

# Do New Patients Displace Existing Patients' Treatment?\*

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## Abstract

This paper estimates the effect of a physician's number of registered patients ("enrollment") on short-run treatment intensity in the context of Norwegian primary care. I instrument for enrollment with quasi-random administrative patient assignments. The estimated effect of enrollment is negative but small for several measures of treatment intensity. For example, with one new patient registration, the average physician spends 3 fewer minutes per month across incumbent patients. Descriptive evidence suggests that crowd-out exacerbates undertreatment. Crowd-out is larger among physicians who reach their stated capacity, initially work part-time, or earn higher reimbursement rates. Drawing on a model of physician decision-making, this heterogeneity implies that capacity constraints dominate income effects in explaining crowd-out. With capacity constraints, increasing the number of physicians may more effectively reduce crowd-out than incentives for greater treatment per physician. Fixing physician supply, an alternative patient assignment rule could reduce crowd-out from administrative assignment by 88 percent.

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# 1 Introduction

Healthcare policy interventions often target the supply of physicians, underpinned by the assumption that physicians who take on too many patients may deliver an inadequate amount (“intensity”) of treatment. For example, regulatory bodies impose patient limits on physicians, and governments incentivize entry into underserved and less profitable areas. The assumption aligns with economic theory, which predicts that an increase in a physician’s workload could lead to a decrease in patients’ treatment intensity, due to time constraints or stronger incentives for leisure. Suggestive evidence reinforces the theoretical prediction: health outcomes tend to be worse in areas with more patients per physician (Macinko, Starfield and Shi, 2007; Chang, O’Malley and Goodman, 2016; Falcettoni, 2018; Vallejo-Torres and Morris, 2018; Basu et al., 2019).

However, due to the challenges of causal inference, evidence is limited on whether increasing the number of patients per physician impacts treatment or damages health. Related correlations may be biased because unobserved factors likely influence the equilibrium number of patients per physician. For example, patients with worse health may live in areas that are less attractive to physicians. Within an area, patients may choose to receive treatment in greater numbers from relatively high-quality physicians.

In this paper, I estimate the effect of a primary care physician’s number of registered patients (“enrollment”) on short-run treatment intensity. I find that enrollment lowers several measures of treatment intensity, but this crowd-out effect is economically small. I present a model of physician decision-making to illustrate competing explanations for crowd-out: capacity constraints and income effects. Building on the model, heterogeneity across physicians suggests that capacity constraints dominate. Consequently, increasing the number of physicians may reduce crowd-out more effectively than incentives for existing physicians to increase treatment. I contextualize findings by bounding the effects of counterfactual registration policies on treatment intensity and introducing suggestive evidence that crowd-out exacerbates undertreatment.

Norway’s institutional features are ideal for isolating exogenous variation in enrollment from potential confounding factors. First, Norwegian municipalities often automatically reassign patients from physicians exiting the market to nearby physicians. Auto-reassignment is quasi-random, so the resulting changes to enrollment are plausibly independent of patient health and physician quality. The mechanical increase in enrollment from auto-reassigned patients is compounded by the fact that other patients in the same region suddenly must choose among fewer nearby physicians. Both mechanisms result in a

persistent increase in nearby physicians' enrollment. Second, Norway's registration system encourages long-term patient-physician relationships, which allows me to create a large balanced panel of patients. With a balanced panel, I can control for persistent heterogeneity and make relatively weak assumptions about patient composition and unobserved determinants of health. With an unbalanced panel, average treatment intensity may vary due to the idiosyncratic health of others joining or leaving the physician, leading to biased estimates. Third, national agreements dictate an identical reimbursement schedule for physicians, ruling out confounding variation in treatment intensity from financial incentives. In other contexts, physicians with greater enrollment may be able to negotiate higher reimbursement rates, which in turn incentivize greater treatment intensity and attenuate estimates. Fourth, virtually all of Norway's primary care physicians and residents are part of the country's universal public healthcare system, so the design of the registration system can have far-reaching consequences for health and public expenditure. Moreover, the scale of administrative data provides the statistical power to estimate even small effects, particularly for subsamples to test model predictions, e.g., part-time physicians or chronically ill patients.

I estimate the effect of enrollment on short-run treatment intensity using two-stage least squares, instrumenting for enrollment with the number of auto-reassigned patients. Each observation is a physician's aggregate monthly treatment intensity among incumbent patients. I find suggestive evidence supporting the exclusion assumption that auto-reassignments' timing and size are independent of factors determining changes to existing patients' health that are specific to a physician. First, the composition of nearby physicians' patients does not predict the number of auto-reassigned patients, conditional on availability, municipality, and at least one auto-reassigned patient. Second, prior to auto-reassignment, trends in incumbents' treatment intensity are uncorrelated with the number of auto-reassigned patients. Third, consistent with monotonicity and relevance assumptions, auto-reassignment shifts the entire distribution of enrollment increases relative to other months. To minimize threats to identification, I include fixed effects for each physician, calendar month, and event month.

I find that an increase in enrollment results in no more than a small decrease in several measures of primary care treatment intensity among incumbent patients in the short run. For example, one new patient registration results in 3 fewer minutes of encounters among all incumbent patients. This small decrease is consistent across subsets of patients and physicians and across alternative specifications. Physicians leave revenue unchanged by replacing high-value services like diagnostics and procedures with high-reimbursement services. When including both incumbents and new patients, I do not find evidence of a net change in physicians' treatment intensity. Physicians lower treatment intensity among

incumbent patients just enough to meet the needs of new patients. Fixed aggregate treatment intensity is most consistent with capacity constraints.

Heterogeneity in the effect of enrollment on physician hours helps distinguish between the mechanisms of income effects and capacity constraints. First, physicians who reach their stated capacity experience larger crowd-out effects. Second, physicians with greater marginal revenue have larger crowd-out effects, consistent with a combination of binding capacity and concave preferences over wealth. Third, part-time physicians have larger crowd-out effects. Given other findings, this heterogeneity suggests that capacity constraints are idiosyncratic and physicians with lower capacity select into part-time work. Descriptive evidence is consistent with idiosyncratic constraints among a fraction of physicians: for a small number of physicians, over ten years, weekly hours bunch near a physician-specific maximum.<sup>1</sup>

Capacity constraints suggest that increasing the supply of physicians would most reduce crowd-out. However, with large fixed costs of physician entry and small crowd-out effects, such a policy may not be cost-effective. Also, Norway’s current policy limiting maximum enrollment may not have meaningful impacts on treatment intensity, because crowd-out effects are largest among low-workload physicians. To illustrate the limitations of a fixed supply of physicians, I explore the implications of a counterfactual registration policy. I simulate a new auto-reassignment rule for patients of departing physicians designed to minimize crowd-out. This exercise incorporates estimated heterogeneity in predicted crowd for combinations of patient and physician characteristics. Relative to status quo random assignment, targeted assignment can eliminate 88 percent of the crowd-out from status-quo auto-reassignment. However, without evidence that baseline treatment intensity is too low, I cannot conclude that it is efficient to limit crowd-out.

I contextualize findings with three stylized facts. First, incumbent patients in the analysis sample have lower initial treatment intensity and higher avoidable hospitalizations than observably similar patients in the full population (5 percent of the mean). Crowd-out effects increase that gap. Second, prior survey evidence suggests that both patients and physicians consider treatment intensity to be too low. Third, national statistics show that treatment intensity is low in Norway relative to most OECD countries.

