Impact of Individual versus Environmental Effects on Payments to Physicians

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Pharmaceutical and medical device companies make direct payments to physicians as speaking fees, gifts, travel expenses, and other payments while marketing their products. Numerous studies have investigated the impact of these payments on physicians' treatment choices, however, they are limited in their ability to draw causal inference. This study contributes to the question by providing insight into what drives physicians to accept payments. I employ a "movers" panel design to estimate the relative contribution of individual effects versus environmental effects on the amount of payments received. I examine the impact of environmental factors on the annual amount of small payments received by US physicians before and after a cross-state move. The key finding is that geographical variation in these payments is driven primarily by individual effects (~80%) and only modestly by environmental effects (~20%). This finding is robust to using different subsets of the movers population. This implies that policies focused on individual effects are more likely to be effective than those addressing environmental factors. For example, a policy applied during training in medical school (individual effect) is more likely to be effective than a policy applied to workplace norms (environmental effect).

Introduction

Pharmaceutical and medical device companies spend considerable amounts of money marketing their products. Payments to physicians include gifts, food and beverages, education, and travel, as well as larger payments like royalties and speaking fees which can be valued at tens or hundreds of thousands of dollars per year. Many studies have shown an association between payments to physicians and the use of products marketed by the corresponding company. Most note the correlation without attempting to draw casual conclusions [1] [2] [3] [4]. Other studies have shown that physicians respond to other types of economic incentives when making treatment choices [5] [6] [7] [8]. Studying the impact of industry payments on prescribing behavior is hampered by endogeneity and simultaneity. There could be unobserved factors that cause physicians to both accept more payments and prescribe certain types of treatments. Alternatively, companies may be targeting physicians who are prone to be or who are already high prescribers of their products.

The question of what drives physicians to accept these payments has gone unaddressed in this debate. Understanding the drivers of variation in physician payments could have important policy implications. For example, should policies be directed at individuals or environments? Individual characteristics in this case include medical training, age, and beliefs, while environmental characteristics include norms, other peer effects, company sales practices, hospital market structure, and local rules and regulations. Policies attempting to address physician payments may be ineffective when targeted towards individual characteristics if environmental factors are in fact the major drivers. For example, if individual effects are much less important than environmental effects, a policy targeted at physician training in medical school is unlikely to be effective. On the other hand, efforts at changing workplace norms may be ineffective if it is shown than physicians moving between areas with different norms are largely unaffected. Supposing there is a causal effect between payments and prescribing behaviors, policies addressing physician payments could be of practical interest for modifying behavior or understanding the causal path.

This paper addresses the question of individual versus environmental effects on payments by exploiting the movement of physicians between states in a "movers" design. Recent papers have used this design in healthcare [9] [10] [11] and in other fields [12] [13] [14] [15]. Physician movement in this study provides a natural experiment where payments to the same physician are observed in different environments. This allows for the disentangling of environmental and individual effects and relies on the key assumption that physician movements are exogenous. To support this assumption, this study focuses on small payments which are less likely to affect physician moving behavior. This study uses the CMS Open payments database, a comprehensive record of payments to US physicians. Fixed effects and random effects models are used to estimate the impact of movement on physician payments. The key finding is that environmental effects have an impact of approximately 20%. This suggests that individual effects play the major role in determining physician payments and policies should therefore be directed at individuals, not environments.

Literature Review

Physician Incentives

There is considerable research on the impact of various types of payments on physician treatment choices. These studies take advantage of an exogenous shock to physician payments and look at the impact on treatment decisions. Chen 2016 looks at physicians who have ownership in pharmacies and who therefore benefit from prescribing certain drug treatments [5]. The study exploits variation in restrictions on pharmacy ownership and finds that the elimination of the financial incentive reduced drug prescriptions. Jensen 2014 uses variation in payment contracts to show that physician payments affected infant health outcomes [6]. Similarly, Currie 1995 finds that increasing the fees paid to physicians for treating Medicaid patients relative to private patients reduces infant mortality [7]. Lastly, Clemens 2014 uses heterogenous geographical adjustments in Medicare payments to show that payment amount affects whether physicians choose to accept patients [8].

Studies with CMS Open Payments

The CMS Open Payments database reports payments from marketers of drugs and medical devices to physicians in the US. The objective of collecting this information is to shed light on the relationship between industry payments and physician behavior. Many papers merely provide descriptive statistics of the data [1] [2] [3] [4] [16] [17]. Other studies have looked at payments to physicians and their use of drugs marketed by those companies by linking Open Payments with a dataset of physician prescriptions [18] [19] [20] [21]. They find that payments are generally associated with increased prescribing, but they do not address causality. Two studies attempt to show causality in payments to opioid prescribers though econometric techniques: Zezza 2018 uses a difference-in-difference approach [22] and Inou 2020 uses propensity score matching [23]. I believe that neither can show causation because the treatment assignment in Inou 2020 is not independent of the key regressor (payments received) and the matching in Zezza 2018 suffers from missing or unobservable controls which violates the conditional independence assumption.

Movers Design

A growing number of papers exploit the movement of individuals to study the impact of individual and environmental effects. Chetty 2014 exploits the movement of teachers to estimate the impact of teacher quality on educational outcomes [14] [15]. Chetty 2018 exploits the movement of children to estimate the impact of neighborhoods on intergenerational mobility [12] [13]. Hull 2018 provides an econometric review of movers designs and states 3 sufficient conditions under which movers estimates are causally interpretable: homogeneous treatment effects, orthogonality of the move, and impersistent outcomes for double movers [24].

Movers Design in Healthcare

The movers design has been used in healthcare to study observed geographical variation. Finkelstein 2016 looks at variation in healthcare consumption between different regions by exploiting the movement of patients [10]. She looks at Medicare patients moving between hospital referral regions to compare the degree to which healthcare consumption is driven by what she calls demand factors (patient individual characteristics) versus supply factors (environmental factors). She finds that 40-50% of the geographic variation is driven by individual effects while the remaining 50-60% is therefore explained by environmental effects.

