,497
Total	805	1,371,604[a]	7,789,908

[a] The sum of never-treated and treated patient observations does not equal the total number of patients because some patients are observed at two clinics if exposed to a physician exit.

C Definition of scaling factor

Our scaling factor is based on the difference in mean prescribing to untreated patients rather than the difference in unconditional mean prescribing as used for example by Fadlon and Van Parys (2020). We thus prevent that our estimates of the share of provider effects in antibiotic prescribing differences become affected by the share of treated patients who cause an overlap in patient pools.

To see the effect of the share of treated patients in a simplified setting, let all treated patients change from physicians j to j' and ignore time-varying characteristics x_{it}. Denote average patient effects in the pool of treated patients assigned to physician j by $\alpha^j = \mathbb{E}[\alpha_i | j(i) = j, D_{it} = 0]$ and note that these patients are not-yet-treated. Average patient effects in the pool of never-treated patients assigned to physician j' are $\alpha^{j'} = \mathbb{E}[\alpha_i | j(i) = j', D_{it} = 0]$. Patient pools treated by j and j' prior to the physician exit differ arbitrarily, $\alpha^j \neq \alpha^{j'}$. Mean prescribing is determined by $\mathbb{E}[y_{ijt}] = \alpha^j + \delta_j$.

Unconditional mean prescribing can be written as a weighted sum of mean prescribing to never-treated or not-yet-treated patients ($D_{it} = 0$) and mean prescribing to patients exposed to physician exit ($D_{it} = 1$). By construction, all patients assigned to j are not yet treated, but patients assigned to j' are either never-treated or exposed to physician exit. The difference in unconditional mean prescribing is $\tilde{\Delta}_i = \{w_D \mathbb{E}[y_{ij't} | D_{it} = 1] + (1 - w_D)\mathbb{E}[y_{ij't} | D_{it} = 0]\} - \mathbb{E}[y_{ijt} | D_{it} = 0]$, where $w_D \in [0, 1]$ denotes the proportion of patients of j' who changed from j to j'.

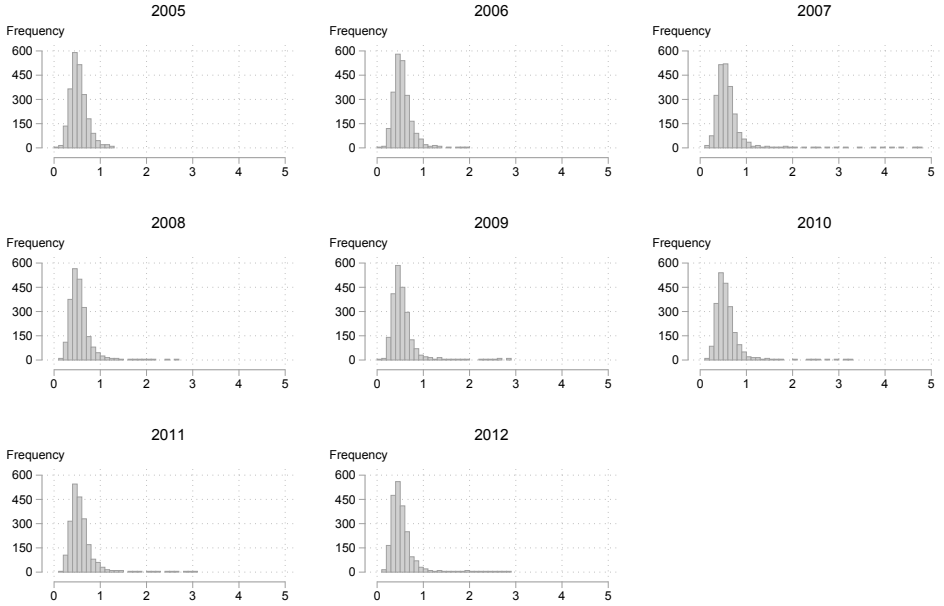
Because patient effects are fixed over time, only provider effects change once patients are exposed to physician exit. Mean prescribing to the pool of treated patients pre-exit is $\mathbb{E}[y_{ijt} | D_{it} = 0] = \alpha^j + \delta_j$, and it is $\mathbb{E}[y_{ij't} | D_{it} = 1] = \alpha^j + \delta_{j'}$ post-exit. Mean prescribing to the never-treated patient pool is always $\mathbb{E}[y_{ij't} | D_{it} = 0] = \alpha^j + \delta_{j'}$. The difference in unconditional mean prescribing can now be written as follows: $\tilde{\Delta}_i = (\delta_{j'} - \delta_j) + (1 - w_D)(\alpha^{j'} - \alpha^j)$. Scaling provider effects $\delta_{j'} - \delta_j$ by $\tilde{\Delta}_i$ implies that provider effects are weighted more the larger the proportion of treated patients w_D for a given difference in patient pools $\alpha^{j'} - \alpha^j$.

D Further descriptives

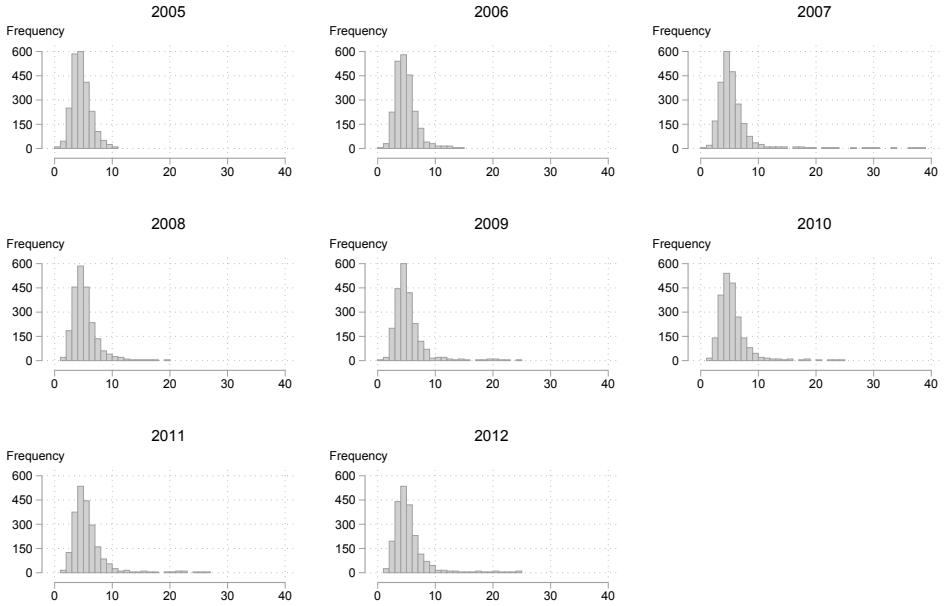
D.1 Distribution of antibiotic prescribing over clinics

Figure A.1 shows the distribution of average antibiotic prescribing per patient over general practice clinics in Denmark for each year of our sample period from 2005 to 2012. While average prescribing in Denmark is low, there is substantial and persistent heterogeneity between clinics.

Figure A.1: Distribution of average antibiotic prescribing per patient over general practice clinics



(a) Number of antibiotic prescriptions (levels)



(b) Daily Defined Dose (levels)

Notes: Average antibiotic prescriptions dispensed per patient and year at the clinic-level. Bunched in groups of five clinics to ensure the required data anonymization. The upper five percentiles are omitted.

D.2 Origin and destination clinics

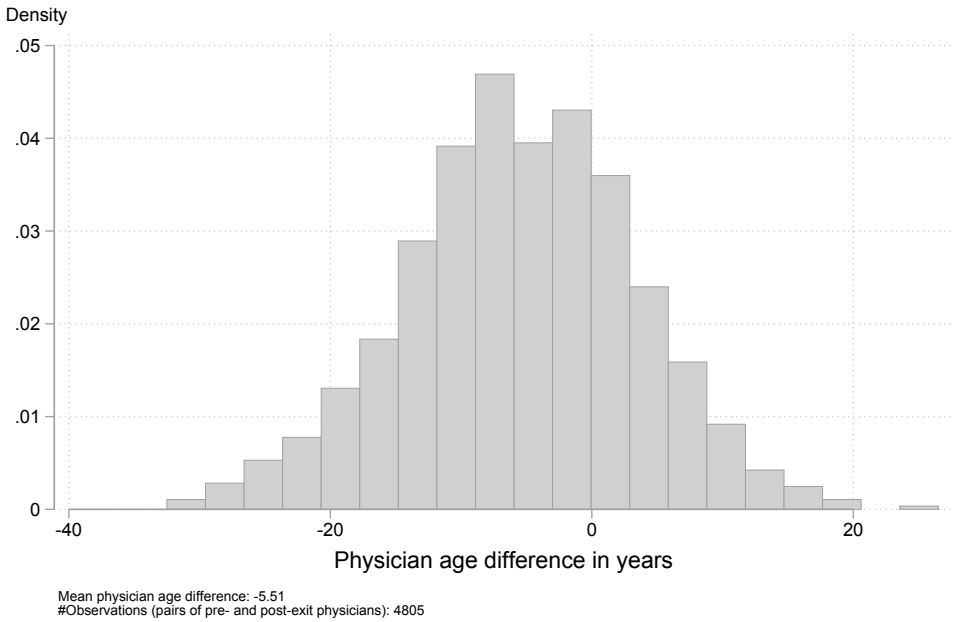
Table A.2 shows summary statistics for treated clinics strictly before the physician exit (241 unique clinics, 1 clinic without clinic observables), as well as characteristics for all destination clinics that absorb any treated patients after they were exposed to a physician exit (563 unique clinics). Destination clinics are similar on average compared to the full set of never-treated control clinics described in Table 3 in the main text. This is because most never-treated control clinics, 539 out of the 563 clinics, act as destination clinics for treated patients at some point.

In order to investigate the shift in physician age descriptively, Figure A.2 shows histograms of the age difference between pre- and post-exit physicians, where age is averaged over all years observed for a given clinic. Figure A.2a shows the distribution of age differences for all pairs of pre- and post-exit physicians. Figure A.2b shows the distribution of age differences weighted by patient-year observations. These figures show that, while the majority of reassignments for treated patients is from older to younger physicians, we also observe a number of reassignments from younger to older physicians.