This paper contributes to several branches of literature studying disruption effects in healthcare. First, I extend well-documented disruption effects in emergency care (Jena et al., 2017; Gruber, Hoe and Stoye, 2018; Hsia and Shen, 2019; Hoe, 2022) to the less-studied context of primary care. Representing a third of physicians in Norway, primary care physicians deliver the bulk of diagnoses, basic procedures,

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<sup>1</sup>By contrast, the distribution of physician labor supply does not bunch near a shared limit, e.g., 60 hours per week.

and chronic disease management, with large impacts on patient health, specialist referrals, and total healthcare spending. Second, I estimate the effect of a persistent shock to workload, rather than a temporary disruption (Shurtz et al., 2018; Harris, Liu and McCarthy, 2020; Freedman et al., 2021; Kovacs and Lagarde, 2022), and point to a different mechanism behind disruption effects. Variation from persistent shocks may have stronger external validity for answering the central policy question of whether health systems have a sufficient supply of physicians. Other persistent shocks are relatively difficult to study due to simultaneous changes to incentives, e.g., insurance expansions (Garthwaite, 2012; Carey, Miller and Wherry, 2020). Third, I complement studies of physician exit by measuring impacts on the patients of nearby physicians. Prior work focuses on the patients of departing physicians (Kwok, 2018; Fadlon and Van Parys, 2020; Bischof and Kaiser, 2021; Simonsen et al., 2021; Zhang, 2022; Sabety, 2023). Switching physicians disrupts care differently than workload shocks, e.g., new physicians may lack soft information from long-term relationships. I also show suggestive evidence of a limitation of this literature: patients’ choice of a new physician may be endogenous even if the timing of physician exit is exogenous. The few patients who make active choices experience a different trajectory of treatment intensity than those who are quasi-randomly reassigned.

The remainder of the paper proceeds as follows. Section 2 describes the empirical setting including identifying variation and data. Section 3 presents a model of physician-making and uses its comparative statics to guide the empirical strategy. Section 4 describes the baseline estimates of crowd-out, heterogeneity for subsamples of physicians and patients, and robustness. Section 5 discusses policy implications with suggestive evidence of status quo undertreatment and a counterfactual assignment rule. Section 6 concludes.

## 2 Background

### 2.1 Institutional Setting

Norway’s public healthcare system guarantees all residents access to a primary care physician. Norwegians frequently visit their physician – on average 2.5 times per year – for chronic disease management, consultations about symptoms, diagnostic tests, and general medical procedures, but also sick leave certification and referrals to specialists and non-urgent hospital care. Patients must be referred by physicians to specialists and non-emergency hospital visits. Norwegians may elect to purchase private health insurance to lower wait times for private specialists, but primary care nearly exclusively occurs within the

public system.

To facilitate access, Norwegian primary care is carefully regulated. First, the number of registered patients per physician must generally remain between 500 and 2500 (Lovdata, 2017). Second, national guidance states that patients should not wait more than five days for a consultation in most circumstances. Within these limits, physicians should prioritize the treatment of patients with the greatest health need. Third, Norway regulates the supply of primary care physicians through a fixed number of contracts in each municipality. Physicians may move across municipalities or retire, but the total number of contracts and the locations of practices are slow to change. Fourth, patients register with physicians through a centralized system. Patients can request a new physician twice each year, but switches are rare. Physicians must accept all new patients until reaching a maximum number of patients. This upper bound varies across physicians and infrequently changes. Physicians and municipalities must agree on the upper bound and weekly hours of operation to provide sufficient capacity for all nearby residents. Fifth, prices for healthcare services are generally fixed across physicians. Some prices change once per year when renegotiated between the regulator and the physicians' union. Physicians also receive a fixed fee for each registered patient. In heterogeneity analyses, I exploit one exception to fixed prices: physicians with additional training receive supplementary reimbursement per patient visit. Sixth, when registered physicians are unavailable, patients can receive treatment at primary care emergency centers, which are comparable to stand-alone urgent care centers in the United States. Patients can also seek second opinions from other physicians.

The identifying variation in this paper comes from administrative assignment, which occurs when an exiting physician ends his contract and no new physician accepts ownership of the patient list. Contracts typically end because the physician is retiring or moving to a different municipality. Exiting physicians provide the municipality with six months to find a replacement. In 30 percent of exits, no new physician accepts ownership of the list and the municipality notifies patients on the list that they might be reassigned. Approximately 10 percent of patients actively choose a new physician and the rest are administratively assigned. Patient reassignment is random among nearby physicians with enrollment lower than their upper bounds.<sup>2</sup> Appendix Table A.1 verifies that patient composition is conditionally uncorrelated with auto-reassignments. Appendix Figure A.2 illustrates the distribution of enrollment increases induced by auto-reassignments. Typically, auto-reassigned patients are divided among several physicians and each receiving physician grows by just a few patients. Municipalities do not have access

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<sup>2</sup>Administrative assignments frequently coincide with an increase in physicians' upper bound on enrollment. This increase may reflect renegotiation so that a municipality can satisfy requirements for capacity.

to patient characteristics when determining reassignment. 83 percent of auto-reassigned patients choose to stay at their assigned physician for at least six months. If auto-reassigned patients do not request a preferred physician, they may be auto-reassigned again to expand the patient list of entering physicians.

## 2.2 Data

The estimation sample is a balanced panel of physician-months in the six months before and after auto-reassignment. Outcomes reflect total treatment intensity among incumbent patients who are registered to physicians both before and after auto-reassignment. The panel structure helps attribute short-term changes in treatment intensity to sudden changes in enrollment rather than the composition of patients' underlying treatment need. I construct the sample using restricted administrative records on registration, individual demographics, and healthcare reimbursement, which are maintained by the Norwegian Directorate of Health and Statistics Norway.<sup>3</sup> These records contain nearly all of Norway's residents and primary care physicians from 2008 to 2017.

The estimation sample excludes potentially confounding variation. Each physician must practice only in one location during the entire period and each patient must be registered for the entire period. I also exclude physicians with fewer than 500 patients or with increasing reimbursement due to additional training. Both the physician and patient must have identification numbers to attribute treatment intensity to a particular physician of interest, which excludes recent migrants. I also exclude temporary replacement physicians and shared patient lists.

To assess pre-trends in treatment intensity before auto-reassignment, physicians must not receive auto-reassignments from exiting physicians in the six months before a focal auto-reassignment. Physicians may receive subsequent auto-reassignments during the following six months. Moreover, I restrict auto-reassignments to those coming from exiting physicians with a dissolved patient list of at least 20 auto-reassigned patients. On average, exiting physicians are 10 years older and 11 percentage points more male than the set of nearby physicians in the sample. I exclude physicians who immediately lower their enrollment upper bound. In these cases, incumbent patients might be auto-reassigned. This restriction reinforces that physicians in the sample experience a persistent increase in enrollment from auto-reassignment.

The final analysis sample reflects nearly one-third of patients. Appendix Figure A.3 shows that sample restrictions result in only negligible changes to the distribution of enrollment changes. The vast

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<sup>3</sup>See Appendix A.1 for additional details.

Table 1: Summary Statistics: Treatment Intensity per Physician

Variable	Mean	Std. Dev.	10th Percentile	Median	90th Percentile
Enrollment	1,262.00	354.23	811.00	1,237.50	1,710.00
Visits	372.61	211.04	51.00	370.00	642.00
Spending	10,837.85	26,126.46	1,035.83	10,146.45	17,828.48
Hours	103.25	42.86	45.34	108.16	152.69
Unusual	23.18	21.94	3.00	18.00	48.00
Follow-up Visits	110.30	74.44	22.00	102.00	204.00
Bill Lines	1,140.72	701.29	321.00	1,064.50	2,011.00
Diagnostics	72.52	88.66	9.00	52.00	152.00
Procedures	273.99	215.61	57.00	228.00	540.00
per Visit	740.58	442.04	231.08	701.17	1,288.52
Physicians	2,722				

*Notes:* Summary statistics reflect monthly totals six months prior to auto-reassignment. In Panel A, the unit of observation is an incumbent patient-month. In Panel B, the unit of observation is a physician-month. A patient or physician may appear more than once if they experience multiple auto-reassignment spells. All treatment intensity measures are restricted to primary care at the assigned provider. Spending (reimbursement) is measured in NOK. Minutes (encounter length) is the maximum number of minutes a consultation encounter could be based on reimbursement codes, e.g., 20, 35, 50, 65, etc.

majority of incumbents experience a negligible number of auto-reassigned patients joining their physician. 0.55 percent of patient-spells in the analysis sample receive at least 20 auto-reassigned patients.<sup>4</sup> For comparison, in more than half of patient-spells, only one auto-reassigned patient joins the physician. The final sample reflects 2,336,042 patients at 2,053 unique physicians. Table 1 shows the distribution of aggregate treatment intensity six months before new patients are auto-reassigned to the physician. Treatment intensity varies widely across physicians, and the median physician spends less than 40 hours per week with patients.