Dunn 2020 looks at the probability of physicians accepting Medicaid patients [11]. One specification employs physician movers to control for individual differences (such as altruism towards Medicaid patients) to study the impact of different Medicaid physician payments by region.

In the study most closely related to this one, Molitor 2018 studies cardiologist migration to disentangle the role of physician-specific factors versus environmental factors on the choice of a particular heart attack treatment [9]. Molitor finds that environmental factors explain 60-80% of a physician's treatment choice after moving. Molitor also draws a distinction between fast and slow effects. If behavior changes immediately upon move, it supports mechanisms such as access to capital or peer effects rather than slower acting effects like learning.

Data

CMS Open Payments

This dataset originated from the Physician Payments and Sunshine Act as part of the Affordable Care Act of 2010 in the United States [25]. The act requires marketers of drugs and medical devices to report all financial dealings with physicians. The data is collected by the Center for Medicare & Medicaid Services (CMS) and has been reported annually since 2013.

There are 10–12 million general payments reported each year for just over 600 thousand unique physicians (Table A.3). The nature of payments is labeled as one of 16 categories such as gift, food and beverage, education, and travel. The information reported for each payment includes the value of the payment, the nature of payment, and demographic information on the recipient including a unique ID and their business address. Table A.4 shows the payments grouped by nature of payment for 2016. The statistics for other years are similar.

The Movers Dataset

This study uses the total annual value of small payments to physicians over a six-year period. Movers are identified as those who change states in the observation period subject to the criteria defined here.

Annual Sum of Small Payments by Physician

This paper uses the six full years of observations covering calendar years 2014 to 2019. This analysis focuses on the five payment categories in Table A.4 with considerably smaller mean and median payment sizes: food and beverage, travel and lodging, education, gifts, and entertainment. The median payment is below $200 in all six years and both the mean and median for these payments are much smaller than the other 10 payment types. Large annual payments (above $5000) within these categories are also excluded. These small payments make up 96% of all general payments by count and 18% by value. The total value of payments in any of these five categories is calculated annually for each physician in each year containing observations. The distribution of payment size for food and beverage payments is shown in Figure A.2. The other payment categories exhibit a

similar left-skewed distribution where payments are centered around a low value with a tail to the right for large payments. The full study population contains 3,520,480 annual payment measures for 1,019,646 unique physicians.

Identifying Movers

Movers are defined as physicians who receive payments in the same state for at least two consecutive years and then immediately receive payments in a different state for at least two additional consecutive years. Physicians 2 and 3 in Table A.5 illustrate physicians meeting the movers criteria. Physicians 3, 4, 5, and 6 may have moved but are not classified as movers according to these criteria. Some physicians, such as physician 7, received payments in multiple states in a single year and are not treated as movers. These were often neighboring states or the physician lists both states in subsequent years suggesting that the physician is practicing in both states. These physicians made up less than 0.1% of the population and were excluded from the analysis because they may be falsely classified as movers and might bias the mean payment calculations in their respective states. Physician 8 is classified as a mover but returns to their original state during the observation period and physician 9 is classified as a mover but moves to a neighboring state. These types of mover make up 10% and 24% of movers respectively and it is possible that some of these physicians are really practicing in both states. Scenarios are considered in which these types of movers are excluded. Table A.6 summarizes the number of observations in each category of physician mover. The empirical results also look at movers from subsets of the most popular starting states which are described in Table A.7.

The set of observations meeting these criteria contains 33,545 observations of 12,486 unique physicians. Comparing to the other study of physician movers, Molitor 2018 identifies 1-2% of cardiologists as movers between 1998 and 2012 and observes that nearly 80% changed states [9]. This agrees reasonably well with estimates here of 0.95-1.22% (Table A.6). Since Molitor observed physicians over a longer period, the more restrictive definitions of movers would be more closely aligned with his study. It is also possible that the movement rate of cardiologists is different than physicians in general or that the movement rate was different at the time of that study.

Empirical Strategy

I employ a model similar to Molitor 2018 [9]. Total payments for physician i in year t is the sum of individual fixed effects α_i, time effects τ_t, initial state effects λ_i, and treatment effects $\Delta_{jk,t}$.

$$y_{it} = \alpha_i + \tau_t + \lambda_i + \sum_{s=0}^{3} \beta_{is} \Delta_{jk,t} \mathbf{1}(s = m) + \epsilon_{it}$$

The variable m is equal to years since moving for a physician who moves and is always not equal to s for one who does not move. The variable $\Delta_{jk,t}$ corresponds to the treatment exposure at time t for a physician that moved from state j to state k and is given by $\Delta_{jk,t} = p_{kt} - p_{jt}$, where p_{kt} is the average total annual payments accepted by physicians in state k at time t, minus p_{jt} which is the average total annual payments accepted by physicians in state j at time t. To illustrate, suppose a physician moved from Delaware to Colorado and the current period is 2017. The average physician received \$646 in small payments annually in Delaware and \$880 in Colorado in 2017. The treatment exposure is therefore $\Delta_{DE-NY,2017} = \$234$. Figure A.3 gives an additional intuitive illustration.

The variables of interest in this model are the β_{is} coefficients. They correspond to the degree to which a physician adopts the payment-accepting behaviors of their new environment and should take on a value between 0 and 1. If physicians are unaffected by their move, they will continue to accept the same amount of payments and the estimated β_{is} coefficients will be close to 0. Conversely, if physicians move and adopt the behaviors of those in their new state, the estimated β_{is} coefficients will be close to 1. Figure A.4 and Figure A.5 illustrate these two extremes. There are four β_{is} coefficients because of the definition of movers and the 6-year span of the dataset.