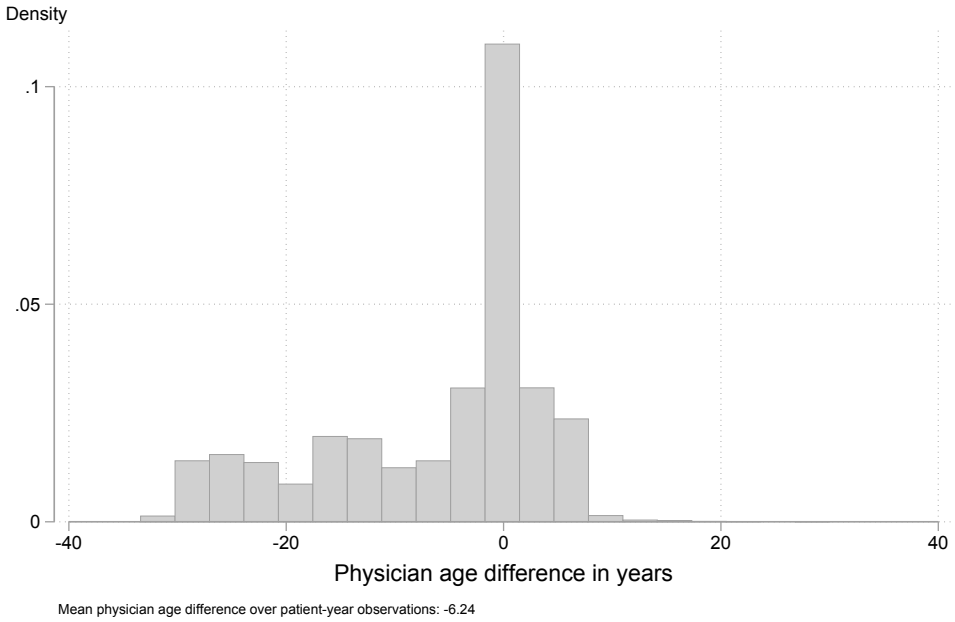
Table A.2: Summary statistics for pre-exit origin clinic and post-exit destination clinics

	Pre-exit origins		Post-exit destinations	
	Mean	SD	Mean	SD
A: Average number of antibiotic prescriptions per patient				
All antibiotics (All J01)	0.58	(0.20)	0.55	(0.16)
Penicillins (J01 C)	0.35	(0.12)	0.34	(0.10)
Second-line (J01 F, D, or M)	0.12	(0.08)	0.12	(0.07)
Other (Other J01)	0.10	(0.06)	0.09	(0.04)
B: Average physician characteristics				
Age	59.35	(5.88)	56.06	(6.43)
Female	0.24	(0.37)	0.37	(0.43)
First generation migrant (nordic)	0.006	(0.075)	0.004	(0.051)
First generation migrant (other country)	0.02	(0.15)	0.03	(0.16)
Second generation migrant	0.01	(0.08)	0.01	(0.08)
Phd education	0.01	(0.07)	0.01	(0.08)
C: Size and equipment				
Number of physicians	1.39	(0.80)	1.47	(0.86)
Number of interns	0.12	(0.39)	0.29	(0.56)
Number of patients per physician	1857.23	(858.76)	1931.22	(674.38)
Diagnostic culture available	0.94	(0.24)	0.98	(0.15)
Diagnostic microscopy available	0.77	(0.42)	0.75	(0.44)
Telephone consultation available	1.000	(.)	1.000	(.)
Total observations (clinic-years)	906		2,844	

Figure A.2: Difference in average age between pre- and post-exit providers



(a) Distribution over pairs of pre- and post-exit providers



(b) Distribution over treated patients, weighted by years observed

Notes: In Figure A.2a, values are bunched for groups of five clinics with similar age differences due to data anonymization. In Figure A.2b, values are bunched for groups of five patients.

D.3 Summary statistics for out-of-sample clinics and patients

We compute summary statistics for characteristics in out-of-sample clinics which are listed in the Danish registry of clinics but which we have excluded from our analyses, as well as for patients assigned to those clinics. In particular, these are general practice clinics that underwent physician entries or multiple long-term staff changes over our period of observation from 2005 to 2012.

Table A.3 shows summary statistics for patient-year observations and Table A.4 shows average clinic-level characteristics. Most noticeably, staff sizes for out-of-sample clinics are larger than for in-sample clinics. This is not surprising, as larger clinics may have more fluctuation in staff. Moreover, patients assigned to out-of-sample clinics tend to be younger. However, antibiotic prescribing does not differ substantially from our main sample.

Table A.3: Summary statistics for out-of-sample observations

	Out of sample	
	Mean	SD
A: Number of antibiotic prescriptions		
All antibiotics (All J01)	0.54	(1.24)
Penicillins (J01 C)	0.34	(0.80)
Second-line (J01 F, D, or M)	0.11	(0.44)
Other (J01 excluding J01 C, F, D, M)	0.09	(0.64)
B: Basic demographics and health		
Age	41.21	(23.53)
Female	0.54	(0.50)
Pregnant	0.02	(0.15)
Household size	2.61	(1.37)
Any visit to an emergency department	0.15	(0.360)
Any call to an emergency doctor	0.18	(0.39)
Any hospitalization for infection (ACSC)[a]	0.005	(0.069)
C: Family background and education		
Married couple	0.54	(0.50)
Cohabiting couple with children	0.07	(0.25)
Cohabiting couple without children	0.07	(0.26)
Single	0.32	(0.47)
First generation migrant (nordic)	0.01	(0.08)
First generation migrant (other country)	0.06	(0.24)
Second generation migrant	0.03	(0.16)
Missing education	0.21	(0.40)
School grade 7 to 10	0.27	(0.47)
High school or vocational training	0.32	(0.47)
Short higher education	0.03	(0.17)
Medium higher education	0.12	(0.32)
Long higher education	0.05	(0.21)
Phd education	0.003	(0.052)
No education	0.001	(0.029)
Total observations (patient-years)	15,691,250	

[a] Hospitalizations for acute ambulatory care-sensitive conditions (ACSC) commonly caused by bacterial and non-bacterial infections considered (see Appendix I for a complete list of ICD-10 codes). Referrals from general practitioners and delayed internal hospital referrals are excluded.

Table A.4: Summary statistics for out-of-sample clinics

	Out of sample	
	Mean	SD
A: Average number of antibiotic prescriptions per patient		
All antibiotics (All J01)	0.54	(0.16)
Penicillins (J01 C)	0.33	(0.10)
Second-line (J01 F, D, or M)	0.11	(0.06)
Other (J01 excluding J01 C, F, D, M)	0.09	(0.04)
B: Average physician characteristics		
Age	55.63	(6.31)
Female	0.360	(0.39)
First generation migrant (nordic)	0.01	(0.06)
First generation migrant (other country)	0.03	(0.15)
Second generation migrant	0.01	(0.07)
Phd education	0.01	(0.08)
C: Size and equipment		
Number of physicians	1.88	(1.36)
Number of interns	0.25	(0.53)
Number of patients per physician	1878.69	(781.37)
Diagnostic culture available	0.98	(0.16)
Diagnostic microscopy available	0.80	(0.40)
Telephone consultation available	0.999	(0.027)
Total observations (clinic-years)	6,853	

D.4 Summary statistics for excluded patient-year observations

We further compute summary statistics for observations of patients in our sample but which we have excluded from the final panel of patient-years. We exclude patient-year observations in order to ensure that any switch in a patient's general practice clinic is associated with the treatment, a physician exit, and we exclude observations when treated patients are assigned to out-of-sample clinics. For a subset of never-treated and treated patients in our sample, we thus drop observations and end up with an unbalanced panel.

Table A.5 shows averages in observations which we drop for in-sample patients. In the case of never-treated patients, most noticeably the average age is lower than in our main sample. We might observe a lower average age because these observations are dropped when never-treated patients switch clinics for reasons unrelated to a physician exit as we then only keep observations at the modal clinic. Presumably, switching clinics is more common among younger patients, who could for example be more likely to move geographically or be more selective about choosing their physicians. In the case of treated patients, average characteristics are similar to the main sample. In both cases, antibiotic prescribing in the excluded observations does not differ substantially from our main sample, alleviating concerns about selective attrition based on antibiotic prescribing.

Table A.5: Summary statistics for excluded observations of in-sample patients

	Never-exposed to physician exit		**Exposed to physician exit**	
	Mean	SD	Mean	SD
A: Number of antibiotic prescriptions				
All antibiotics (All J01)	0.53	(1.21)	0.52	(1.31)
Penicillins (J01 C)	0.34	(0.79)	0.33	(0.80)
Second-line (J01 F, D, or M)	0.10	(0.43)	0.09	(0.40)
Other (J01 excluding J01 C, F, D, M)	0.09	(0.61)	0.10	(0.80)
B: Basic demographics and health				
Age	36.42	(21.67)	43.30	(23.22)
Female	0.57	(0.49)	0.58	(0.49)
Pregnant	0.04	(0.20)	0.03	(0.17)
Household size	2.56	(1.37)	2.56	(1.36)
Any visit to an emergency department	0.16	(0.37)	0.15	(0.360)
Any call to an emergency doctor	0.22	(0.41)	0.22	(0.41)
Any hospitalization for infection (ACSC)[a]	0.005	(0.073)	0.005	(0.073)
C: Family background and education				
Married couple	0.45	(0.50)	0.52	(0.50)
Cohabiting couple with children	0.08	(0.26)	0.06	(0.24)
Cohabiting couple without children	0.11	(0.31)	0.08	(0.27)
Single	0.360	(0.48)	0.34	(0.47)
First generation migrant (nordic)	0.01	(0.09)	0.01	(0.08)
First generation migrant (other country)	0.07	(0.26)	0.07	(0.25)
Second generation migrant	0.03	(0.17)	0.03	(0.17)
Missing education	0.20	(0.40)	0.17	(0.38)
School grade 7 to 10	0.25	(0.43)	0.26	(0.44)
High school or vocational training	0.32	(0.47)	0.33	(0.47)
Short higher education	0.03	(0.17)	0.03	(0.18)
Medium higher education	0.13	(0.33)	0.13	(0.33)
Long higher education	0.06	(0.24)	0.06	(0.24)
Phd education	0.003	(0.054)	0.003	(0.059)
No education	0.001	(0.030)	0.001	(0.040)
Total observations (patient-years)	245,030		68,039	

[a] Hospitalizations for acute ambulatory care-sensitive conditions (ACSC) commonly caused by bacterial and non-bacterial infections (see Appendix I for a complete list of ICD-10 codes). Referrals from general practitioners and delayed internal hospital referrals are excluded.

E Staggered difference-in-differences assumptions

Assumptions 3-5 are standard in a staggered difference-in-differences design and sufficient to identify $\delta_{j'} - \delta_j$.

Assumption 3 The potential outcome under no exposure to exit follows parallel trends, $\mathbb{E}[y_{it'}(0) - y_{it}(0) \mid E_i = e] = \mathbb{E}[y_{it'}(0) - y_{it}(0)] \; \forall \; t, t'$. This assumption requires that, were it not for the physician exit, antibiotic prescribing to treated patients would have followed the same trend as prescribing to untreated patients. The parallel trends assumption implies that any change in prescribing to a treated patient i after treatment onset can be attributed to the physician exit, rather than to underlying differences in trends between cohorts, including the never-treated group. As the timing of physician exits is arguably exogenous to underlying patient trends in antibiotic prescribing, we believe this assumption to be plausible. In a sensitivity analysis, we relax the parallel trends assumption to hold conditional on time-varying patient characteristics.

Assumption 4 Patients do not change their antibiotic consumption in anticipation of a physician exit, $\mathbb{E}[y_{it}(1) - y_{it}(0) \mid E_i = e] = 0 \; \forall \; t < e$. This assumption requires that treated patients do not engage in anticipatory behavior regarding their antibiotic consumption prior to being exposed to the physician exit. If this assumption holds for all pre-treatment periods, treated patients do not exhibit pre-trends in antibiotic consumption. To test this assumption, in an event study specification we allow for pre-trends that differ between treated and never-treated patients.

Assumption 5 Attrition of patients from our panel of patient-calendar year observations is independent of potential outcomes. Our panel is unbalanced as some patients are unobserved in the beginning or the end of the sample period, their assigned general practice clinic is not matched to our sample of clinics, or they change their clinic without being exposed to physician exit. Absence of selective attrition requires that patients do not leave our panel

systematically with regard to their potential antibiotic prescribing outcomes.[1]

F Further results

F.1 Any prescribing

As a sensitivity check, we also measure the role of provider practice styles in antibiotic consumption using indicator variables for any prescribing. The indicator variable is one if a patient in a given year was prescribed any systemic antibiotic in primary care. As in our main analysis, we also investigate penicillins, second-line antibiotics, and other antibiotics as separate categories.