### 3 Research Design

#### 3.1 Conceptual Framework

To guide intuition about the treatment intensity effects of increased enrollment, I extend the model of physician decision making in Ellis and McGuire (1986). Distinguishing between mechanisms is important because disruption in treatment intensity due to income effects can be mitigated through reimbursement

<sup>4</sup>A patient-spell includes the six months before and after other patients are auto-reassigned to the same physician.



incentives with a fixed supply of physicians, while avoiding disruption due to capacity constraints may require increasing the supply of healthcare providers.<sup>5</sup>

Consider a physician who simultaneously chooses treatment intensity  $m_i$  for each registered patient  $i \in 1, \dots, N$ , given that patient's initial illness severity. The physician has additive preferences over net income, leisure, and health production. Each patient draws a random severity from a distribution  $\lambda_i \sim F$ . Importantly,  $F$  is independent of enrollment  $N$ . Health production  $h(m_i, \lambda)$  is a function that measures the value of health given each patient's initial severity and treatment intensity. Net income  $\sum_i \pi(m_i)$  and workload  $\sum_i m_i$  aggregate across patients, so the choice of  $m_i$  incorporates other patients' severity  $\lambda_{i'}$ . The physician's relative weight on health production is altruism  $\alpha$ . Functions  $u, \pi, h$  are strictly increasing and weakly concave, while distaste for workload  $l$  is strictly increasing and strictly convex. Finally, the physician has a capacity constraint on workload,  $\sum_{i'} m_{i'} \leq \bar{M}$ , with shadow cost  $\mu$ . The problem takes the form,

$$\begin{aligned} \max_{m_i \geq 0, \forall i \in 1, \dots, N} & u\left(\sum_i \pi(m_i)\right) - l\left(\sum_i m_i\right) + \alpha \sum_i h(m_i, \lambda) \\ \text{s.t.} & \sum_i m_i \leq \bar{M} \quad [\mu] \end{aligned}$$

with the following optimality conditions  $\forall i' \in 1, \dots, N$ ,

$$\begin{aligned} u'\left(\sum_i \pi(m_i)\right) \pi'(m_{i'}) - l'\left(\sum_i m_i\right) + \alpha h_m(m_{i'}, \lambda) + \mu &= 0 \\ \sum_i m_i &\leq \bar{M}, \end{aligned}$$

resulting in the optimal choice of treatment intensity  $m_i^*(\lambda_1, \dots, \lambda_N)$ .

If enrollment  $N$  exogenously increases and capacity is slack ( $\mu = 0$ ), then expected treatment intensity decreases through income effects. In expectation, new patients require some treatment, resulting in higher aggregate treatment intensity, which lowers leisure, weakly increasing the marginal utility of leisure and decreasing the marginal utility of net income. The physician responds by setting the loss in marginal health production equal to the loss in marginal utilities of net income and leisure. For each realization of severity  $\lambda$ , these changes unambiguously lower optimal treatment intensity for an incumbent patient. Enrollment only lowers treatment intensity in expectation because realized treatment intensity may

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<sup>5</sup>Perhaps a regulator can incentivize investments in increased capacity, but healthcare is labor-intensive with respect to high-skilled labor, technology investments are unlikely to change the fundamental tradeoffs, especially in the short and medium run.

increase due to idiosyncratic draws of  $\lambda$ .

Curvature of preferences results in larger decreases in treatment intensity, e.g., if the physician's initial workload is large. A physician with a relatively large initial workload has a high marginal distaste for incremental treatment intensity relative to leisure. When enrollment increases, any new treatment intensity from new patients has to be compensated by relatively large decreases in treatment intensity for incumbent patients. On the other hand, there is an ambiguous relationship between crowd-out and observed correlates of severity  $\lambda$ . If sicker patients benefit more from marginal treatment ( $\frac{d^2 h}{dm d\lambda} > 0$ ), then their crowd-out effects should be smaller.

The capacity constraint also drives incumbents' treatment intensity to decrease in enrollment. When the constraint binds, the total workload stays the same, so incremental treatment for new patients must correspond to lower treatment for incumbents. The distaste for the total workload is unaffected. With decreasing returns to wealth ( $u'' < 0$ ), incumbents' crowd-out will be larger when new patients are relatively profitable. Greater total profit corresponds to lower marginal incentives for treatment intensity. If capacity evolves gradually, a binding capacity constraint implies that no policy can fully counteract the short-run crowd-out effect of increased enrollment. By contrast, with slack capacity, income effects imply that well-targeted reimbursement incentives ( $\frac{d\pi}{dm}$ ) can mitigate crowd-out effects.

The intuition behind these comparative statics also holds with several extensions to the model. First,  $F$  can vary arbitrarily across patients and physicians. Second,  $u, \pi, l, \alpha, h$ , and  $\bar{M}$  can vary arbitrarily across physicians as long as they are unaffected when  $N$  exogenously changes. Third, physicians may choose treatment intensity sequentially in expectation over other patients' severity.

### 3.2 Empirical Strategy

To estimate the effect of enrollment on treatment intensity, I use two-stage least squares:

$$Y_{jt} = \beta_1 \widehat{\text{Enroll}}_{jt} + \beta_{e(j,t)} + \beta_j + \beta_t + \epsilon_{jt} \quad (1)$$

$$\text{Enroll}_{jt} = \gamma_1 \text{Auto}_{jt} + \gamma_{e(j,t)} + \gamma_j + \gamma_t + \varepsilon_{jt} . \quad (2)$$

Here,  $Y_{jt}$  is the outcome of interest, e.g., physician hours with incumbent patients, where subscript  $j$  indexes physicians,  $t$  indexes calendar months, and  $e$  indexes months relative to auto-reassignment ( $e = -6, -5, -4, \dots, 4, 5, 6$ ).<sup>6</sup>  $\text{Enroll}_{jt}$  is physician  $j$ 's total enrollment in month  $t$ , including remaining in-

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<sup>6</sup>I omit the fixed effect on  $e = -6$ , the first of each 13-month spell. Month fixed effects also absorb the fixed effect for  $e = 6$ .

cumbents and newly joined patients.  $\text{Auto}_{jt}$  reflects the cumulative number of patients auto-reassigned.<sup>7</sup>  $\beta_1$  is the coefficient of interest, representing the causal effect of increasing enrollment by one patient.  $\gamma_1$  represents the effect of one recently auto-reassigned patient on enrollment.  $\beta_j, \beta_t$  are fixed effects for physician-spell  $i$  and calendar month  $t$ , controlling for unobserved heterogeneity in average treatment intensity across patients and seasonality.<sup>8</sup>  $\beta_e$  residualizes trends in treatment intensity relative to auto-reassignment, absorbing general disruption effects of auto-reassignment.  $\epsilon_{jt}$  and  $\varepsilon_{jt}$  are random idiosyncratic errors. All regressions cluster standard errors by physician. The empirical strategy requires three identifying assumptions.

**EXCLUSION.** The exclusion assumption is that the number of auto-reassigned patients only affects incumbent patients' treatment intensity through the change in enrollment. In the econometric model, physician-spell fixed effects absorb time-invariant characteristics, and event-month fixed effects absorb physician-invariant trends from receiving auto-reassigned patients, so the timing and size of auto-reassignment must be independent of factors determining *changes* to incumbent illness severity that are specific to a physician, e.g., missed preventative care or a local viral outbreak.

Ginja et al. (2022) report that administrative assignment is conditionally random and show that assigned physicians' value-added does not correlate with reassigned patient characteristics. Godøy and Dale-Olsen (2018) and Markussen and Røed (2017) also argue that auto-reassignment is quasi-random, showing that auto-reassigned patient characteristics do not predict the change in propensity to approve sick leave between the downsizing and new physician. In particular, auto-reassignment is random conditional on availability and municipality, which are absorbed by physician-spell fixed effects. Appendix Table A.1 verifies that the number of auto-reassigned patients does not correlate with destination physician characteristics conditional on availability, a shared municipality, and the exiting physician. Fixed effects absorb any level differences in treatment intensity across physicians.