The key model assumption is strict exogeneity of treatment variables $\Delta_{jk,t}$ with residuals. This would mean that physicians did not choose to move in pursuit of additional payments or, if they chose to move, that they were not influenced by payments when choosing their destination. I believe this to be a reasonable assumption due to the small value of payments relative to physician total income and the costs of moving. The model also assumes that the treatment effect is additive (rather than multiplicative) with the difference in mean payments between states. For example, moving

between states with average annual payments of \$500 and \$1000 is a treatment effect of +\$500 and not multiplication by 2.

No assumptions are made about the correlation between α_i and the observables. It seems logical that those with a propensity to take more payments might want to move to an environment with larger payments, but the small monetary value of the payments makes this unclear. The model is estimated using both fixed and random effects and a Hausman test is used to compare the estimates. The Hausman-Taylor specification is included to incorporate the time-invariant starting state controls.

The model assumes constant fixed effects and universal time trends. Using a universal time trend disregards any unique trends within a state. Observation of the state-specific time trends suggests that this is a reasonable assumption (Figure A.6). The constant fixed effects assumption means that a physician's propensity to take payments due to unobserved individual characteristics does not change over time. This is unlikely to be completely accurate. For example, older and more experienced physicians may be targeted more frequently by influence operations from pharmaceutical companies. On the other hand, physicians earn more income as they gain experience which could reduce their interest in seeking payments. Given the short observation period (4-6 years) and perhaps contradictory time-based effects, I believe that the assumption of constant fixed effects is justified.

Lastly, the model relies on the proper identification of movers. A conservative definition of movers was chosen to aid this assumption and subsets with more restrictive movers conditions are analyzed as well. The risk of bias from labeling non-movers as movers is greater than the reverse. Non-movers do not experience the impact of a move so their inclusion biases the estimated impact downwards. Movers are not numerous enough to affect the non-movers population so mistakenly rejecting true movers only biases results if done systemically and in the presence of heterogeneous treatment effects. The exact time of moving is also hard to determine. Depending on when in the year a physician moves, the impact might be captured either at some point in the first year of the move or in what looks like the year before moving.

Empirical Results

The key empirical result is that environmental factors explain around 20% of the variation in physician payments. The coefficients for the impact of the move on annual payments (β_{is}) are estimated to be approximately 0.12-0.25 across all models (Table 1). Fixed effect estimates are distinct from OLS (Hausman test p=0.00003). Without starting state controls, fixed effects and random effects estimates are indistinguishable (Hausman test p=0.98), however, they become distinct when including starting state controls (Hausman test p=0.0005). The impact of a move is felt immediately (year 1 coefficients statistically significant) with years 3 and 4 being somewhat higher than years 1 and 2. This suggest that the environmental factors that do influence physician behavior are those that act quickly with some potential contribution from slower-acting effects.

Imperfect labeling of movers and non-movers could bias these estimates. If non-movers are falsely labeled as movers, this would bias the β_{is} coefficients downwards. Table 2 examines the model estimates for different populations of movers. Excluding physicians who moved back to their initial state (Column 3) provides similar estimates to the full dataset. Excluding physicians who moved to neighboring states (Column 4) shows higher estimates than the full population (Hausman test p=0.003) which may indicate that some movers are falsely labeled. If could be that some physicians are really practicing in both states and happen to list different states in years that met the movers definition in this study. Alternatively, perhaps moves to neighboring states have a lower environmental impact. These could include small geographic moves (from just on one side of the boarder to another) which would have a smaller environmental shock than a move crossing multiple states.

Subsetting the population by the top 5, 10 and 20 starting states gives some insight into potential heterogeneity in treatment effects (Table 2). Estimates for years 1 and 2 are similar across these populations but differ somewhat for years 3 and 4. This points to some difference in the impact for movers between certain states. Regardless, the estimates remain similar to the those for the full population and support the general finding that environmental effects explain only a minority of the behavior.

Table 1. Movers impact coefficients for four years post move estimated with OLS, fixed effects (FE), and random effects (RE) with and without controls for starting state division using all physicians and movers.

	OLS (1)	**FE (2)**	**RE (3)**	**OLS (4)**	**Hausman-Taylor (5)**	**RE (6)**
Year 1	0.1531*** (0.0463)	0.1260** (0.0386)	0.1431*** (0.0001)	0.1912*** (0.0462)	0.1442*** (0.0368)	0.1520*** (0.0001)
Year 2	0.1499*** (0.0434)	0.1163** (0.0362)	0.1335*** (0.0001)	0.1842*** (0.0434)	0.1329*** (0.0344)	0.1415*** (0.0001)
Year 3	0.2178*** (0.0624)	0.2117*** (0.0513)	0.2262*** (0.0001)	0.2525*** (0.0624)	0.2204*** (0.0491)	0.2348*** (0.0001)
Year 4	0.1665 (0.0962)	0.1760* (0.0775)	0.1872*** (0.0001)	0.1999* (0.0961)	0.1811* (0.0750)	0.1956*** (0.0001)
First Division Controls	-	-	-	Yes	Yes	Yes
Individuals	1,019,646	1,019,646	1,019,646	1,019,646	1,019,646	1,019,646
Years	1-6	1-6	1-6	1-6	1-6	1-6
Observations	3,520,480	3,520,480	3,520,480	3,520,480	3,520,480	3,520,480
F-statistic	9.51 (df=4, 3520475) (p<0.0001)	7.35 (df=4, 2500825) (p<0.0001)		270.45 (df=13, 3520466) (p<0.0001)		
Chi-squared			12622900 (df=4) (p<0.0001)		372 (df=13) (p<0.0001)	417089000 (df=13) (p<0.0001)

Table 2. Movers impact coefficients for four years post move estimated with fixed effects for subsets of all physicians. Movers-only (2) excludes physicians who were not identified as movers. No move-backs (3) includes non-movers but excludes physicians who moved but returned to their starting state by the end of observations. No neighbors (4) includes non-movers but excludes physicians who move to neighboring states. Top 5, 10 and 20 starting states include only physicians who are first observed in the top 5, 10, and 20 most frequent starting states (both movers and non-movers).