A.6 shows summary statistics for any prescribing by subcategory of our analysis, and Panel A of Table 1 in the main text shows summary statistics by ATC 3 class. On average, we observe any antibiotic prescribing in about 30.55% of patient-years. Penicillins are, also on the extensive margin, the most commonly prescribed antibiotic class.

Table A.7 and Figure A.3 present the results from this sensitivity check. Our main conclusions remain essentially unchanged when compared with the main results. For any overall antibiotic consumption, provider effects are somewhat larger, at 56.8 rather than 49.4 percent as in the main analysis, which is driven by larger effects in any penicillin prescribing. Compared to the main analysis, we observe a lower share of provider effects in other antibiotic prescribing. However, we draw similar qualitative conclusions compared to the main analysis. Prescribing practice styles determine about half of the clinic differences in whether antibiotic treatments are initiated, and the share of provider effects is larger in any prescribing of second-line antibiotics.

[1] In Table A.5 of Appendix D.4 we show that there are no substantial differences in average antibiotic prescribing between our main sample and excluded observations from a subset of patients with incomplete spells. We show summary statistics for excluded observations of patients for whom a clinic change does not correspond to a physician exit or the assignment pre- or post-treatment is to an out-of-sample clinic.

Table A.6: Descriptive statistics for antibiotic prescribing in primary care (Any prescription)

Any antibiotic prescription by subcategory			
		Mean	SD
All antibiotics	All J01	0.31	(0.461)
Penicillins	J01 C	0.23	(0.421)
Second-line	J01 F, D, M	0.09	(0.281)
Other antibiotics	J01 Others	0.05	(0.220)

Table A.7: Estimation results for the share of provider effects in antibiotic prescribing (Any prescription)

Panel A	**Any prescription** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.568***	0.493***	0.820***	0.397***
	(0.023)	(0.025)	(0.027)	(0.049)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	no	no	no	no
Observations	7,789,908	7,789,908	7,789,908	7,789,908
Groups (patients)	1,371,604	1,371,604	1,371,604	1,371,604
Panel B	**Any prescription** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.591***	0.501***	0.828***	0.429***
	(0.026)	(0.028)	(0.027)	(0.050)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	yes	yes	yes	yes
Observations	7,647,003	7,647,003	7,647,003	7,647,003
Groups (patients)	1,344,910	1,344,910	1,344,910	1,344,910

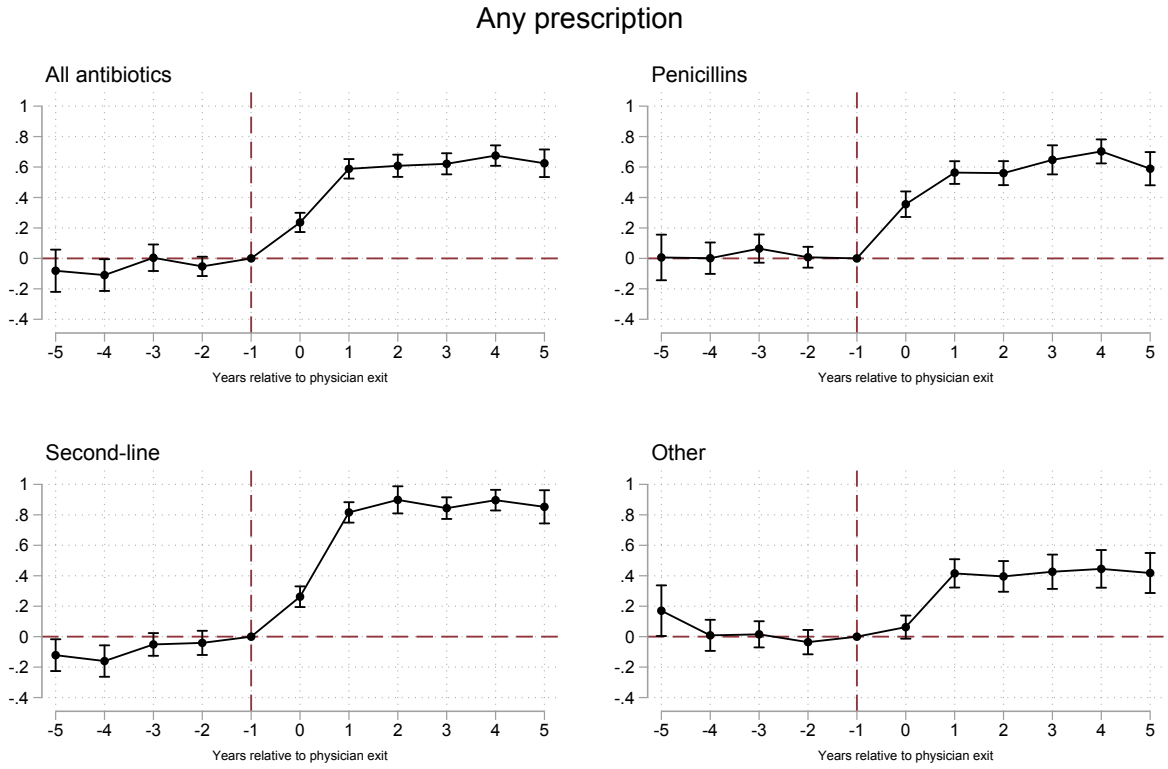
This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

Figure A.3: Event study estimates of the share of provider effects (Any prescription)



Notes: The figures display event study estimates for the share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences. Estimations include patient fixed effects, calendar year fixed effects, and as time-varying characteristics indicators for the year of treatment onset and the post-exit period. Relative year -1 is the last pre-exit period, relative year 0 is a transitional period, and relative year 1 is the first post-exit period. Lines represent the 95% confidence intervals, with standard errors calculated using a bootstrap with 50 repetitions at the patient level.

F.2 Daily Defined Dose

We also measure antibiotic prescribing using Daily Defined Dose (DDD) as an alternative approach. DDD is a commonly used, technical unit of measurement defined by the World Health Organization that expresses the average dose per day for a drug used in adults under the drug's main indication.

Table A.8 shows summary statistics based on DDD. The average total DDD per prescription varies strongly between antibiotic classes. Notably, the share of total prescriptions measured by DDD differs considerably from the share of the total number of prescriptions for some antibiotic classes, particularly for classes other than penicillins and second-line antibiotics (Other antibiotics), such as Tetracyclines (J01 A) or Other antibacterials (J01 X). We also observe a high average DDD for these antibiotic classes, compared to other antibiotics. Due to this variation in DDD, we focus our main analysis on antibiotic prescribing measured by the number of prescriptions.

Table A.9 and Figure A.4 re-estimate our main specifications. The findings are generally consistent with our primary results, except in the case of non-penicillin, non-second line antibiotics (other antibiotics). The difference for other antibiotics compared to our main results might be due to variation in average Daily Defined Dose per prescription in this subcategory.

Table A.8: Descriptive statistics for antibiotic prescribing in primary care (DDD)

Panel A	**Antibiotic prescribing by ATC 3 class**			
ATC 3[a]	Pharmacological subgroup	Share of total prescribing (number)	Share of total prescribing (DDD)	Average DDD
J01 C	Beta-lactam antibacterials, penicillins	62.49%	58.85%	8.82
J01 F	Macrolides, lincosamides and streptogramins	17.18%	15.09%	8.22
J01 E	Sulfonamides and trimethoprim	9.84%	7.61%	7.24
J01 A	Tetracyclines	3.83%	6.88%	21.26
J01 M	Quinolone antibacterials	3.57%	2.75%	7.21
J01 X	Other antibacterials	3.03%	8.74%	21.38
J01 D	Other beta-lactam antibacterials	0.06%	0.83%	12.7
All J01	Antibacterials for systemic use	100%	100%	9.36

Panel B	**Daily Defined Dose of antibiotic prescriptions by subcategory**		
		Mean	SD
All antibiotics	All J01	5.24	(20.619)
Penicillins	J01 C	3.08	(8.571)
Second-line	J01 F, D, M	0.94	(4.906)
Other	J01 Others	1.22	(17.004)

[a] Prescriptions of J01 G (Aminoglycoside antibacterials) are omitted due to their low frequency in order to ensure anonymity.

Table A.9: Estimation results for the share of provider effects in antibiotic prescribing (DDD)

Panel A	**Daily Defined Dose** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.3600***	0.458***	0.702***	0.073
	(0.041)	(0.033)	(0.041)	(0.061)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	no	no	no	no
Observations	7,789,908	7,789,908	7,789,908	7,789,908
Groups (patients)	1,371,604	1,371,604	1,371,604	1,371,604
Panel B	**Daily Defined Dose** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.387***	0.479***	0.711***	0.073
	(0.042)	(0.037)	(0.042)	(0.059)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	yes	yes	yes	yes
Observations	7,647,003	7,647,003	7,647,003	7,647,003
Groups (patients)	1,344,910	1,344,910	1,344,910	1,344,910

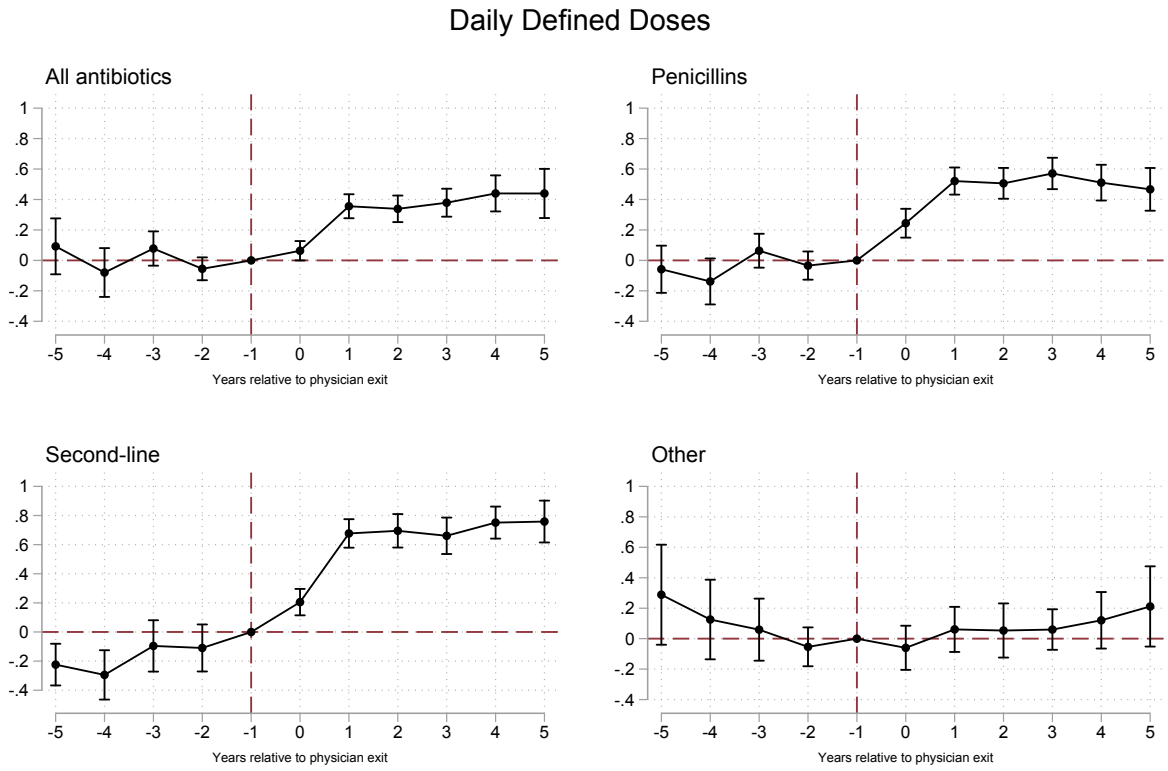
This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

Figure A.4: Event study estimates of the share of provider effects (DDD)



Notes: The figures display event study estimates for the share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences. Estimations include patient fixed effects, calendar year fixed effects, and as time-varying characteristics indicators for the year of treatment onset and the post-exit period. Relative year -1 is the last pre-exit period, relative year 0 is a transitional period, and relative year 1 is the first post-exit period. Lines represent the 95% confidence intervals, with standard errors calculated using a bootstrap with 50 repetitions at the patient level.