**RELEVANCE AND MONOTONICITY.** Auto-reassignments must strictly increase enrollment. Identifying variation for enrollment comes from the fact that auto-reassigned patients are joining rather than exactly replacing incumbent patients. The relevance assumption is directly testable through the first-stage F-statistic ( $F > 108$ ) for the baseline specification). Consistent with a mechanical increase in enrollment, the first stage coefficient is precise and indistinguishable from 1. Appendix Figure A.3 shows that auto-reassignments shift the full distribution of enrollment changes rightward. In months with auto-

<sup>7</sup>  $\text{Auto}_{jt}$  is similar to the interaction of post-treatment and treatment status in a difference-in-differences design, where  $\text{Auto}_{jt} = 0 \forall e(j, t) < 0$ . Sometimes, additional patients are auto-reassigned after event-month 0, in which case  $\text{Auto}_{jt}$  will increase.

<sup>8</sup> A physician-spell includes the six months before and after auto-reassignment for physician receiving auto-registrations.

reassignments, large enrollment increases become more likely and small increases (or decreases) become less likely.

## 4 Enrollment and Treatment Intensity

### 4.1 Baseline Results

Table 2 shows that enrollment lowers physician treatment intensity, but the effects are small. One additional patient lowers hours spent in incumbent patient encounters by 0.057, equal to 0.05 percent of the mean. Importantly, this crowd-out effect is shared among all incumbents. With average enrollment of 1262, each incumbent loses just 0.16 seconds of treatment per month. Bill lines, which reflect the count of distinct services, decrease by 0.472. Estimates for total reimbursement and patient visits are imprecise, but the confidence intervals rule out large decreases. Counterintuitively, the point estimate on spending is positive. Taken at face value, estimates suggest that enrollment affects the qualitative composition of treatment, replacing relatively low-reimbursement treatment with high-reimbursement alternatives. Columns (6)-(10) consider effects on subsets of treatment. Physicians perform fewer services per visit. Moreover, relative crowd-out is similar among high-value services like procedures and diagnostics. Hours outside of conventional shifts and follow-up visits also decline with enrollment. Finally, Column (1) shows that cumulative auto-reassigned patients is a relevant instrument for enrollment. The point estimate implies that one additional auto-reassigned patient increases enrollment by approximately 1.

By contrast, Table 3 fails to find evidence that enrollment lowers physician’s total labor supply. In this table, outcomes reflect the treatment intensity among all registered patients rather than only incumbent patients. Point estimates are generally small and imprecise, with confidence intervals ruling out large decreases. No effect on total treatment intensity would be consistent with the theoretical framework: physicians meet the needs of new patients by reducing the treatment intensity of existing patients. Both income effects and capacity constraints can explain the decrease among incumbents.

### 4.2 Heterogeneity and Mechanisms

Drawing on the comparative statics of the conceptual framework, physician heterogeneity helps distinguish income effects and capacity constraints as explanations for crowd-out. In this section, I focus on heterogeneity in the effect of enrollment on physicians’ total hours spent treating incumbent patients. Appendix Tables A.2, A.3, A.4, and A.5 show heterogeneity for the first-stage and other measures of

Table 2: Effect of Enrollment Among Incumbent Patients

	Enrollment (1)	Hours (2)	Bill Lines (3)	Spending (4)	Visits (5)
Cuml. Auto-Joins	1.079 (0.056) [<0.001]				
Enrollment		−0.057 (0.023) [0.014]	−0.472 (0.059) [<0.001]	0.704 (3.944) [0.858]	−0.029 (0.138) [0.832]
Dep. Var. Mean	1274.953	101.357	1126.667	10290.566	370.223
F-Statistic	108.086	3.081	8.687	2.124	1.841
Observations	35,381	35,381	35,381	35,381	35,381
	Unusual Hours (6)	Lines Per Visit (7)	Procedures (8)	Diagnostics (9)	Follow-ups (10)
Enrollment	−0.014 (0.007) [0.036]	−0.240 (0.057) [<0.001]	−0.039 (0.021) [0.058]	−0.093 (0.018) [<0.001]	−0.052 (0.016) [<0.001]
Dep. Var. Mean	22.942	728.213	70.887	270.519	135.079
F-Statistic	1.148	4.365	1.859	6.032	74.347
Observations	33,398	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equations 1 and 2. Each column represents a separate regression with the dependent variable as indicated in the table. The physician-month sample reflects aggregate treatment intensity among a fixed set of incumbent patients. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. "Cuml. Auto-Joins" indicates the number of patients auto-reassigned to a physician since the start of the spell. Regressions also include fixed effects for spell, calendar month, and event-month.

treatment intensity. First, columns (1) and (2) show that crowd-out is larger for physicians who have plausibly binding capacity. To proxy capacity, I divide the sample based on whether physicians reach 99 percent of their contracted upper bound on enrollment. For physicians near capacity, crowd-out is precise and similar in magnitude to the full sample. For physicians with slack capacity, the point estimate is positive and imprecise. The subsample with binding capacity has a greater average workload, so income effects could also explain the heterogeneity.

Second, columns (3) and (4) show that crowd-out is larger for high-fee physicians, which is consistent with a combination of binding capacity, relatively profitable new patients, and concave preferences over wealth. Over half of primary care physicians are certified as general practitioners, and certification entitles physicians to supplementary reimbursement for each patient visit. When capacity binds, physicians allocate time toward new patients by reducing the treatment intensity of incumbent patients. Such substitution should be even larger for high-fee physicians since marginal reimbursement for new patients may be higher than for incumbent patients. New patients may require more attention than existing

Table 3: Effect of Enrollment Among All Registered Patients

	Enrollment (1)	Hours (2)	Bill Lines (3)	Spending (4)	Visits (5)
Cuml. Auto-Joins	1.079 (0.056) [<0.001]				
Enrollment		−0.037 (0.052) [0.483]	−0.180 (0.283) [0.523]	6.096 (8.678) [0.482]	0.179 (0.327) [0.584]
Dep. Var. Mean	1274.953	133.327	1461.240	13164.059	474.616
F-Statistic	108.086	1.362	1.528	1.124	1.359
Observations	35,381	35,381	35,381	35,381	35,381
	Unusual Hours (6)	Lines Per Visit (7)	Procedures (8)	Diagnostics (9)	Follow-ups (10)
Enrollment	−0.016 (0.005) [<0.001]	−0.001 (0.001) [0.320]	−0.055 (0.044) [0.214]	0.010 (0.095) [0.918]	0.019 (0.068) [0.777]
Dep. Var. Mean	21.659	2.922	92.374	346.966	169.897
F-Statistic	1.697	0.640	1.739	1.741	79.168
Observations	35,381	33,398	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equations 1 and 2. Each column represents a separate regression with the dependent variable as indicated in the table. The physician-month sample reflects aggregate treatment intensity among all currently registered patients. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. "Cuml. Auto-Joins" indicates the number of patients auto-reassigned to a physician since the start of the spell. Regressions also include fixed effects for spell, calendar month, and event-month.

patients when physicians re-screen for illness.<sup>9</sup>

Third, columns (5) and (6) show that crowd-out is larger for part-time physicians which is inconsistent with symmetric income effects. I classify full-time status based on average hours worked before auto-reassignment. Part-time physicians have a lower initial workload, so greater crowd-out is surprising whether income effects or (symmetric) capacity constraints dominate. All else equal, with income effects, they should have a lower marginal taste for leisure and smaller crowd-out. Likewise, with a symmetric capacity constraint, e.g., 60 hours per week, capacity should be slack for part-time physicians, and crowd-out should be smaller or non-existent. To distinguish between these explanations, Appendix Figure A.4 plots the distribution of weekly hours. Although hours do not bunch near a global maximum (Panel A), hours sometimes bunch near a physician-specific maximum (Panel B). Taken together, this evidence suggests that, at least in the short run, physicians have idiosyncratic capacity constraints. Idiosyncratic

<sup>9</sup>Consistent with studies like Kwok (2018), Appendix Figure A.1 shows treatment intensity is greater after patients switch physicians.