	All Physicians (1)	**Movers only (2)**	**No move-backs (3)**	**No neighbors (4)**	**Top 5 starting states (5)**	**Top 10 starting states (6)**	**Top 20 starting states (7)**
Year 1	0.1260**	0.2564*	0.1385***	0.1949***	0.1303	0.1300*	0.1019*
	(0.0386)	(0.1221)	(0.0415)	(0.0430)	(0.0826)	(0.0622)	(0.0520)
Year 2	0.1163**	0.2345*	0.1154**	0.1539***	0.1282	0.1544**	0.1120*
	(0.0362)	(0.1149)	(0.0390)	(0.0404)	(0.0780)	(0.0578)	(0.0481)
Year 3	0.2117***	0.2914*	0.2231***	0.2556***	0.2730*	0.1517	0.1664*
	(0.0513)	(0.1282)	(0.0531)	(0.0579)	(0.1102)	(0.0800)	(0.0679)
Year 4	0.1760*	0.2354	0.1798*	0.2375**	0.5080**	0.2178	0.0490
	(0.0775)	(0.1397)	(0.0776)	(0.0875)	(0.1652)	(0.1211)	(0.1026)
Individuals	1,019,646	12,486	1,019,646	1,019,646	286,959	562,541	777,557
Years	1-6	2-4	1-6	1-6	1-6	1-6	1-6
Observations	3,520,480	33,545	3,517,147	3,512,281	994,675	1,956,231	2,714,371
F-statistic	7.35 (df=4, 2500825) (p<0.0001)	1.48 (df=4, 21052) (p=0.2058)	7.22 (df=4, 2497492) (p<0.0001)	10.4 (df=4, 2492626) (p<0.0001)	3.78 (df=4, 707707) (p=0.0044)	3.12 (df=4, 1393681) (p<0.0001)	2.93 (df=4, 1936805) (p=0.0195)

A common robustness check in movers designs is to estimate coefficients for years prior to the move. In this study, a physician should not be impacted by their new state before moving. Figure 1 shows the coefficients estimated with fixed effects plotted over years from move. The impact of years before moving is centered near zero and there is a clear jump post-move. Table A.8 shows the estimates for OLS, fixed effects, and random effects. The estimates for the first year prior to moving are slightly higher than earlier years and this could be due to the challenge of identifying the exact year of move. It is possible for a physician to move part of the way through the year before their address is changed which causes some of the impact of the move to show up one year before moving.

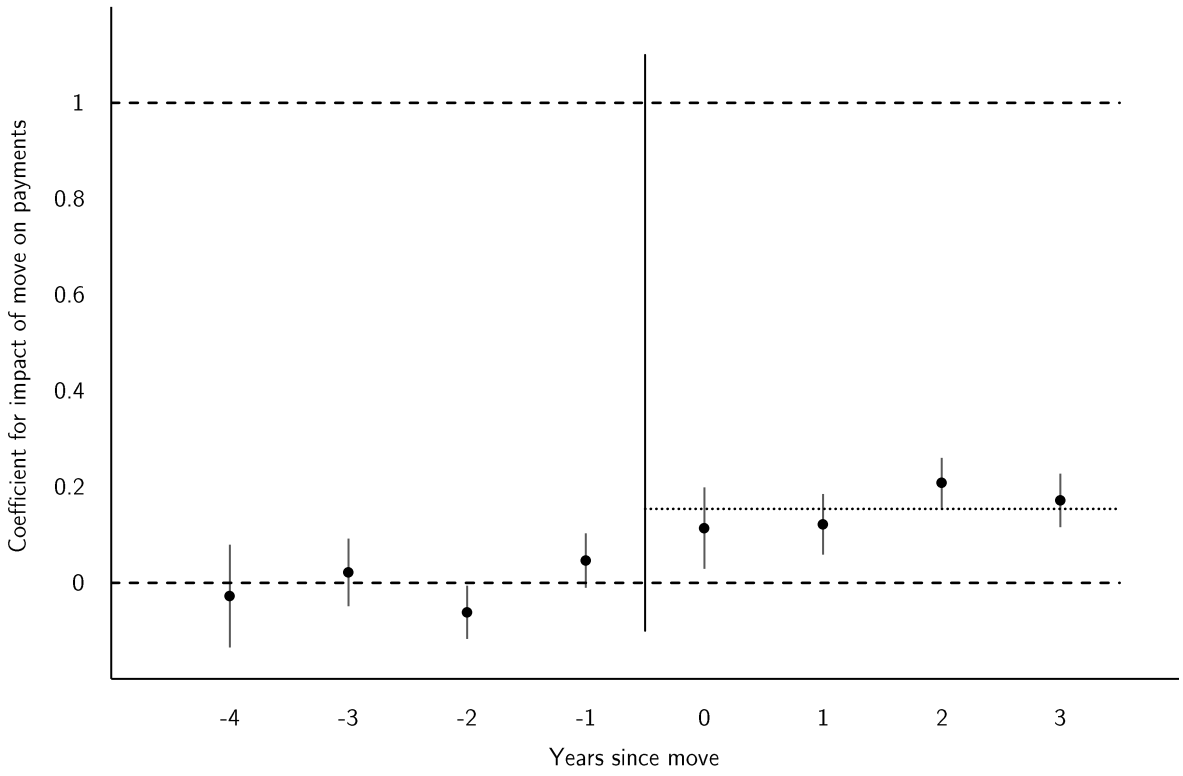

Figure 1. Movers impact coefficients for four years pre- and post-move estimated using fixed effects. The y-axis corresponds to the degree to which a physician adopts the payment-accepting behavior of physicians in the destination state. The horizonal dashed lines highlight the expected bounds of 0 and 1 for the estimated β_{is} coefficients. The solid vertical line separates the years before and after moving. The horizontal dotted line for years after moving corresponds to the average value for those years.