F.3 Excluding clinics with multiple physicians

We confirm that our main results are not substantially affected by restricting our sample to single-physician clinics.

In our main analysis we consider physician exits from both clinics with only one practicing physician and clinics with multiple physicians. A physician exit from a single-physician clinic implies that all former patients are assigned to a new physician and exposed to a new practice style. In contrast, when a physician leaves from a clinic with multiple physicians, the physician-patient assignment might not change for some patients if they are treated by one of those physicians who stay at the clinic.

Our measure, the share of provider effects in antibiotic prescribing differences, is consistent across both types of treatment events, regardless of whether all or only some physicians at a treated clinic exit. Our empirical strategy relies on scaling the changes in antibiotic prescribing to a treated patient by the difference in average antibiotic consumption at the two sets of physicians that may prescribe to the treated patient. As long as there is a change in the set of physicians that a treated patient can be assigned to, patients are *on average* exposed to a different post-exit practice style compared to pre-exit, and the scaling factor adjusts accordingly.

Table A.10 describes the sample once we exclude clinics with multiple physicians. That is, we only consider treated patients who are exposed to a physician exit from a single-physician clinic as well as never-treated patients at single-physician clinics. The number of treated clinics exposed to a physician exit drops from 242 clinics in the full sample to 169 clinics.[2] The number of destination clinics, to which patients switch after an exit, drops from 556 clinics in our full sample to 390 clinics.

Table A.11 shows estimates for the share of provider effects in antibiotic prescribing in

[2]By construction, a physician exit from a single-physician clinic leads to clinic closure. For one treated clinic within the full sample, the physician exit (in December 2008) and the official reported clinic closure date (in January 2009) do not coincide and we do not code the exit event as clinic closure. This does not affect our results.

our sample of single-physician clinics. The estimated provider effect shares in prescribing for antibiotics overall, penicillins, and second-line antibiotics are somewhat higher than in our main analysis. Figure A.5 reveals that, once we allow for effects to differ by relative years, almost all 95% confidence intervals overlap with the event study estimates on the full sample. Qualitatively, the results based on the restricted sample of single-physician clinics are similar to the results based on the full sample.

Table A.10: Number of observations, excluding clinics with multiple physicians

	Clinics	**Patients assigned to clinics**	**Observations**
Never-treated	414	601,189	3,379,289
Treated	172	152,284	641,064
Total	586	725,946	4,020,353

[a] The sum of never-treated and treated patient observations does not equal the total number of patients because some patients are observed at two clinics if exposed to a physician exit.

Table A.11: Estimation results for the share of provider effects in antibiotic prescribing, excluding clinics with multiple physicians

Panel A	**Number of prescriptions** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.607***	0.588***	0.918***	0.572***
	(0.042)	(0.046)	(0.049)	(0.172)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	no	no	no	no
Observations	4,018,137	4,018,137	4,018,137	4,018,137
Groups (patients)	723,730	723,730	723,730	723,730
Panel B	**Number of prescriptions** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.641***	0.595***	0.931***	0.609***
	(0.041)	(0.046)	(0.050)	(0.172)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	yes	yes	yes	yes
Observations	3,944,700	3,944,700	3,944,700	3,944,700
Groups (patients)	709,217	709,217	709,217	709,217

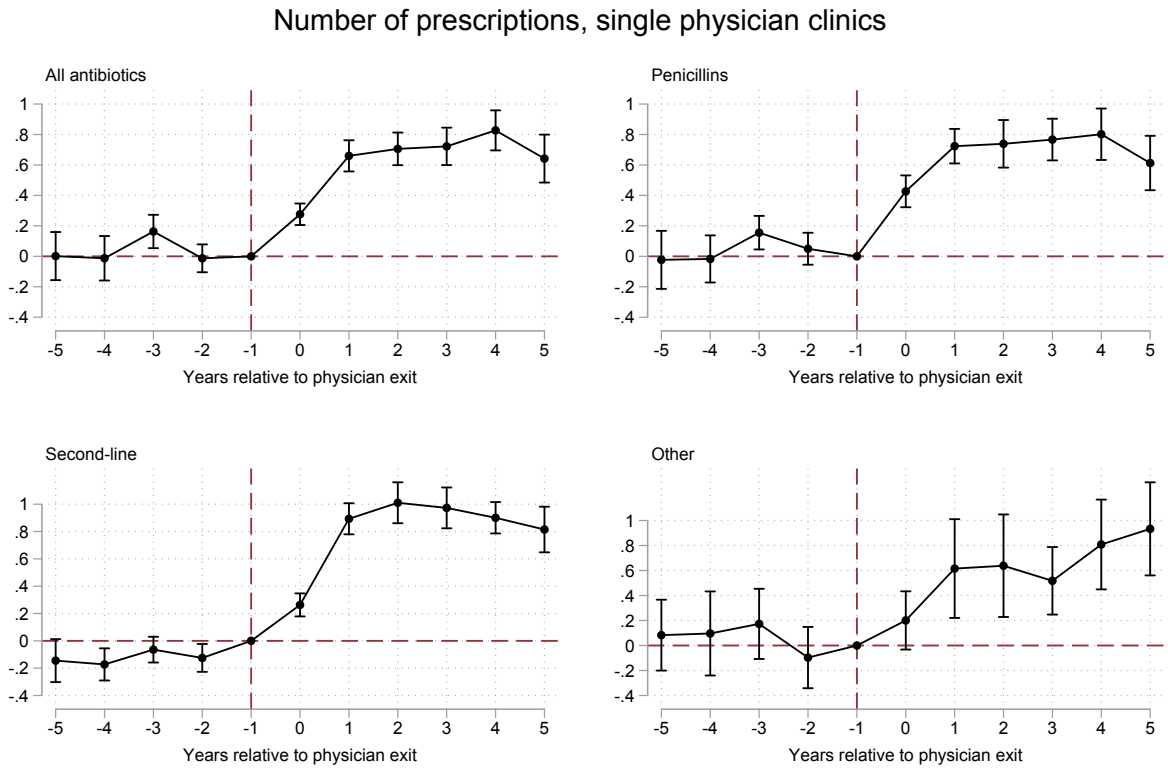
This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

Figure A.5: Event study estimates of the share of provider effects, excluding clinics with multiple physicians



Notes: The figures display event study estimates for the share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences. Estimations include patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. Relative year -1 is the last pre-exit period, relative year 0 is a transitional period, and relative year 1 is the first post-exit period. Lines represent the 95% confidence intervals, with standard errors calculated using a bootstrap with 50 repetitions at the patient level.

F.4 Analysis for second-line antibiotic drugs

Table A.12 shows estimation results for the share of provider effects in second-line antibiotic drugs separately for each ATC level 3 drug class: macrolides, lincosamides, and streptogramins (J01 F), cephalosporins (J01 D), and quinolones (J01 M). Columns (1) to (3) of Table A.12 show baseline estimation results using as outcomes the number of antibiotic prescriptions, Columns (4) to (6) show estimation results when we allow for time-varying control variables, and Column (7) to (9) show estimation results when we measure prescribing by Daily Defined Dose. The results indicate that the substantial share of provider effects from analyzing these classes collectively are driven by the group of macrolides, lincosamides, and streptogramins (J01 F), and the group of quinolones (J01 M). In contrast, provider effects are much smaller in the group of cephalosporins (J01 D).

Table A.13 shows estimation results for the share of provider effects in broad-spectrum antibiotic drugs. Specifically, this analysis includes all macrolides, lincosamides, and streptogramins (J01 F), cephalosporins (J01 D), and quinolones (J01 M), but excludes erythromycin. Broad-spectrum antibiotic drugs are active against a large range of bacterial groups. However, their excessive consumption can disrupt the native bacterial flora and enable multidrug resistances. Physicians are therefore in general advised to avoid prescribing broad-spectrum antibiotics .[3] The results show that the share of provider effects remain large in broad-spectrum antibiotic prescriptions.

The categorization into broad- and narrow-spectrum classes is not fixed.[4] For example, in the ESAC framework macrolides, lincosamides, and streptogramins, excluding erythromycin (J01 F, D, M, excluding J01 FA01), are considered broad-spectrum antibiotics,[5] whereas

[3]See Levy, Stuart B. 1998. "The Challenge of Antibiotic Resistance." Scientific American, 278(3): 46–53.

[4]See Acar, Jacques. 1997. "Broad- and Narrow-Spectrum Antibiotics: An Unhelpful Categorization." Clinical Microbiology and Infection, 3(4): 395–396.

[5]See ECDC (European Centre for Disease Prevention and Control), EFSA BIOHAZ Panel (European Food Safety Authority Panel on Biological Hazards) and CVMP (EMA Committee for Medicinal Products for Veterinary Use), 2017. "ECDC, EFSA and EMA Joint Scientific Opinion on a List of Outcome Indicators as Regards Surveillance of Antimicrobial Resistance and Antimicrobial Consumption in Humans and Food-Producing Animals." EFSA Journal 2017, 15(10):5017, 70 pp.

macrolides, lincosamides, streptogramins (J01 F) are not considered broad-spectrum antibiotics by the Danish Health Data Authority (https://medstat.dk/en).

Table A.12: Estimation results for the share of provider effects in antibiotic prescribing, second-line antibiotic drugs

Panel A	**Number of prescriptions** Two-way fixed effects estimation[a]		
	J01 F	J01 D	J01 M
$\hat{\Delta}_i \times D_{it}$	0.870***	0.046	0.559***
	(0.038)	(0.090)	(0.058)
Event dummies[b]	yes	yes	yes
Time-varying controls[c]	no	no	no
Observations	7,789,908	7,789,908	7,789,908
Groups (patients)	1,371,604	1,371,604	1,371,604
Panel B	**Number of prescriptions** Two-way fixed effects estimation[a]		
	J01 F	J01 D	J01 M
$\hat{\Delta}_i \times D_{it}$	0.877***	0.051	0.586***
	(0.039)	(0.090)	(0.058)
Event dummies[b]	yes	yes	yes
Time-varying controls[c]	yes	yes	yes
Observations	7,647,003	7,647,003	7,647,003
Groups (patients)	1,344,910	1,344,910	1,344,910

This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

Table A.13: Estimation results for the share of provider effects in antibiotic prescribing, second-line antibiotic drugs excluding erythromycin

	Number of prescriptions Two-way fixed effects estimation[a]	
	J01 F, D, M, excl. J01 FA01	
	(1)	(2)
$\hat{\Delta}_i \times D_{it}$	0.849***	0.868***
	(0.040)	(0.041)
Event dummies[b]	yes	yes
Time-varying controls[c]	no	yes
Observations	7,789,908	7,647,003
Groups (patients)	1,371,604	1,344,910

This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

G Alternative econometric specifications

We relax a number of our identifying assumptions and present results for these sensitivity analyses.