Table 4: Heterogeneity in the Effect of Enrollment on Hours

	Reached Capacity		High Fee		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.005 (0.029) [0.851]	-0.059 (0.025) [0.016]	-0.047 (0.026) [0.067]	-0.085 (0.023) [<0.001]	-0.077 (0.008) [<0.001]	-0.023 (0.008) [0.003]
Subsample	X		X		X	
Dep. Var. Mean	94.503	107.540	84.562	113.259	78.095	113.788
1 <sup>st</sup> Stage F-Stat.	22.246	134.713	93.965	44.128	137.381	60.721
Observations	16,783	18,598	14,677	20,701	12,319	23,059
	Age 65+		Chronic Illness		Female	
	(7)	(8)	(9)	(10)	(11)	(12)
Enrollment	-0.045 (0.019) [0.018]	-0.012 (0.005) [0.006]	-0.038 (0.018) [0.037]	-0.019 (0.006) [<0.001]	-0.016 (0.006) [0.010]	-0.041 (0.017) [0.017]
Subsample	X		X		X	
Dep. Var. Mean	72.298	29.059	58.024	43.333	42.897	58.460
1 <sup>st</sup> Stage F-Stat.	108.086	108.086	108.086	108.086	108.086	108.086
Observations	35,381	35,381	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equation 2. Each column represents a separate regression among a subsample with the dependent variable as indicated in the table. Columns (1-6) reflect aggregate treatment intensity among all incumbent patients for subsets of physicians. Columns (7-12) reflect aggregate treatment intensity among subsets of incumbent patients. For example, Column (1) includes physicians with enrollment consistently less than 99 percent of initial stated capacity, and Column (2) includes all other physicians. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. High-fee physicians receive supplementary reimbursement for each visit due to a certificate from additional training. Full-time physicians treat patients for at least 6 hours per weekday, on average, during the six months prior to auto-reassignment. Regressions also include fixed effects for spell, calendar month, and event-month.

capacity constraints also rationalize the precise crowd-out among physicians that reach their stated capacity, which can be as low as 500 patients.

Finally, columns (7)-(12) show precise crowd-out among six subsets of patients. In each subset, outcomes reflect sums of treatment intensity among the indicated subset of incumbent patients. The sample still includes all physician-months in the sample. Crowd-out is smaller among older, chronically ill, and male patients. To the extent that such characteristics proxy for severity, this heterogeneity is consistent with marginal crowd-out less negatively impacting the health of low-severity patients.

### 4.3 Robustness

Table 5 shows that the effect of enrollment on hours is precise, small, and similar in magnitude across nine alternative specifications and samples. First, I add physician time-varying controls for stated capacity

and patient composition, e.g., the share age 65 or older and mean income. The coefficient is stable which further allays concerns about instrument validity. Second, I restrict the sample to physicians who receive the most auto-reassigned patients. Even with the small sample, the estimate is marginally precise. If auto-reassignment directly affected treatment intensity, then the estimate might change. Third, I remove fixed effects for the month relative to auto-reassignment. Fourth, I include fixed effects for calendar months rather than the month of date. Fifth, I exclude physicians who ever have less than 8 hours of treatment per month to address the possibility of intertemporal substitution. Physicians might respond to a temporary constraint in one month by increasing treatment intensity in another month. Sixth, for the same reason, I exclude the month of auto-reassignment and surrounding months. Seventh, I subset to physicians that have at least one avoidable hospitalization six months before auto-reassignment. Counterintuitively, crowd-out is larger despite incumbent treatment intensity being more salient. The larger estimate may reflect sample selection and regression to the mean after unusually high treatment intensity between hospitalization and auto-reassignment. Eighth, I use an alternative specification for the first stage which interacts total auto-reassignments with the number of months relative to auto-reassignment. Ninth, I weight observations by the number of patients because underlying treatment decisions are at the patient level and effects might correlate with baseline enrollment.

Table 5: Robustness of the Effect of Enrollment on Hours

		Estimate			Mean	F-Stat.	Obs.
(1)	Add Controls	-0.052	(0.028)	[0.061]	101.357	86.493	35,381
(2)	Top 5%	-0.053	(0.029)	[0.070]	96.738	74.393	2,155
(3)	Drop Event-Month	-0.060	(0.023)	[0.008]	101.357	321.150	35,381
(4)	Calendar Month	-0.061	(0.023)	[0.008]	101.357	114.135	35,386
(5)	Hours Always 8+	-0.051	(0.019)	[0.007]	110.673	61.862	30,454
(6)	Drop Middle Months	-0.068	(0.030)	[0.022]	101.034	55.275	27,215
(7)	Avoidable Hosp.	-0.087	(0.007)	[<0.001]	103.072	82.867	32,066
(8)	Alt. 1st Stage	-0.057	(0.023)	[0.015]	101.357	1918.249	35,381
(9)	Weighted	-0.065	(0.021)	[0.002]	101.357	94.628	35,381

*Notes:* This table displays estimates of coefficients from regressions that vary the specification in Equation 2. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. The other columns are the mean of the dependent variable, the first-stage F-statistic, and the number of observations (physician-months). Variations to the specification are not cumulative. Specification (1) adds controls, including stated capacity, system entry and exit, and average patient characteristics: age 65+, chronic illness, female, income, and disability benefit receipt. (2) subsets to spells with auto-reassignments per incumbent above the 95th percentile. (3) drops fixed effects for months relative to auto-reassignment. (4) includes fixed effects for calendar months, e.g., January, rather than every month. (5) subsets to spells during which physician total hours are always above 8 per month. (6) drops observations within 1 month of auto-reassignment. (7) subsets to spells that begin with at least one avoidable hospitalization. (8) Alt. 1st Stage uses an alternative specification: enrollment is a function of event-months interacted with the number of total auto-reassignments per incumbent during the 13-month spell. (9) weights observations by the number of incumbents.



## 5 Policy Discussion

The previous sections show that registration of new patients lowers the treatment intensity of existing patients. The effect is small overall but larger for low-severity patients, and idiosyncratic capacity constraints offer the best explanation. Going forward, I consider the policy implications of these findings. Section 5.1 explores whether crowd-out should be avoided. Several stylized facts suggest that baseline treatment intensity is low in Norway, so crowd-out may exacerbate undertreatment. To eliminate crowd-out, capacity constraints imply that incentivizing the entry of physicians would be most effective. However, such policies may be prohibitively expensive, so Section 5.2 bounds the effects of a costless intervention. Instead of randomly assigning patients of exiting physicians, Norway can target new patient-physician assignments with low expected crowd-out and eliminate 88 percent of the effect.

### 5.1 Broader Evidence of Undertreatment

Three pieces of evidence suggest that auto-reassigned patients inefficiently lower the treatment intensity of incumbent patients. First, I use data on the universe of Norwegian primary care utilization to compare the treatment intensity and health outcomes of incumbent patients in the analysis sample. Table 6 shows this comparison, using all Norwegian patient-months in 2015. The coefficient of interest is the mean difference for in-sample patient-months after flexibly controlling for month, age, sex, tenure, and chronic illnesses. Relative to a mean of 0.122 hours per month, in-sample patients receive 0.006 fewer hours of treatment. Fewer hours do not necessarily imply undertreatment, e.g., if out-of-sample patients receive too much treatment. Comparing health outcomes within Norway can alleviate this concern. Relative to a mean of 0.0034 avoidable hospitalizations, in-sample patients have 0.0002 more avoidable hospitalizations. Taken together, these associations highlight the potential for policy interventions to mitigate crowd-out of primary care treatment intensity and perhaps improve health outcomes.