These results can be contrasted with the other movers studies in healthcare. Finkelstein finds that individual patient characteristics explain 40-50% of patient healthcare spending [10] and Molitor finds that individual characteristics explain only 20-40% of regional disparities in prescribing behavior for cardiologists treating heart attacks [9]. The environmental factors affecting prescribing behavior in Molitor are perhaps different or stronger than those affecting the acceptance of small payments. Although not investigated in this paper, it would be possible to estimate this payments model for only cardiologists or other specialties.

Conclusions

- This study contributes the understanding of the impact of industry payments to physicians on their prescribing habits by providing insight into what drives physician payments.
- The key finding is that individual effects explain much more of the geographical variation in small payments to physicians (~80%) than do environmental effects (~20%).
- The results are robust to using different movers subsets. Appropriately labeling movers is challenging and there is some evidence of mislabeling movers or other neighboring state differences.
- The finding is somewhat contrary to other movers designs in healthcare which find environmental factors to play a larger role, however, none have looked at this specific outcome.
- The implication is that policies focused on individual effects are more likely to be effective than those addressing environmental factors. For example, a policy applied during training in medical school (individual effect) is more likely to be effective than a policy applied to workplace norms (environmental effect).

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Appendix Tables

Table A.3. Annual payments and unique physicians in the CMS Open Payments database.

Year	Payment Count (millions)	Unique Physicians (thousands)
2013	4.1	481
2014	11.3	625
2015	11.6	636
2016	11.7	638
2017	11.4	633
2018	10.9	629
2019	10.3	614
2014-2019	67.2	1,061

Table A.4. Summary statistics for the Open Payments dataset grouped by nature of payment for 2016. Rows in bold correspond to payments analyzed in this study.

Nature of Payment	Number of Payments	Total Value($M)	Mean ($)	Median ($)	Standard Deviation ($)
Food and Beverage	**10,304,240**	**250**	**24**	**15**	**50**
Travel and Lodging	**596,146**	**200**	**335**	**187**	**753**
Education	**273,594**	**57**	**208**	**11**	**2,033**
Compensation for services other than consulting, including serving as faculty or as a speaker at a venue other than a continuing education program	261,860	595	2,274	1,900	30,752
Consulting Fee	121,703	413	3,396	1,770	10,617
Gift	**57,472**	**35**	**602**	**100**	**5,290**
Honoraria	22,459	53	2,374	2,000	3,881
Royalty or License	15,157	1,027	67,753	3,866	501,066
Space rental or facility fees (teaching hospital only)	11,220	25	2,247	1,000	14,433
Compensation for serving as faculty or as a speaker for a non-accredited and noncertified continuing education program	9,794	21	2,109	1,500	2,642
Entertainment	**9,507**	**1**	**100**	**31**	**963**
Grant	9,004	126	14,000	2,500	190,017
Compensation for serving as faculty or as a speaker for an accredited or certified continuing education program	2,580	9	3,368	2,500	4,410
Charitable Contribution	1,635	17	10,592	1,500	46,660
Current or prospective ownership or investment interest	795	77	96,886	4,500	459,983
Total	11,697,166	2,907			

Table A.5. Illustration of the movers definition. The state name corresponds to the state listed by each physician for each year of observation. State codes: NY represents New York, CA represents California, and NJ represents New Jersey.

Physician	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Mover**	**Reason**
1	NY	NY	NY	NY	NY		No	Same state for every observation
2	NY	NY	CA	CA			Yes	Meets criteria
3		NY	NY	NY	CA	CA	Yes	Meets criteria
4				NY	NY	CA	No	Did not spend 2 years in new state
5	NY	CA	CA				No	Did not spend 2 years in old state
6	NY		NY	CA		CA	No	Did not spend 2 consecutive years in new or old state
7	NY	NY	NY, CA	CA	CA		No	Listed multiple states in 2016
8	NY	NY	CA	CA	NY		Yes – move-back	Ended in original state
9		NY	NY	NJ	NJ		Yes – neighbor	Moved to neighboring state

Table A.6. Observations and count of physicians and physician movers.

	All Physicians	**Movers**	**Movers – no move-backs**	**Movers – no neighbors**
Observations	3,520,480	33,545	30,212	25,346
Unique physicians	1,019,646	12,486	11,234	9,684
Percent of all physicians	100%	1.22%	1.10%	0.95%

Table A.7. Observations and counts of physician movers from most popular states listed in the first year of observation (starting states).

	States	**Observations (% of total)**	**Physician movers (% of total)**
Top 5	NY, PA, IL, MI, TX	994,675 (28.3%)	3,894 (31.2%)
Top 10	NY, PA, IL, TX, MI FL, OH, CA, NJ, MO	1,956,231 (55.6%)	6,517 (52.2%)
Top 20	NY, PA, IL, TX, MI FL, OH, CA, MO, NJ GA, MA, NC, VA, MD, AZ, IN, TN, SC, LA	2,714,371 (77.1%)	9,477 (75.9%)

Table A.8. Movers impact coefficients for four years pre- and post-move estimated using OLS, fixed effects (FE) and random effects (RE) without starting state controls.