Table A.14 shows results for our static sensitivity specifications. In Panel A of Table A.14, we estimate the share of provider effects in antibiotic prescribing accounting for time-varying observable patient characteristics. In Panel B, we estimate Sun-Abraham style interaction-weighted specifications, which account for treatment heterogeneity by the year of treatment onset.

We present the corresponding dynamic effect estimates in Figure A.6. Figure A.6a shows estimates of provider effects over relative years when we control for time-varying characteristics. Figure A.6b shows estimate provider effects over relative years based on Sun-Abraham interaction-weighted specifications.

Overall, the results are similar to our main estimates. In the Sun-Abraham interaction-weighted estimations, we obtain smaller estimates of provider effects in second-line antibiotic prescribing and non-penicillin, non-second line prescribing. However, our conclusions remain the unchanged.

Table A.14: Estimation results for the share of provider effects in antibiotic prescribing, alternative specifications

Panel A	**Number of prescriptions** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.53***	0.456***	0.841***	0.509***
	(0.035)	(0.039)	(0.037)	(0.071)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	yes	yes	yes	yes
Observations	7,647,003	7,647,003	7,647,003	7,647,003
Groups (patients)	1,344,910	1,344,910	1,344,910	1,344,910
Panel B	**Number of prescriptions** Sun-Abraham interaction-weighted estimation[d]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.486***	0.515***	0.743***	0.228***
	(0.036)	(0.053)	(0.041)	(0.059)
Event dummies[c]	yes	yes	yes	yes
Time-varying controls[d]	no	no	no	no
Observations	7,789,908	7,789,908	7,789,908	7,789,908
Groups (patients)	1,371,604	1,371,604	1,371,604	1,371,604

This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. *** $p < 0.01$.

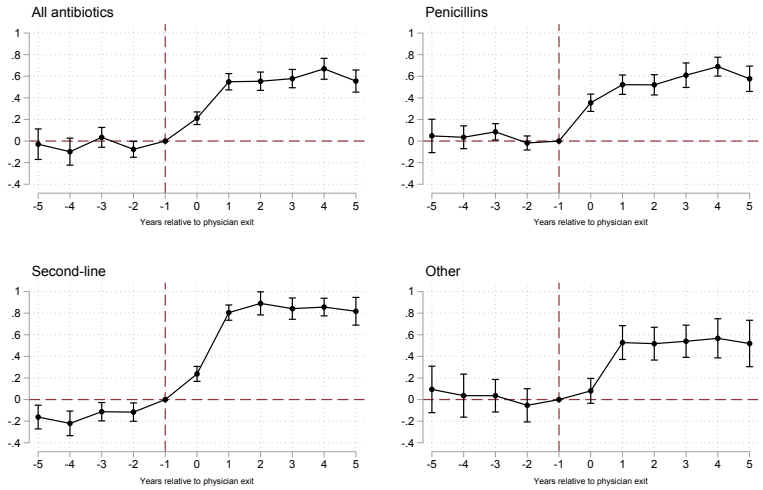
[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

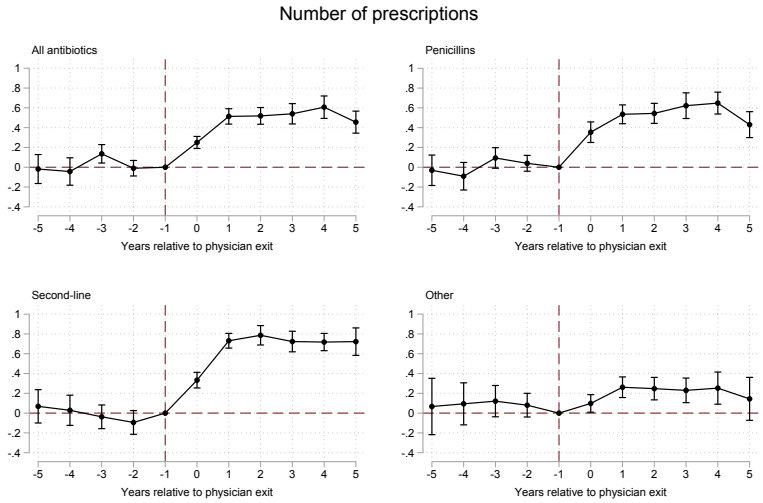
[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

[d] Sun-Abraham style interaction weighted estimation based on fully saturated fixed effects specifications including patient and calendar year fixed effects as well as interactions between relative period indicators and cohort indicators, where cohorts are defined by the calendar year of treatment onset. Reported coefficients correspond to estimated treatment effects aggregated over cohorts and relative year, weighted by cohort size.

Figure A.6: Event study estimates of the share of provider effects, alternative specifications



(a) Time-varying controls



(b) Sun-Abraham interaction-weighted estimation

Notes: Lines represent the 95% confidence intervals. Standard errors are calculated using a parametric bootstrap to draw mean prescribing on the level of physician sets, with 50 repetitions at the patient level. Figure A.6a displays event study estimates from estimations that include patient fixed effects, calendar year fixed effects, and indicators for treatment onset, post-exit, pregnancy, any visit to an emergency department, any call to an emergency department, any call to an emergency doctor, and as continuous variables age squared and household size. Figure A.6b displays Sun-Abraham style interaction weighted estimates from fully saturated fixed effects specifications that include patient and calendar year fixed effects as well as interactions between relative period indicators and cohort indicators, where cohorts are defined by the calendar year of treatment onset. In a first step, cohort-relative year specific treatment effects are estimated. In the second step, relative year specific treatment effects are calculated as relative cohort size weighted averages by relative year.

H Estimation of practice style correlates

H.1 Observable physician and clinic characteristics

Below we describe how the variables in our practices style correlates analysis are defined.

Physician characteristics. We construct physician individual-level characteristics and aggregate them over all physicians in a given set of physicians. We have to aggregate the individual-level characteristics as we can only observe the identity of the clinic in a given year for each prescription, but not the identity of the prescribing physician.

As personal characteristics we consider the average age, the share of physicians with a PhD degree, the share of female physicians, and the share of physicians with migration backgrounds. We separate migration backgrounds by Nordic origin country (Finland, Iceland, Norway and Sweden), and non-Nordic origin country.

Clinic-level characteristics. We further include a set of variables to describe diagnostic availability and staff size at a general practice clinic. From claims data, we construct dummy variables that indicate whether microscopy, bacterial culture, and teleconsultations were available. We assume that either diagnostic method was available in a given year if any of the corresponding claim code were used at least once in a given year.[6] We also impute diagnostic methods as available if both in the previous and the following year any of the corresponding claim codes have been used. To describe staff size, we include the maximum number of general practitioners, the number of unique patients per general practitioner, and the maximum number of short-term medical staff working at the same time in a clinic in a year. We construct the number of unique patients at a clinic as the total number of unique social security numbers in a clinic's claims records. The number of short-term medical staff covers all recorded stays of up to a year. We refer to those short-term medical staff as interns.

[6]We use 6-digit SPECIALE claim codes to identify relevant procedures. For microscopic examinations, we consider the codes 807102 – 807104, 807122 – 807124. For diagnostics based on bacterial cultures, we consider the codes 807105 – 807107. For teleconsulting, we consider the codes 800200–800203, 800500–800501, 803200–803201, 808294.

H.2 Estimation details

We estimate the association between prescribing practice styles and observable physician characteristics in two steps. In the first step, we obtain the pair-specific differences in practice styles by estimating the following equation:

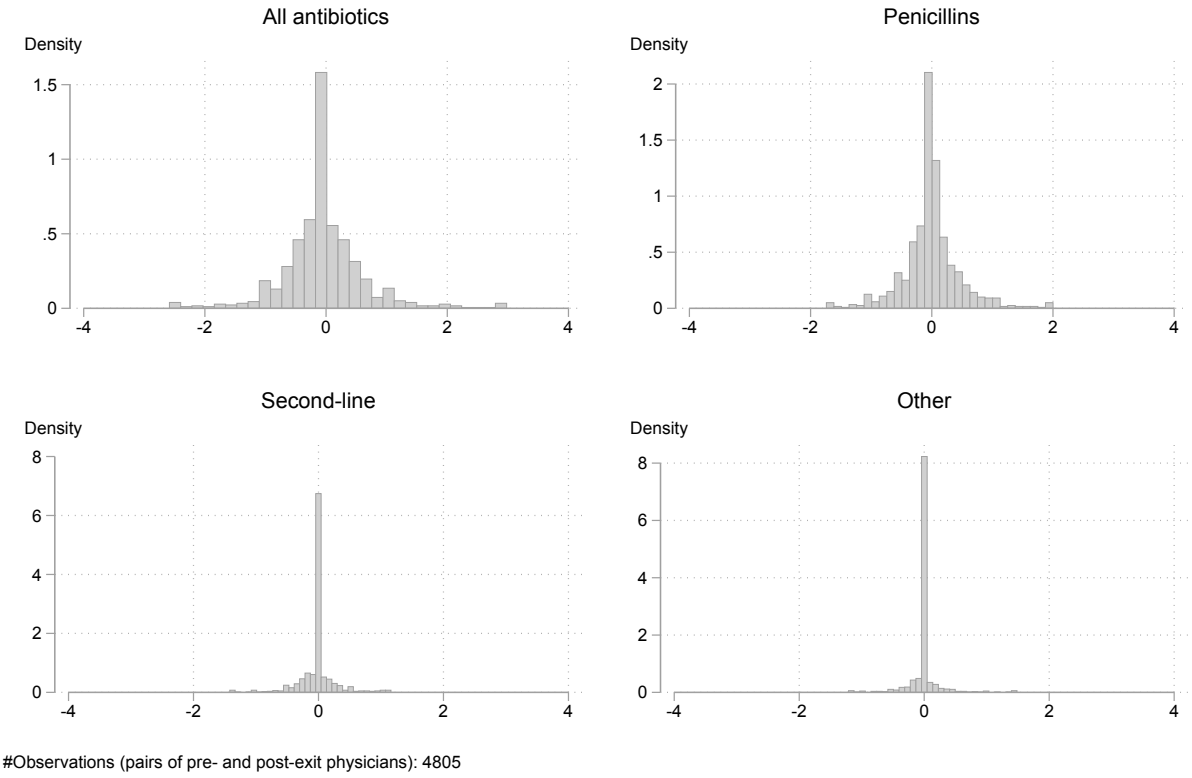
$$y_{it} = \tilde{\alpha}_i + (\delta_{j'} - \delta_j) \times D_{it} \times I_{j(i,t<r_0(i))=j,j(i,t>r_0(i))=j'} + x_{it}\beta + \nu_{it}, \tag{1}$$

where $\tilde{\alpha}_i, \beta$ are parameters and D_{it}, x_{it} are variables as defined above. ν_{it} is the error term. $r_0(i)$ denotes the calendar year in which patient i is exposed to a physician exit. $I_{j(i,t<r_0(i))=j,j(i,t>r_0(i))=j'}$ is an indicator which is one if a treated patient i is assigned to the set of physicians j before the physician exit occurs in $t = r_0(i)$ and to a different set of physicians j' after the physician exit has occurred. $\delta_{j'} - \delta_j$ denotes the difference in prescribing practice styles between the origin and destination physicians j' and j. Estimating Equation (1) fully specified in all possible pairs of sets of physicians $\{j, j'\}$ thus yields estimates for the pair-specific differences in practice styles. Figure A.7 shows histograms of all estimated pair-specific differences in practice styles.