Second, as shown in prior surveys, Norwegian residents are concerned about primary care undertreatment. Over 25 percent express dissatisfaction with the duration of consultations (Kjøllesdal et al., 2020). This number is quite large relative to treatment intensity. On average, only 20 percent of residents visit their registered primary care physicians each month. Likewise, despite national guidance requiring near-immediate access to physicians, 40 to 50 percent of patients are not satisfied with wait times for appointments (Bjertnæs et al., 2023; Kjøllesdal et al., 2020). Long wait times can lead to adverse health outcomes like avoidable hospitalizations when symptoms are not promptly addressed. With short

Table 6: Patients in Sample Experience Gap in Treatment Intensity

	Hours (1)	Avoidable Hosp. (2)
In-Sample	−0.006 (0.001) [<0.001]	0.017 (0.006) [0.002]
Dep. Var. Mean	0.122	0.345
F-Statistic	22.280	9.157
Observations	57,760,517	62,013,800

*Notes:* This table displays estimates of coefficients from regressions of the indicated dependent variable on an indicator for observations in-sample and fixed effects for each combination of month, 5-year age bin, sex, an indicator for recent registration, and indicators for primary and secondary chronic illnesses. The sample includes all patients in Norway for each month in 2015 and outcomes are patient-specific. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. Patient Hours are approximated by multiplying physician-level hours by the share of reimbursement. For Avoidable Hospitalizations, the coefficient, standard, error, and mean are all scaled up by 100.

appointments and long wait times, patients may receive inadequate specialist referrals: 25 percent of patients do not express satisfaction with referrals (Kjøllestad et al., 2020).

Likewise, Norwegian physicians express dissatisfaction about time spent with patients. Rosta, Aasland and Nylenna (2019) document declining overall job satisfaction, largely driven by increasing dissatisfaction with work hours, amount of responsibility given, and freedom to choose treatment methods. In focus groups, physicians express concern that their workloads are growing and large enough to cause issues for patient safety and physician motivation (Svedahl et al., 2019).

Third, as of 2019, average physician visits are much lower in Norway than OECD countries overall: 4.5 vs. 6.8 (Tikkanen and Abrams, 2020). If on average, patients in OECD countries receive appropriate treatment, then lower visits in Norway would be consistent with undertreatment. Cross-country evidence is more mixed when considering specific types of healthcare. Relative to population, fewer elderly residents are immunized but more women are screened for breast cancer. Avoidable hospitalizations from diabetes and hypertension are relatively low. Finally, although capacity constraints best explain crowd-out, it may be difficult for Norway to increase capacity by hiring additional physicians. Norway has among the highest physicians per capita: 4.8 per 100,000 vs. an average of 3.5.

## 5.2 Policy Counterfactual

Since current auto-reassignments crowd out incumbent patients' treatment intensity, and baseline treatment is relatively low, Norwegian policymakers might consider replacing random assignment with tar-

geted assignment. In this section, I show that targeted assignment can lower crowd-out by 88 percent.

First, I estimate crowd-out effects for four subsamples including both physician heterogeneity and patient heterogeneity. High-type physicians either work part-time at baseline or reach 99 percent of stated capacity with reassigned patients. High-type patients are younger than 65. Second, I use point estimates to predict counterfactual crowd-out.<sup>10</sup> For each auto-reassignment event, I only consider assignments to physicians in the same municipality. For each physician, crowd-out is a sum of effects among young and old patients.

For the counterfactual, I first ration auto-reassigned patients to the physicians with the lowest total crowd-out, until updated enrollment reaches 99 percent of stated capacity. When enrollment approaches stated capacity, crowd-out is higher. If physicians in the same municipality do not have enough spots, I assume remaining reassignments to other municipalities have the worst-case crowd-out. I compare aggregate predicted hours of crowd-out under this counterfactual to random assignment across available slots within a municipality.<sup>11</sup> With targeting, predicted crowd-out over ten years drops from 71,913 to 8,508 hours.

## 6 Conclusion

This paper provides causal evidence that new patients minimally crowd out the short-run primary care treatment intensity of existing patients. I leverage administrative assignment of new patients following provider exit that exogenously increases the size of existing patients' physicians. This finding implies that healthcare providers can shift along their labor supply curve without large frictions. In Norway, removing the regulated bounds on enrollment might allow highly demanded physicians to serve more patients without excessive declines in existing patients' treatment intensity. Likewise, existing subsidies for rural physicians through supplementary capitation may be justified. To minimize crowd-out, policymakers might consider linking subsidies to opening hours. If the finding holds in other institutional settings, policies like insurance expansions that increase the number of covered patients can increase healthcare access without resulting in large negative effects for the already-insured. However, estimates may not be informative in settings where patients' treatment needs already meet or exceed physicians' latent capacity.

Guided by a theoretical framework, heterogeneity in treatment effects suggests that idiosyncratic

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<sup>10</sup>I estimate imprecise positive point estimates for subsets with low crowd-out physicians. To be conservative, I treat these as zero reduction in hours per auto-reassigned patient.

<sup>11</sup>As before, I assume reassignments to other municipalities have the worst-case crowd-out.

capacity constraints best explain observed crowd-out. To contextualize estimated crowd-out effects, evidence from out-of-sample comparisons, patient and physician surveys, and cross-country comparisons suggest that baseline treatment intensity is low. As a result, policymakers may seek to increase treatment intensity, especially for incumbent patients of physicians with rising enrollment. Since idiosyncratic capacity constraints better explain crowd-out than income effects, expanding capacity by subsidizing physician entry may better reduce crowd-out than incentivizing existing physicians to work more hours. However, both policies may be quite costly relative to the small level of crowd-out. I show that replacing random auto-reassignment with targeted re-assignment can reduce crowd-out by 88 percent.

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## A Appendix

### A.1 Data Sources

I use several data sources to construct the estimation sample. The Norwegian Control and Payment of Health Reimbursements Database (KUHR) tracks reimbursement for outpatient claims organized at the level of bill line, i.e., reimbursement code, and identifies most patients and physicians. The Norwegian Patient Registry (NPR) is a database of reimbursement for inpatient claims organized at the level of encounter. I use ICD-10 and ICPC-2 codes from both sources to classify chronic illness. I identify avoidable hospitalizations following Table A1 from Page et al. (2007). Capitation payments come from a basic subsidy rate dataset. Various datasets from the Norwegian GP Registry identify spells when patients are registered to patient lists and when physicians are contracted to provide care to those patient lists. The physician-list dataset also identifies contract details: the maximum number of registered patients and indicators for shared lists and fixed-salary reimbursement. I use anonymous identifiers for physicians, lists, and patients to link datasets and convert spells into monthly panels. Patients' birth date, sex, disability payment receipt, and income come from tax records.

### A.2 Additional Tables and Figures

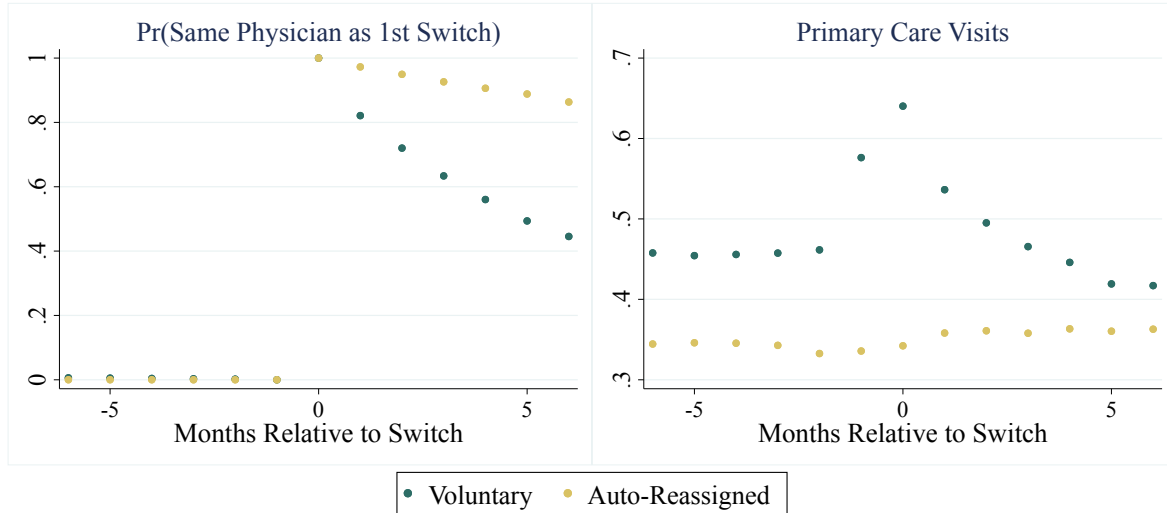
Figure A.1, Panel A shows that in every month after auto-reassignment, some auto-reassigned patients switch again to a third physician, but on average, 83 percent remain for at least six months, so auto-reassignment represents a persistent change in enrollment. For comparison, voluntary switchers are more likely to remain with their new physician, consistent with stronger preferences.<sup>12</sup> Panel B shows that auto-reassigned patients' average treatment intensity is higher after switching physicians, consistent with Kwok (2018), and potentially crowding out incumbents. Compared to auto-reassigned switchers, voluntary switchers have persistently higher treatment intensity, including a sudden large increase in the month before switching. Voluntary switchers' treatment intensity declines after switching but remains much higher than before, and the change in treatment intensity is larger than the change among auto-reassigned switchers. The different trajectories of voluntary and auto-reassigned switchers suggest that endogeneity from patient sorting is important in this context. Even if a health shock prompts voluntary switchers to find new physicians rather than wait to be auto-reassigned, they choose physicians that they