	OLS **(1)**	**FE** **(2)**	**RE** **(3)**
Year 4	0.1665	0.1718*	0.2118***
	(0.0962)	(0.0849)	(0.0001)
Year 3	0.2178***	0.2084***	0.2545***
	(0.0462)	(0.0632)	(0.0001)
Year 2	0.1508***	0.1141*	0.1650***
	(0.0434)	(0.0521)	(0.0001)
Year 1	0.1526***	0.1220*	0.1755***
	(0.0463)	(0.0558)	(0.0001)
1 year before moving	0.0606	0.0465	0.0993***
	(0.0472)	(0.0568)	(0.001)
2 years before moving	-0.0289	-0.0613	-0.0054***
	(0.0462)	(0.0555)	(0.0001)
3 years before moving	0.1231	0.0218	0.0934***
	(0.0706)	(0.0705)	(0.0001)
4 years before moving	0.2754*	-0.0275	0.0860***
	(0.1235)	(0.1071)	(0.0001)
Individuals	1,019,646	1,019,646	1,019,646
Years	1-6	1-6	1-6
Observations	3,520,480	3,520,480	3,520,480
F-statistic	6.01 (df=8, 3520471)	4.35 (df=8, 2500821)	
	(p<0.0001)	(p<0.0001)	
Chi-squared			15153300 (df=8)
			(p<0.0001)

Appendix Figures

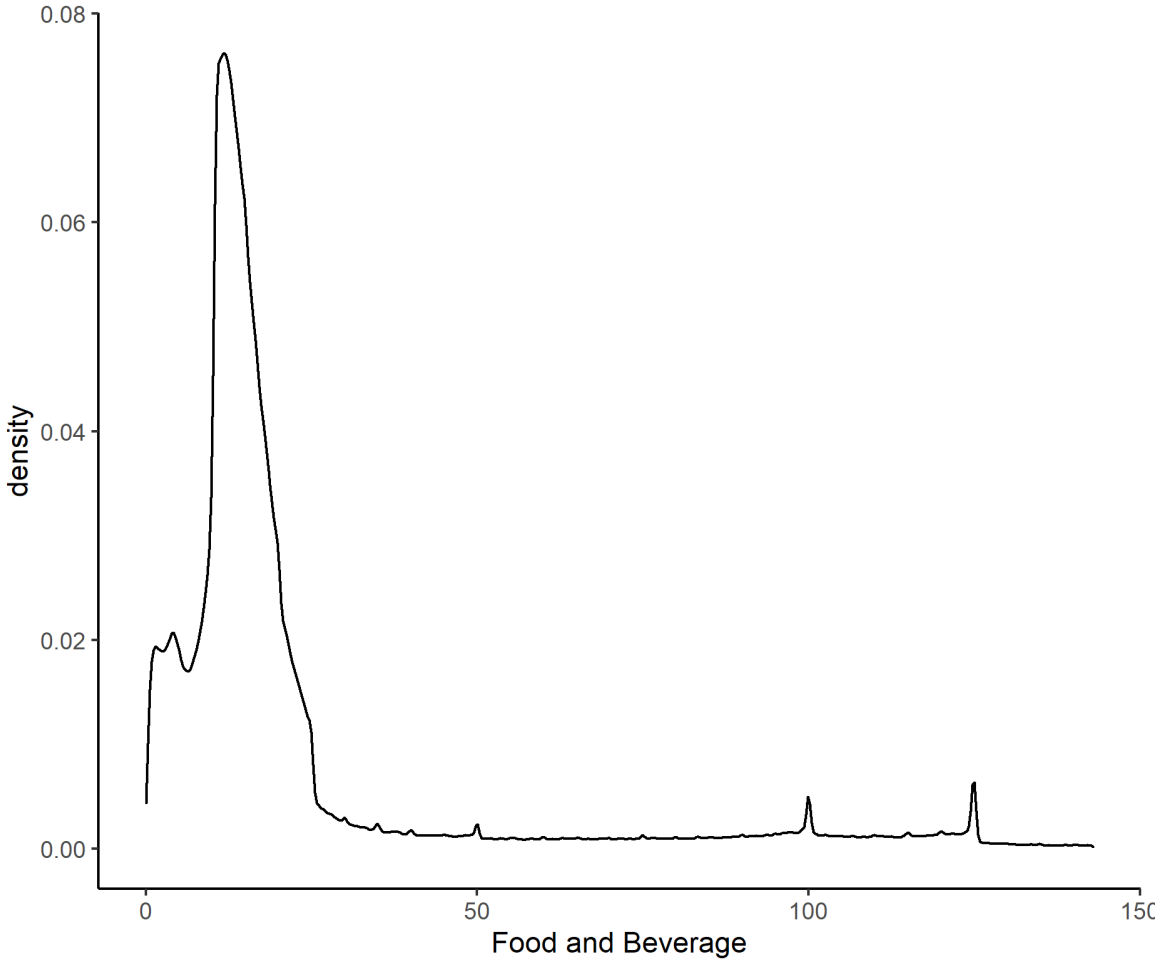

Figure A.2. KDE plot showing the distribution of payment size for food and beverage payments in 2015.