Note that our empirical strategy only allows identification of practice style differences. We therefore also construct pair-wise differences in physician observables when estimating the correlates of practice style differences. For each unique set of physicians, we construct the average over years for each observable characteristic. We then standardize each variable to have mean 0 and standard deviation 1. To obtain the covariates for our second-step regressions, we take the pair-wise difference in the standardized and average observable characteristics for each pair of sets of physicians.

In the second step, we perform either bivariate OLS regressions or multivariate post-LASSO OLS regressions. For the bivariate specifications, we regress the difference in practice styles on the differences in standardized physician characteristics. For the post-LASSO specifications, we regress the difference in practice styles on the differences in all standardized

Figure A.7: Histograms of differences in antibiotic prescribing practice styles between physician pairs



Notes: The figures show pairwise differences in antibiotic prescribing practice styles between pre- and post-exit physicians. Pairwise differences in practice styles correspond to treatment effects from our main analysis, estimated separately for all pairs of pre- and post-physicians treated patients are assigned to. Values are bunched for groups of five patients with similar estimated mean difference in average prescribing due to data anonymization. The top and bottom 0.5 percentiles are winsorized.

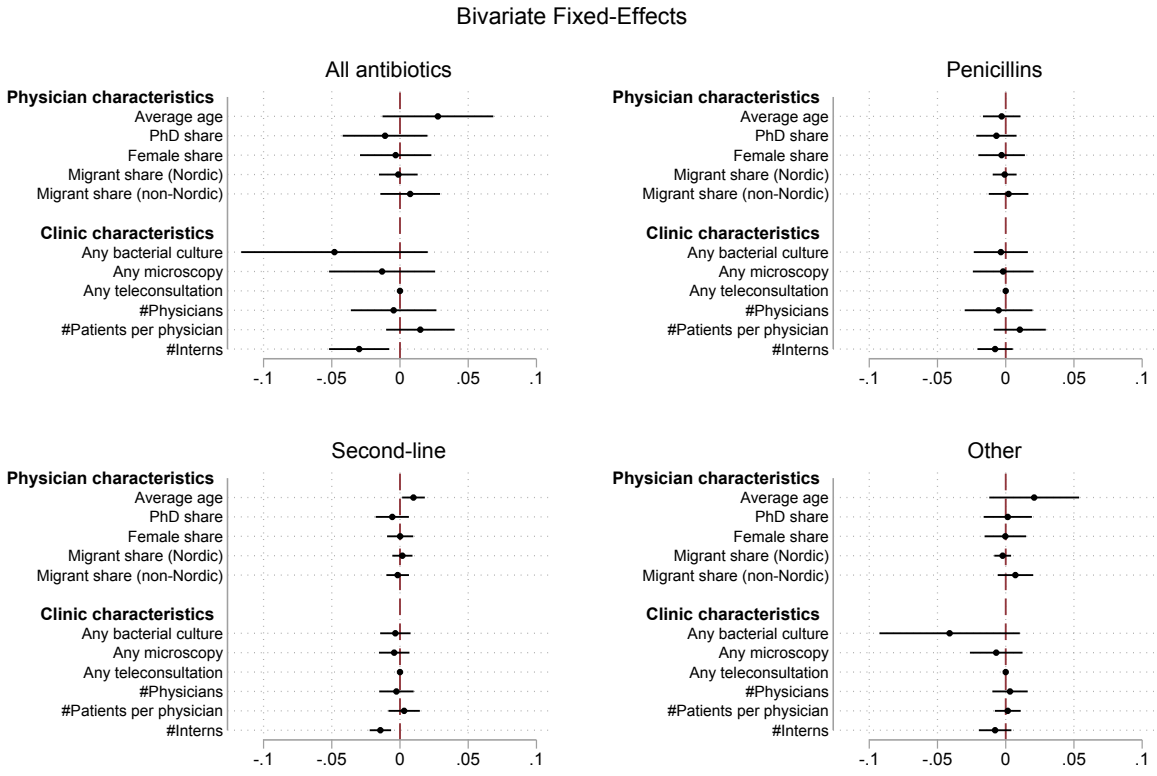
physician characteristics that have been selected by a first-step LASSO regression. The unit of observation is a pair of sets of physicians to which at least one treated patient is assigned.

To obtain standard errors we perform a parametric bootstrap with 50 repetitions. In each repetition, we draw the difference in practice styles for each pair of sets of physicians $\{j, j'\}$ from a normal distribution with mean $\widehat{\delta_{j'} - \delta_j}$ and standard deviation $se(\widehat{\delta_{j'} - \delta_j})$ estimated from our first-step estimation of practice style differences, where *se* denotes the standard error. The bootstrapped standard errors account for estimation error from our first step estimation.

H.3 Correlates with practice style differences estimated by fixed effects

Figure A.8 shows coefficients estimates from bivariate fixed effects regressions, with fixed effects for the initial pre-exit set of physicians that treated patients are assigned to. The fixed effects regressions rely on variation in the difference in physician characteristics that result from patients being assigned to different destination providers after being exposed to an exit at the same origin set of physicians. The results are similar to our main results.

Figure A.8: Correlates of practice style differences, fixed effects



Notes: The figure presents estimated changes in prescribing styles associated with an one standard deviation increase in a physician or clinic characteristics using bivariate fixed effects regression. We obtain these estimates by regressing the difference in antibiotic prescribing practice style on differences in observed characteristics between sets of pre- and post-exit physicians that treated patients are assigned to, with fixed effects for the pre-exit physicians. Standard errors are calculated using a parametric bootstrap with 50 repetitions at the patient level to draw differences in prescribing practice styles. Physician and clinic characteristics are standardized to have mean 0 and standard deviation 1 prior to differencing.

I Practice style differences and quality of care

I.1 Measures of quality of care

We measure the quality of care based on physicians' prescription quality and patients' health outcomes.

To obtain the number of prescriptions without diagnostic test in a given year, we identify diagnostic use based on claims submitted by primary care physicians. However, we only observe the week during which a physician submits claims with the public insurer. In contrast, we know the exact date on which patients purchase the antibiotic prescription. Because claims can be submitted with some delay, but are generally submitted at least once per month in order for physicians to get compensated for services performed, we allow the submission week of a diagnostic test to be up to four weeks from the date of the antibiotic prescription. We use 6-digit SPECIALE claim codes to identify diagnostic tests. As rapid tests (stix tests, strep test), we consider the claim codes 807101, 807109. As microscopic examinations, we consider the codes 807102 – 807104, 807122 – 807124. As bacterial cultures, we consider the codes 807105 – 807107. We consider a prescription as without diagnostic test only if it cannot be linked to any test claim from the same week up to four weeks in the future. To construct our outcome variable, we lastly take the sum over all prescriptions without a diagnostic test in a given year.

We identify ambulatory care sensitive conditions as based on diagnostic codes used in health services research.[7] We restrict the analysis to acute conditions that are both frequently caused by infectious agents including bacteria, and commonly encountered in general practice: cellulitis, ear, nose and throat infect ions, perforated or bleeding ulcer, urinary tract infection, and pneumonia. To measure hospitalizations for infection, we exclude referrals from primary care as well as internal hospital referrals unless the diagnosis was made at the first day of a patient's hospitalization spell. Table A.15 shows means and standard deviations for

[7] See Bardsley et al. (2013).

hospitalizations due to infection-related ambulatory care sensitive conditions. Table A.16 lists the conditions including sub-categories and their corresponding ICD-10 codes.

Table A.15: Summary statistics of prescription quality and hospitalizations due to ambulatory care sensitive conditions

	Mean	SD
Any hospitalization		
All infections	0.005	(0.072)
Cellulitis	0.001	(0.037)
Ear, nose, and throat infections	0.001	(0.033)
Perforated or bleeding ulcer	0.001	(0.022)
Urinary tract infection or pyelonephritis	0.001	(0.036)
Pneumonia	0.001	(0.031)
Number of prescriptions		
Follow-up prescriptions	0.021	(0.195)
Prescriptions without diagnostic tests	0.340	(0.940)
Observations (patient-years)	7,796,767	

Table A.16: List of ICD-10 codes for infection-related ambulatory care sensitive conditions

ICD-10 code	Category
Cellulitis	
L03	Cellulitis
L04	Acute lymphadenitis
L08	Other local infections of skin and subcutaneous tissue
L88	Pyoderma grangrenosum
L980	Pyogenic granuloma
L983	Eosinophilic cellulitis
Ear, nose and throat infections	
H66	Otitis media, unspecified
H67	Otitis media in diseases classified elsewhere
J02	Acute pharyngitis
J03	Acute tonsillitis
J06	Acute upper respiratory infections of multiple and unspecified sites
J312	Chronic pharyngitis
Perforated/bleeding ulcer	
K250-K252	Gastric ulcer
K254-K256	
K260-K262	Duodenal ulcer
K264-K266	
K270-K272	Peptic ulcer, site unspecified
K274-K276	
K280-K282	Gastrojejunal ulcer
K284-K286	
Urinary tract infection/Pyelonephritis	
N10	Acute tubulo-interstitial nephritis
N11	Chronic tubulo-interstitial nephritis
N12	Tubulo-interstitial nephritis, not specified as acute or chronic
N136	Pyonephrosis
N390	Urinary tract infection, site not specified
Pneumonia	
J13	Pneumonia due to Streptococcus pneumoniae
J14	Pneumonia due to Haemophilus influenzae
J153	Pneumonia due to streptococcus, group B
J154	Pneumonia due to other streptococci
J157	Pneumonia due to Mycoplasma pneumoniae
J159	Bacterial pneumonia, unspecified
J168	Pneumonia due to other specified infectious organisms
J181	Lobar pneumonia, unspecified
J188	Other pneumonia, organism unspecified

ICD codes are based on Bardsley et al. (2013).

I.2 Estimation details

Our analysis of correlations between prescribing styles and observable physician and clinic characteristics are based on estimates for differences in prescribing styles between each separate pair of origin- and destination physicians, as described in Section H.

To estimate the change in prescription quality associated with a more intense prescribing style, we use the following baseline specification:

$$h_{it} = \tilde{\alpha}_i + \eta \times D_{it} \times \widehat{(\delta_{j'} - \delta_j)} + x_{it}\beta + \omega_{it}, \tag{2}$$

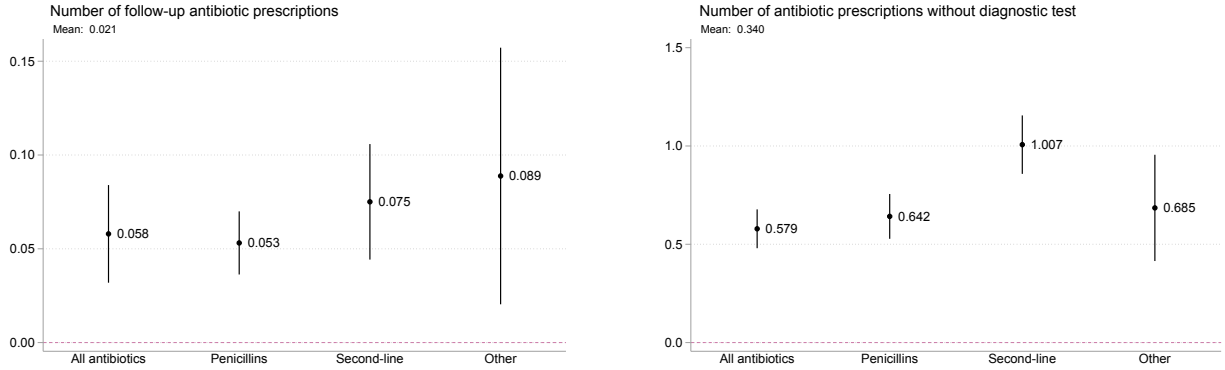
where h_{it} is a measure of prescription quality or health outcome for patient i in year t, α_i denotes patient-fixed effects, x_{it} includes calendar-year fixed effects, the post-exit indicator D_{it}, and an indicator for the year of the exit, and ω_{it} is an error term. Our coefficient of interest is η associated with the interaction between the post-exit indicator D_{it} and the estimated difference in prescribing styles $\widehat{(\delta_{j'} - \delta_j)}$.