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<sup>12</sup>Voluntary switchers do not directly contribute to the identifying variation of this paper. However, they might choose the same physicians to which others are auto-reassigned.

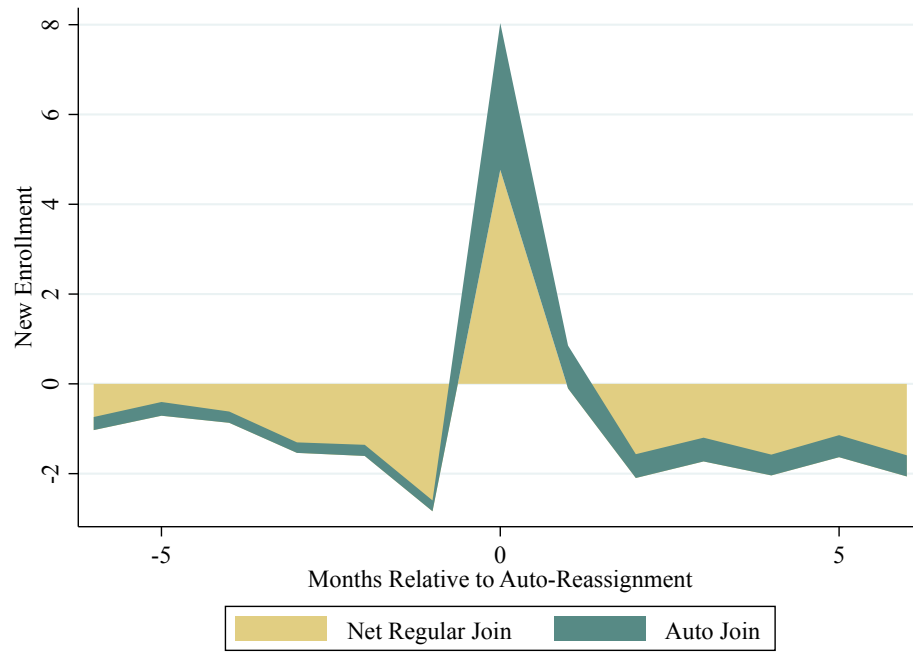
will remain with for longer and visit more often for at least six months. In the United States, patients of exiting physicians must all choose a new provider and the choice of provider likely incorporates unobserved determinants of treatment intensity like match quality even if the timing is exogenous. As examples of match quality, Kristiansen and Sheng (2022) show that low-SES patients assigned to a physician with a low-SES background have lower mortality, and Dahlstrand (2022) shows that matching high-risk patients to high-quality physicians lowers avoidable hospitalizations.

Figure A.1: Patients of Exiting Physicians: Voluntary Switches vs. Auto-Reassigned



*Notes:* Both panels reflect raw means among patient-months within 13-month spells, based on switching patients of exiting physicians whose spells are not necessarily balanced. For auto-reassigned patients, Month 0 is the first month after they are administratively reassigned to an incumbent's physician. For voluntary switching patients, Month 0 is the first month with a new physician, up to 5 months before their previous physician exits. The left panel shows the share of patients registered to their first physician after the previous one exited. The right panel shows average days per month with a physician encounter.

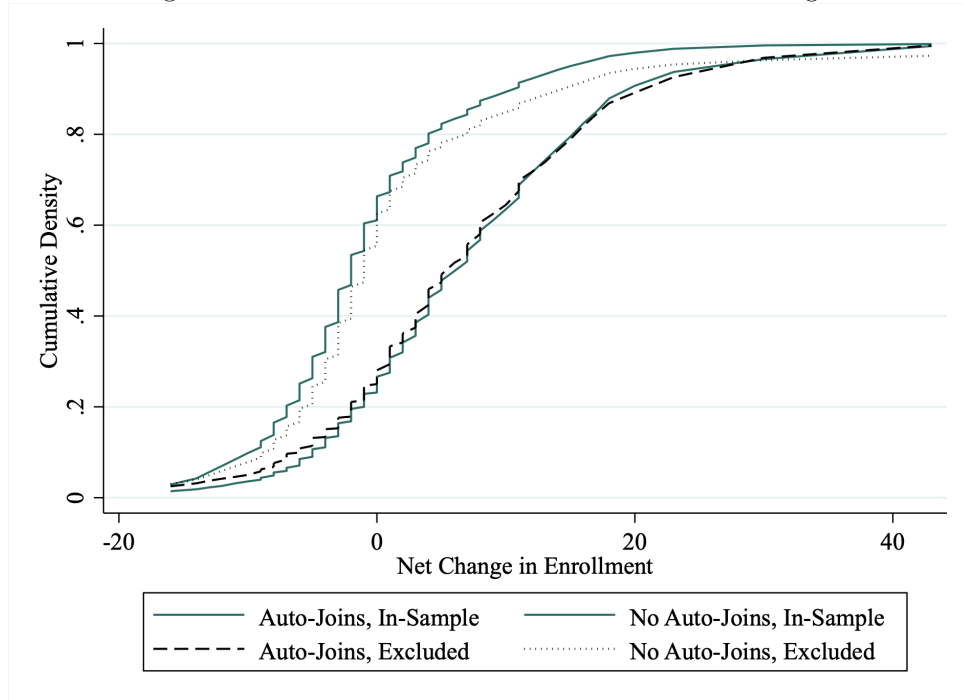
Figure A.2: Average Net Change to Enrollment



*Notes:* This figure decomposes the average one-month net change in enrollment between net regular joins and auto-joins. “Net Regular Join” is the average of the difference between patients that voluntarily leave and patients that voluntarily join. “Auto Join” is the average new registrations of patients that are administratively reassigned from other physicians. I average over physicians in the analysis sample in each month relative to the first auto-reassignment. Auto-reassignment in event-months -6 through -1 are from non-exiting physicians.