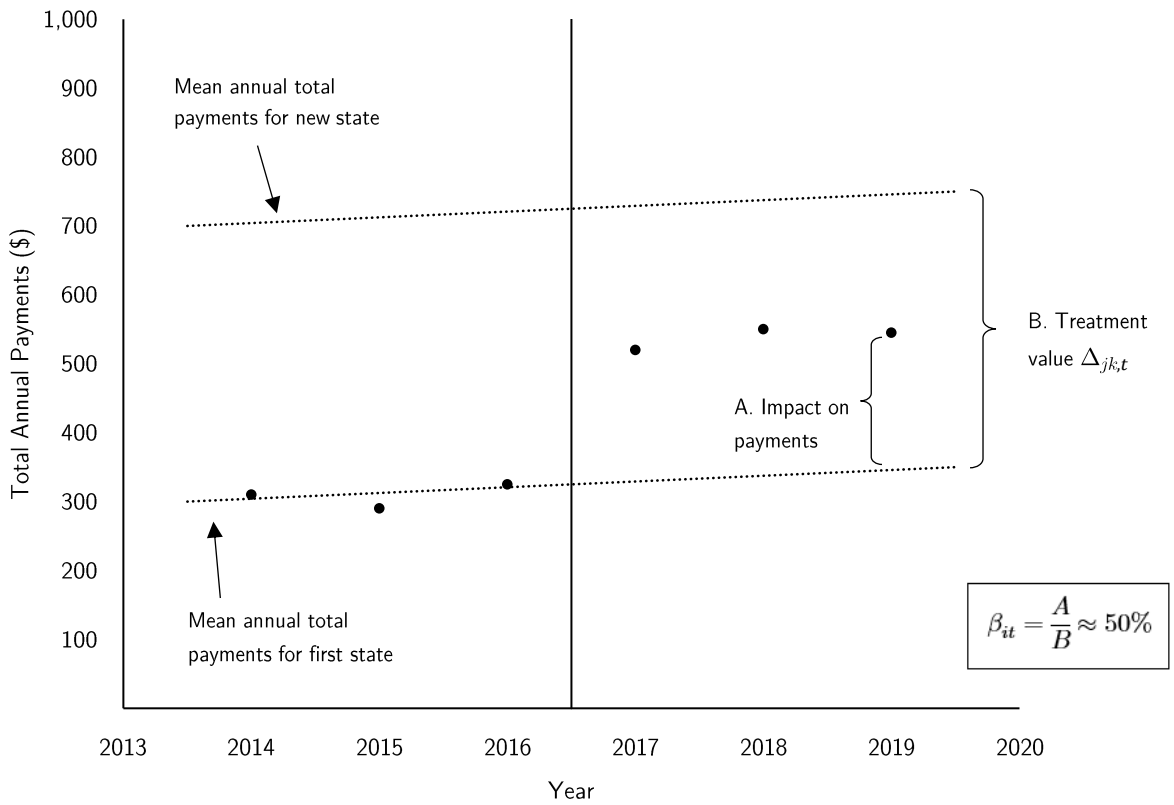

Figure A.3. Illustrative example of the study design. For simplicity, suppose a hypothetical physician accepts annual payments very similar to that of the average physician in their state (approximately $300 per year) for years 2014 - 2016. The physician moves by 2017 to a state with a different amount of average payments (approximately $700 per year). The impact on payments (A) is the difference between the physician's annual payment and the mean annual payment in their initial state. The treatment value (B) is the difference in state means for period t. The β_{is} coefficients estimated in this study correspond to the ratio of A to B for a given year. In this example, the impact of environmental factors in the new state is approximately 50%.

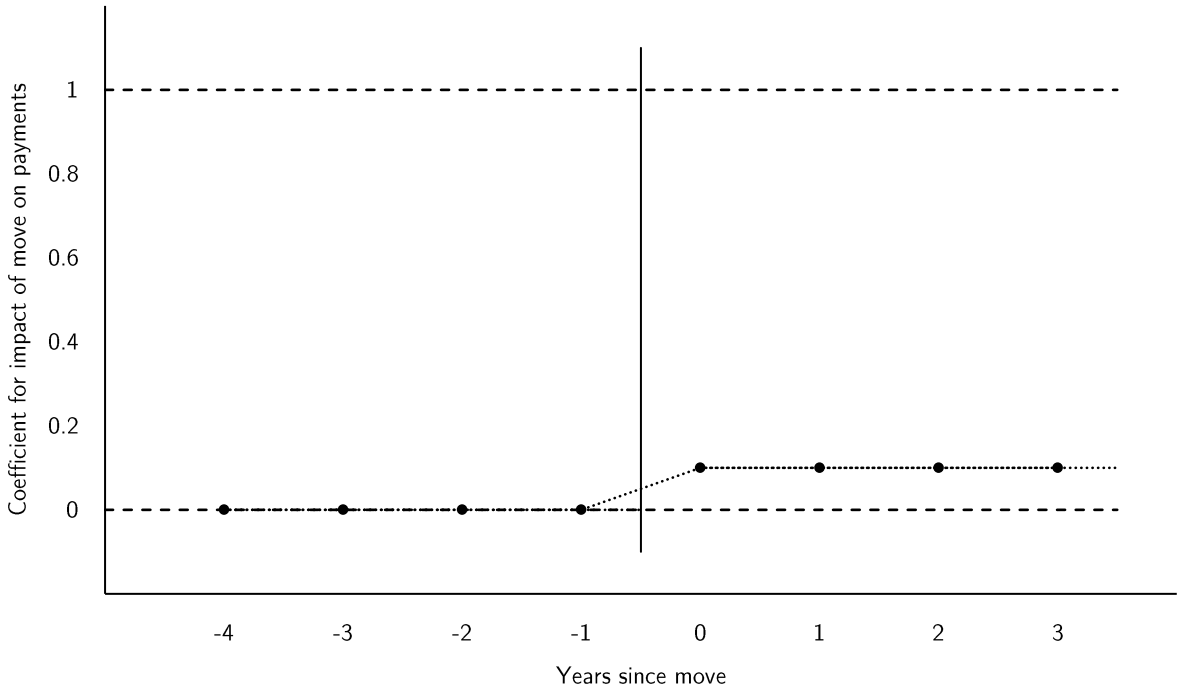

Figure A.4. Predicted movers impact coefficients for four years pre- and post-move where individual effects dominate environmental effects.