We acknowledge that our estimated effects are not necessarily causal. For example, while differences in practice style can affect hospitalization rates, they may not be entirely driven by differences in antibiotic prescribing intensities. However, to investigate a mostly immediate link between antibiotic prescribing and prescription quality, we limit our analysis to direct measures of low-quality prescribing and infection-related hospitalizations, for which antibiotic treatment decisions are integral.

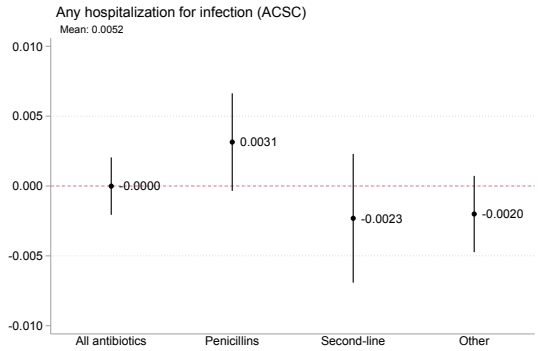
I.3 Sensitivity analysis results

Figure A.9 presents results from alternative specifications, where we control for Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor, in addition to the basic time control variables. The coefficient estimates are weaker but otherwise similar to our main results.

Figure A.9: Quality of care and antibiotic prescribing intensity, time-varying control variables



(a) Low quality prescribing



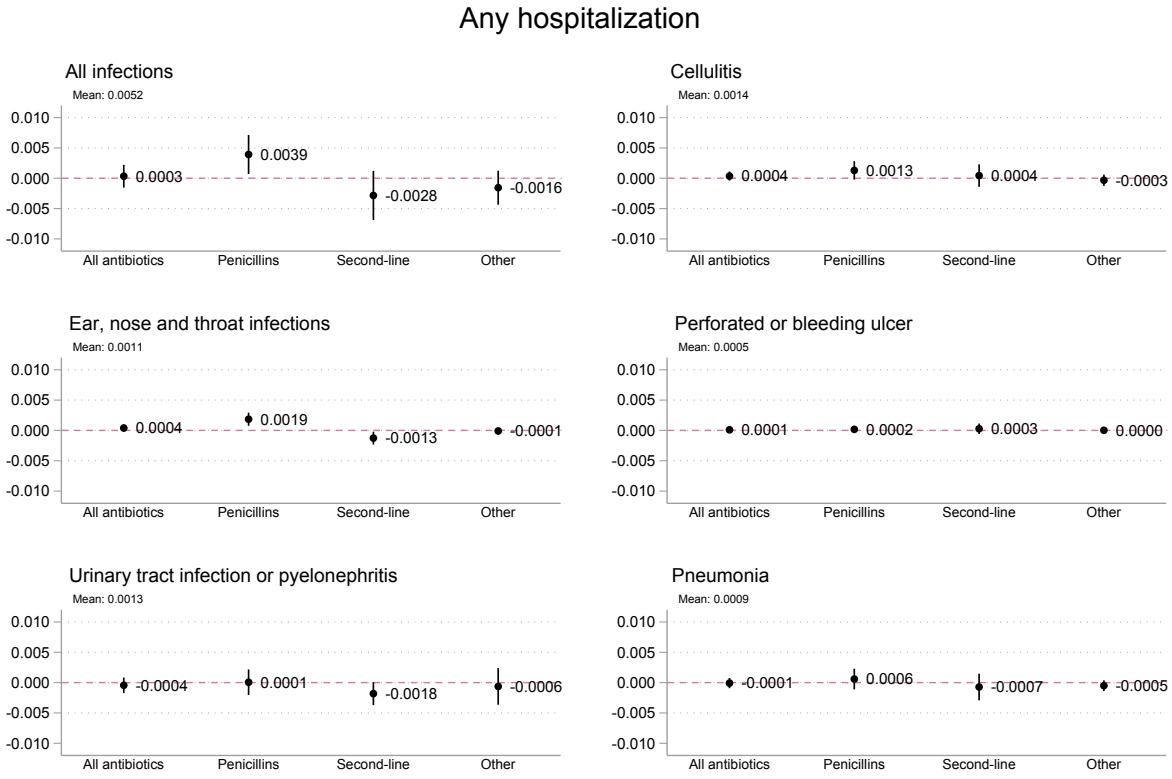
(b) Adverse patient outcomes

Notes: The figure shows the estimated changes in quality of care associated with a practice style of one additional antibiotic prescription, based on patient-year level regressions that include patient fixed effects, calendar year fixed effects, and indicators for treatment onset, post-exit, pregnancy, any visit to an emergency department, any call to an emergency department, any call to an emergency doctor, as well as the continuous variables age squared and household size. We consider an increase by one overall antibiotic prescription, as well as separately one more penicillin, second-line, or other antibiotic prescription. Figure A.9a shows the relation between higher antibiotic prescribing intensity and low quality prescribing, measured by follow-up antibiotic prescriptions within seven days after an initial prescription of a different ATC 4 class (left), and prescriptions without any claim for diagnostic tests (right). Figure A.9b shows the change in adverse patient health outcomes associated with higher antibiotic prescribing intensity, measured by the propensity for any hospitalization for an infection-related ambulatory care sensitive condition (ACSC). We estimate changes in antibiotic prescribing styles as separate provider effects for each pair of physicians among treated patients, controlling for patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. Lines represent the 95% confidence intervals, with standard errors based on a parametric bootstrap with 50 repetitions at the patient level to draw differences in prescribing practice styles.

I.4 Condition-specific hospitalization rates

Figure A.10 shows results for condition-specific estimations for the relation between antibiotic prescribing styles and hospitalization rates. The figure shows that the positive link between hospitalization rates for infection and penicillin prescribing is driven by hospitalizations for ear, nose, and throat infections (statistically significant on the 1% level). We also observe a weaker negative association between increases in second-line antibiotic prescribing and hospitalizations for ear, nose, and throat infections (statistically significant on the 10% level). However, on the margin, we observe no link between second-line antibiotic prescribing and lower hospitalization rates.

Figure A.10: Hospitalization rates for ambulatory care sensitive conditions and antibiotic prescribing intensity, by condition



Notes: The figure shows the estimated changes in hospitalization rates for infection-related ambulatory care sensitive condition associated with a practice style of one additional antibiotic prescription, in the aggregate and by condition, based on patient-year level regressions that include patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. We consider an increase by one overall antibiotic prescription, as well as separately one more penicillin, second-line, or other antibiotic prescription. We estimate changes in antibiotic prescribing styles as separate provider effects for each pair of physicians among treated patients, controlling for patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. Lines represent the 95% confidence intervals, with standard errors based on a parametric bootstrap with 50 repetitions at the patient level to draw differences in prescribing practice styles.

J Restricting shifts in provider age

As physician age for clinics with an exit is roughly four years above that of clinics without a physician exit (see Table 3) and the intensity of second-line antibiotic prescribing is positively correlated with physician age (see Figure 5), generational differences between providers may be important in explaining the identified practice style variation. To investigate whether our results are primarily driven by patients exposed to generational differences after their reassignment, we replicate our analysis on a restricted sample of treated patients. In this analysis, we include only never-treated patients and treated patients who switch to physicians less than one-half standard deviation younger or older than the exiting physician, corresponding to an absolute shift in provider age of at most 3 years.

Table A.17 describes the sample after excluding reassignments with substantial differences in provider age. The total number of clinics decreases from 805 clinics in the full sample to 802 clinics in this specification, with three of the never-treated clinics dropping out. Figure A.11 shows the distribution of provider age differences in the restricted sample, either over pairs of pre- and post-exit physicians in Figure A.11a or over patient-years in Figure A.11b. The restricted sample includes, by construction, only reassignments over a limited range of provider age differences compared to the distribution of age differences shown in Figure A.2.

Table A.18 presents estimates for the share of provider effects in antibiotic prescribing in the restricted sample. Excluding large shifts in assigned physician age results in effect sizes that are approximately one-third smaller than those for the full sample. In overall antibiotic prescribing, provider shares decrease from 49.4 to 35.9 percent. Similarly, provider shares in second-line prescribing drop from 82.8 to 57.9 percent.

Our main conclusions regarding the characterization of antibiotic prescribing styles are not substantially affected by excluding large shifts in provider age. In particular, Figure A.12 shows that diagnostic availability is still correlated with lower prescribing styles, while we no longer find a significant correlation with average physician age. Figure A.13 shows that our results regarding quality of care remain similar to the main analysis. Specifically, we observe

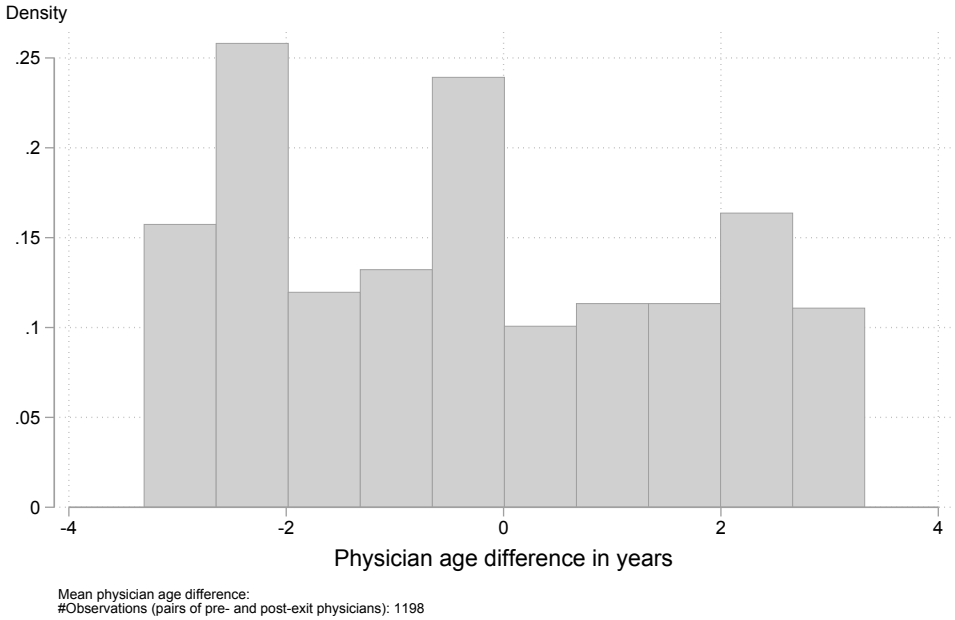
that higher antibiotic prescribing styles are linked to lower-quality prescribing with worse use of diagnostics, and no improvements in patient outcomes. The results from this analysis suggest that provider age is an important driver of practice style differences. However, factors unrelated to provider age still contribute to meaningful differences in practice styles.