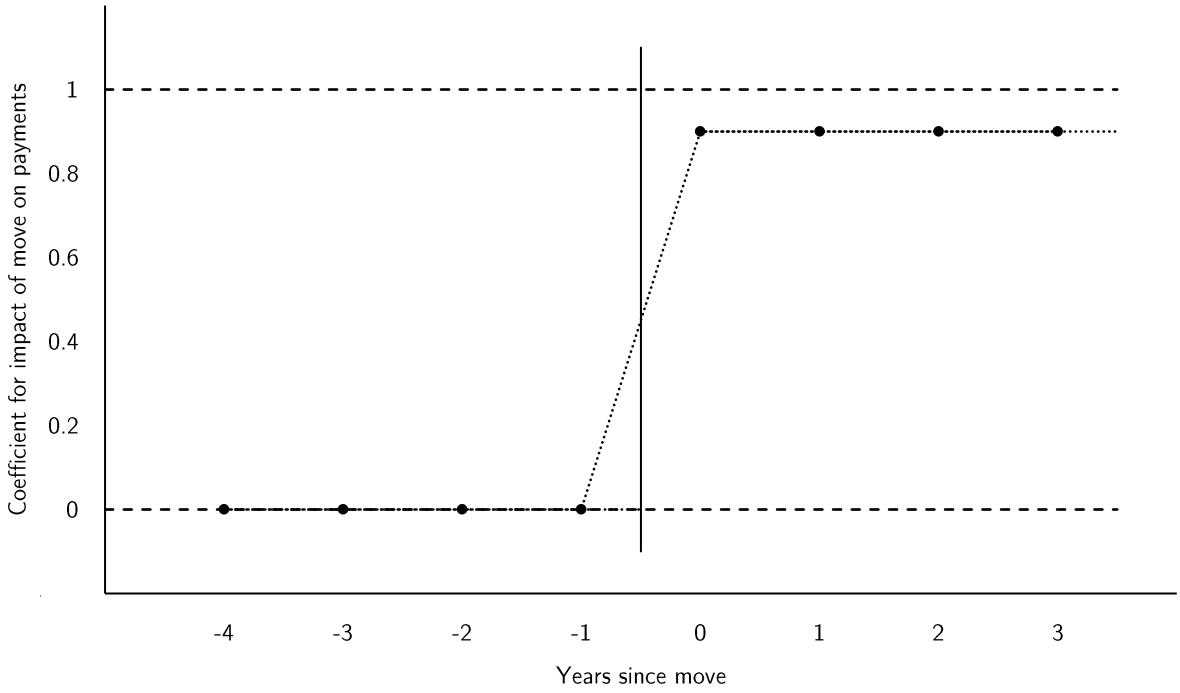

Figure A.5. Predicted movers impact coefficients for four years pre- and post-move where environmental effects dominate individual effects.

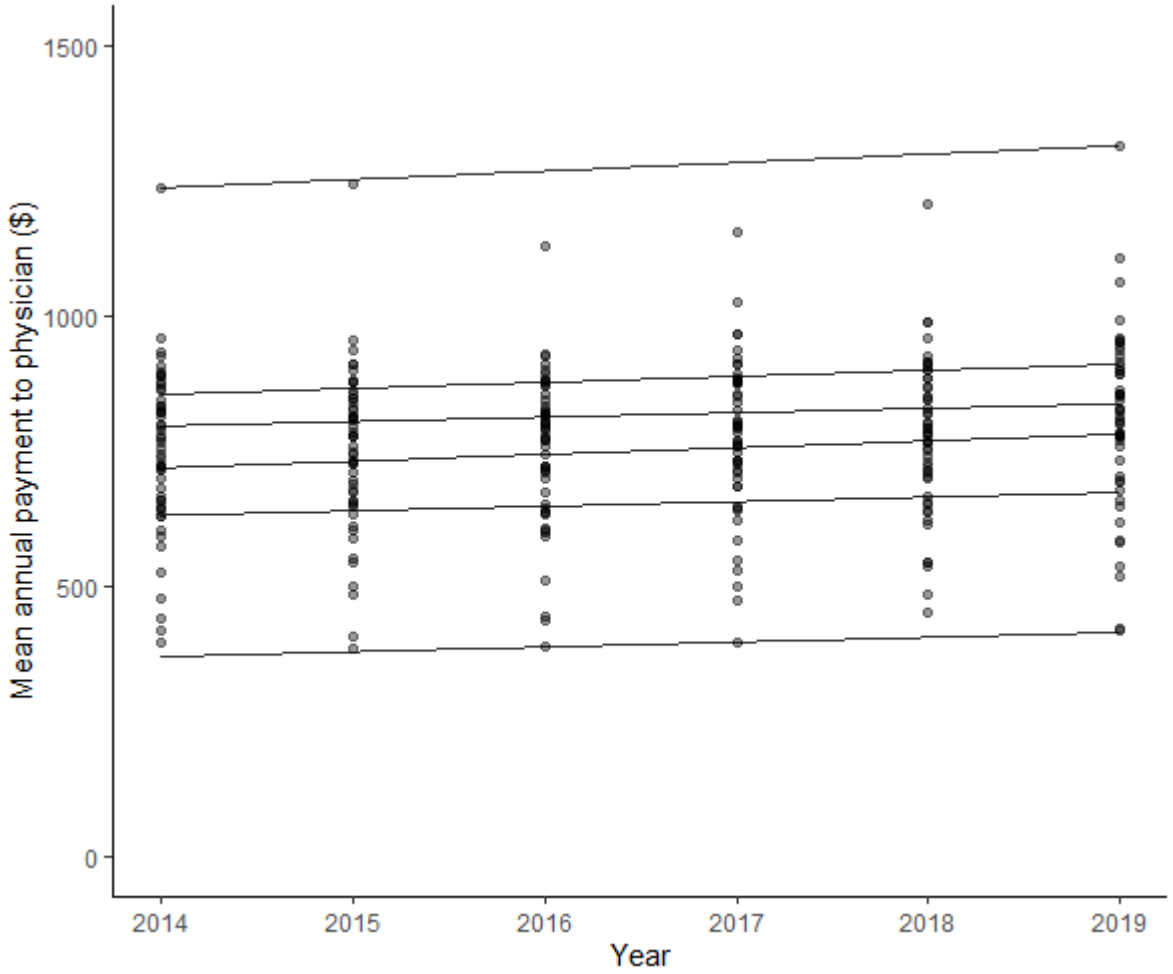

Figure A.6. Average total payments accepted by physicians for each US state. Trend lines correspond to quantiles in increments of 0.2.