Table A.17: Number of observations, excluding treated patients with a shift in provider age > 0.5 SD

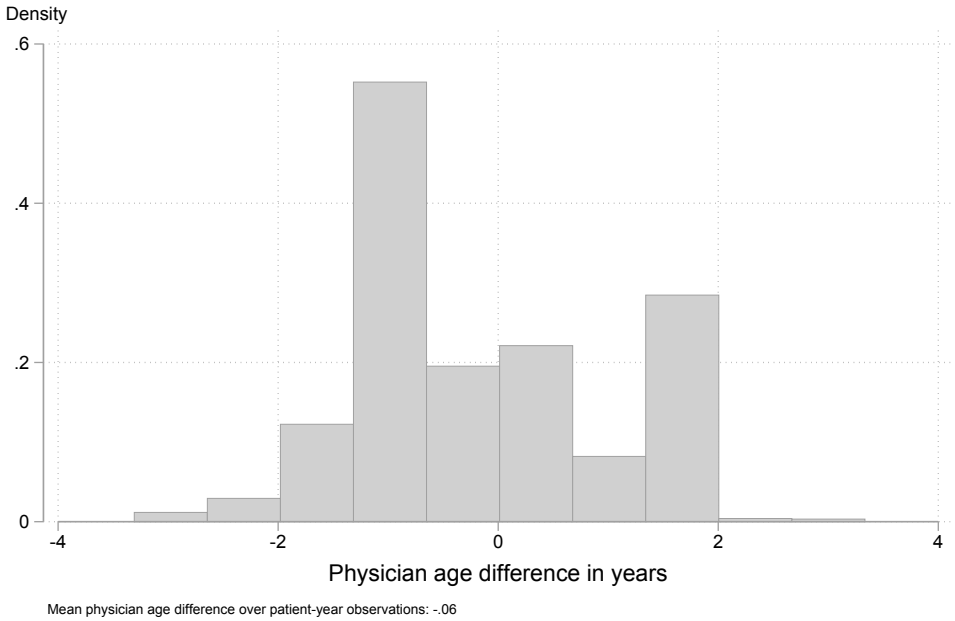
	Clinics	**Patients assigned to clinics**	**Observations**
Never-treated	560	1,053,271	6,092,545
Treated	242	261,958	1,232,612
Total	802	1,304,148	7,325,157

[a] The sum of never-treated and treated patient observations does not equal the total number of patients because some patients are observed at two clinics if exposed to a physician exit.

Figure A.11: Difference in average age between pre- and post-exit providers, excluding treated patients with a shift in provider age > 0.5 SD



(a) Distribution over pairs of pre- and post-exit providers



(b) Distribution over treated patients, weighted by years observed

Notes: In Figure A.11a, values are bunched for groups of five clinics with similar age differences due to data anonymization. In Figure A.11b, values are bunched for groups of five patients.

Table A.18: Estimation results for the share of provider effects in antibiotic prescribing, excluding treated patients with a shift in provider age > 0.5 SD

Panel A	**Number of prescriptions** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.359***	0.255***	0.579***	0.329*
	(0.069)	(0.055)	(0.101)	(0.183)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	no	no	no	no
Observations	7,325,157	7,325,157	7,325,157	7,325,157
Groups (patients)	1,304,148	1,304,148	1,304,148	1,304,148
Panel B	**Number of prescriptions** Two-way fixed effects estimation[a]			
	All antibiotics	Penicillins	Second-line	Other
$\hat{\Delta}_i \times D_{it}$	0.398***	0.267***	0.598***	0.360*
	(0.077)	(0.067)	(0.105)	(0.188)
Event dummies[b]	yes	yes	yes	yes
Time-varying controls[c]	yes	yes	yes	yes
Observations	7,186,036	7,186,036	7,186,036	7,186,036
Groups (patients)	1,277,580	1,277,580	1,277,580	1,277,580

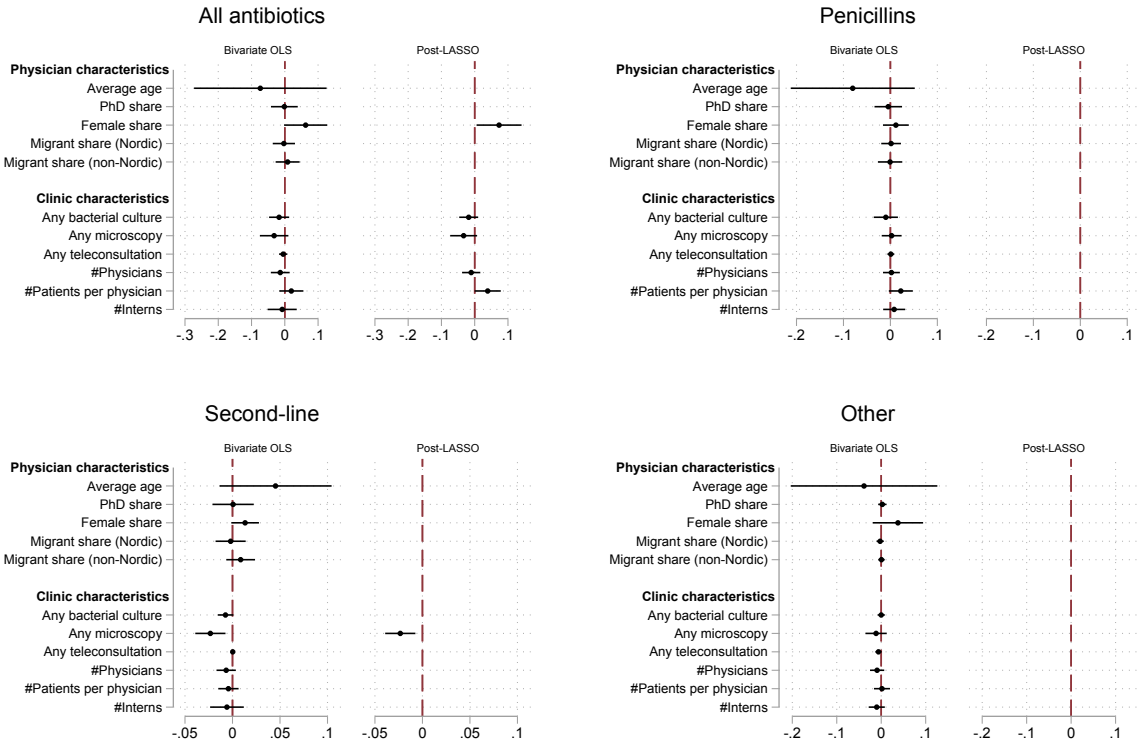
This table reports the average share of antibiotic prescribing differences between clinics that is attributable to provider practice style differences, the coefficient of $\Delta_i \times D_{it}$. Δ_i denotes the difference in mean prescribing between patient i's assigned sets of physicians and is estimated by $\hat{\Delta}_i$, the average prescribing to untreated patients. D_{it} denotes a post-treatment indicator. Standard errors are calculated using a bootstrap with 50 repetitions at the patient level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Two-way fixed effects estimation with calendar year fixed effects and patient fixed effects.

[b] Event dummies include an indicator for treatment onset (relative year 0) and post-treatment.

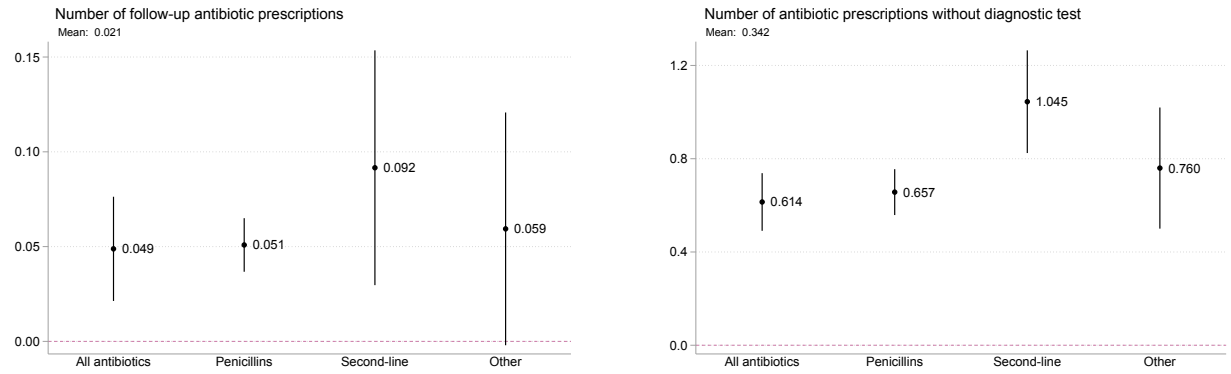
[c] Control variables include Number of interns at the clinic, Age squared, Household size, Pregnant, Any visit to emergency department, and Any call to an emergency doctor.

Figure A.12: Correlates of provider practice style differences in antibiotic prescribing, excluding treated patients with a shift in provider age > 0.5 SD

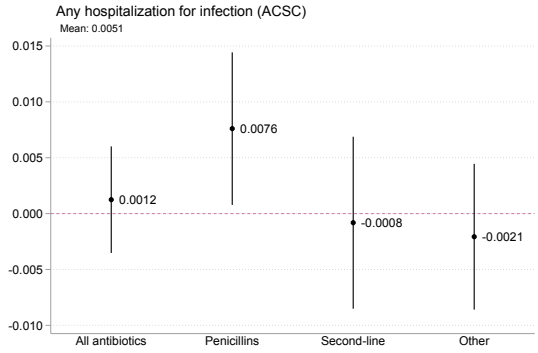


Notes: The figure presents estimated changes in antibiotic prescribing styles associated with a one standard deviation increase in physician or clinic characteristics, with standard deviations determined from the full sample such that estimates are comparable to Figure 5. Estimates are based on bivariate OLS (left) and post-LASSO OLS (right). We obtain these estimates by regressing the estimated difference in antibiotic prescribing practice style on differences in observed characteristics between pairs of physicians that treated patients are assigned to. For the post-LASSO estimates, we first run a LASSO regression on the full set of characteristics, with the penalty level selected via 10-fold cross validation to minimize mean squared error, and then perform OLS regression using only the set of variables selected by the LASSO regression. Missing coefficients indicate that a variable has not been selected in the LASSO regression. Lines represent the the 95% confidence intervals, with standard errors calculated using a parametric bootstrap with 50 repetitions at the patient level (45 replications for Any teleconsultation, due to missing variation) to draw differences in prescribing practice styles. Physician and clinic characteristics are standardized to have mean 0 and standard deviation 1 prior to differencing.

Figure A.13: Quality of care and antibiotic prescribing intensity, excluding treated patients with a shift in provider age > 0.5 SD



(a) Low quality prescribing



(b) Adverse patient outcomes

Notes: The figure shows the estimated changes in quality of care associated with a practice style of one additional antibiotic prescription, based on patient-year level regressions that include patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. We consider an increase by one overall antibiotic prescription, as well as separately one more penicillin, second-line, or other antibiotic prescription. Figure A.13a shows the relation between higher antibiotic prescribing intensity and low quality prescribing, measured by follow-up antibiotic prescriptions within seven days after an initial prescription of a different ATC 4 class (left), and prescriptions without any claim for diagnostic tests (right). Figure A.13b shows the change in adverse patient health outcomes associated with higher antibiotic prescribing intensity, measured by the propensity for any hospitalization for an infection-related ambulatory care sensitive condition (ACSC). We estimate changes in antibiotic prescribing styles as separate provider effects for each pair of physicians among treated patients, controlling for patient fixed effects, calendar year fixed effects, and indicators for treatment onset and post-exit. Lines represent the 95% confidence intervals, with standard errors based on a parametric bootstrap with 50 repetitions at the patient level to draw differences in prescribing practice styles.

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