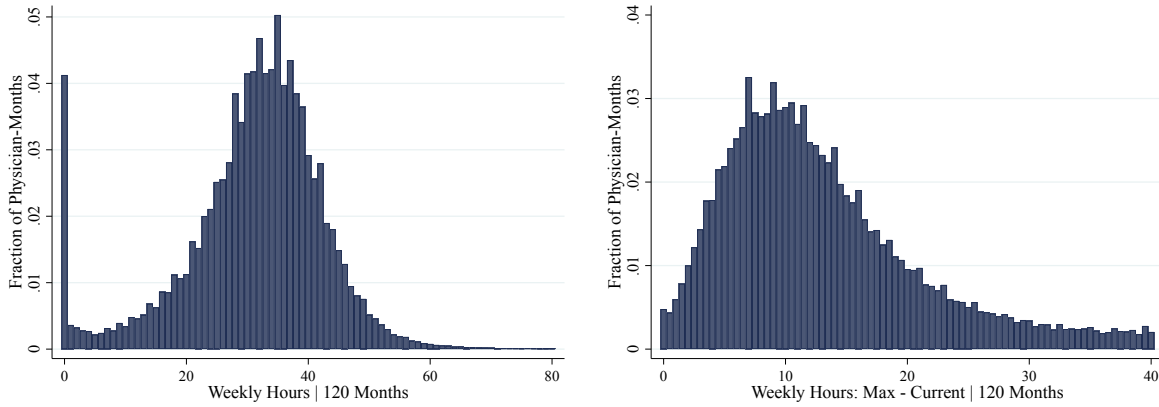


Figure A.3: Cumulative Distribution of Enrollment Changes



*Notes:* This figure shows the cumulative distribution of one-month changes in the number of patients for four subsamples of physicians. “Auto-Joins, In-Sample” includes months with any auto-reassignment to a physician in the analysis sample. “No Auto-Joins, In Sample” reflects other months in the analysis sample. Likewise, out-of-sample physician-months are split between the remaining two categories based on whether an auto-reassigned patient registered with the physician. Out-of-sample indicates with an out-of-sample physician or an out-of-sample month for an in-sample physician.

Figure A.4: Capacity Constraints and Bunching of Workload



*Notes:* Both figures reflect weekly hours for physicians observed for the full sample period, 2008–2017. Weekly hours equal hours per month divided by weeks per month. The left figure shows the untransformed distribution of weekly hours, truncated at 80 hours. The right figure shows the distribution of transformed weekly hours ( $\tilde{M}_{jt}$ ). The transformation is  $\max_t M_{jt} - M_{jt}$ . The x-axis is truncated at 40 and I exclude the first month when a physician works the maximum number of hours.

Table A.1: Test of Conditionally Random Assignment

	(1)	(2)
Availability	0.028 (0.007) [0.000]	0.027 (0.007) [0.000]
Same Municipality	10.542 (1.283) [0.000]	10.562 (1.288) [0.000]
Share Female		1.387 (1.138) [0.223]
Share Chronic		0.398 (1.097) [0.717]
Share Age 65+		-0.324 (0.761) [0.671]
# Observations	10,777	10,777

*Notes:* This table shows regressions of the number of auto-reassignments on the availability (maximum enrollment - lagged enrollment), an indicator for the physician residing in the same municipality as the exiting physician, fixed effects for the combination of the exiting physician and month of exit (not shown), and in column (2), average characteristics of incumbent patients. The unit of observation is a physician-month for physicians receiving auto-reassignments.

Table A.2: Heterogeneity in the Effect of Auto-Reassignment on Enrollment

	Reached Capacity		High Fee		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
Cuml. Auto-Joins	4.436 (0.805) [<0.001]	1.049 (0.039) [<0.001]	1.048 (0.039) [<0.001]	2.479 (0.519) [<0.001]	1.002 (0.028) [<0.001]	1.191 (0.114) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	1184.388	1356.589	1178.162	1343.490	1150.030	1341.655
F-Statistic	22.246	134.713	93.965	44.128	137.381	60.721
Observations	16,783	18,598	14,677	20,701	12,319	23,059
	Age 65+		Chronic Illness		Female	
	(7)	(8)	(9)	(10)	(11)	(12)
Cuml. Auto-Joins	1.079 (0.056) [<0.001]	1.079 (0.056) [<0.001]	1.079 (0.056) [<0.001]	1.079 (0.056) [<0.001]	1.079 (0.056) [<0.001]	1.079 (0.056) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	1274.917	1274.917	1274.917	1274.917	1274.917	1274.917
F-Statistic	108.086	108.086	108.086	108.086	108.086	108.086
Observations	35,381	35,381	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equation 1. Each column represents a separate regression among a subsample with the dependent variable as indicated in the table. Columns (1-6) reflect aggregate treatment intensity among all incumbent patients for subsets of physicians. Columns (7-12) reflect aggregate treatment intensity among subsets of incumbent patients. For example, Column (1) includes physicians with enrollment consistently less than 99 percent of initial stated capacity, and Column (2) includes all other physicians. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. High-fee physicians receive supplementary reimbursement for each visit due to a certificate from additional training. Full-time physicians treat patients for at least 6 hours per weekday, on average, during the six months prior to auto-reassignment. Regressions also include fixed effects for spell, calendar month, and event-month.

Table A.3: Heterogeneity in the Effect of Enrollment on Bill Lines

	Reached Capacity		High Fee		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.293 (0.363) [0.421]	−0.508 (0.067) [<0.001]	−0.376 (0.077) [<0.001]	−0.790 (0.383) [0.039]	−0.382 (0.074) [<0.001]	−0.484 (0.100) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	1032.220	1211.781	808.075	1352.378	792.171	1305.342
1 <sup>st</sup> Stage F-Stat.	22.246	134.713	93.965	44.128	137.381	60.721
Observations	16,783	18,598	14,677	20,701	12,319	23,059
	Age 65+		Chronic Illness		Female	
	(7)	(8)	(9)	(10)	(11)	(12)
Enrollment	−0.384 (0.043) [<0.001]	−0.088 (0.023) [<0.001]	−0.309 (0.037) [<0.001]	−0.163 (0.033) [<0.001]	−0.147 (0.028) [<0.001]	−0.325 (0.038) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	783.635	342.983	604.905	521.713	481.579	645.039
1 <sup>st</sup> Stage F-Stat.	108.086	108.086	108.086	108.086	108.086	108.086
Observations	35,381	35,381	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equation 2. Each column represents a separate regression among a subsample with the dependent variable as indicated in the table. Columns (1-6) reflect aggregate treatment intensity among all incumbent patients for subsets of physicians. Columns (7-12) reflect aggregate treatment intensity among subsets of incumbent patients. For example, Column (1) includes physicians with enrollment consistently less than 99 percent of initial stated capacity, and Column (2) includes all other physicians. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. High-fee physicians receive supplementary reimbursement for each visit due to a certificate from additional training. Full-time physicians treat patients for at least 6 hours per weekday, on average, during the six months prior to auto-reassignment. Regressions also include fixed effects for spell, calendar month, and event-month.

Table A.4: Heterogeneity in the Effect of Enrollment on Visits

	Reached Capacity		High Fee		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	0.145 (0.120) [0.229]	−0.040 (0.145) [0.784]	0.016 (0.147) [0.912]	−0.172 (0.122) [0.160]	−0.176 (0.029) [<0.001]	0.188 (0.043) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	333.035	403.749	296.502	422.449	253.378	432.644
1 <sup>st</sup> Stage F-Stat.	22.246	134.713	93.965	44.128	137.381	60.721
Observations	16,783	18,598	14,677	20,701	12,319	23,059
	Age 65+		Chronic Illness		Female	
	(7)	(8)	(9)	(10)	(11)	(12)
Enrollment	−0.005 (0.121) [0.964]	−0.024 (0.017) [0.164]	−0.011 (0.102) [0.910]	−0.018 (0.037) [0.628]	−0.005 (0.045) [0.905]	−0.024 (0.093) [0.798]
Subsample	X		X		X	
Dep. Var. Mean	261.166	109.045	212.759	157.451	155.912	214.298
1 <sup>st</sup> Stage F-Stat.	108.086	108.086	108.086	108.086	108.086	108.086
Observations	35,381	35,381	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equation 2. Each column represents a separate regression among a subsample with the dependent variable as indicated in the table. Columns (1-6) reflect aggregate treatment intensity among all incumbent patients for subsets of physicians. Columns (7-12) reflect aggregate treatment intensity among subsets of incumbent patients. For example, Column (1) includes physicians with enrollment consistently less than 99 percent of initial stated capacity, and Column (2) includes all other physicians. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. High-fee physicians receive supplementary reimbursement for each visit due to a certificate from additional training. Full-time physicians treat patients for at least 6 hours per weekday, on average, during the six months prior to auto-reassignment. Regressions also include fixed effects for spell, calendar month, and event-month.

Table A.5: Heterogeneity in the Effect of Enrollment on Reimbursement

	Reached Capacity		High Fee		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment	3.608 (3.255) [0.268]	1.117 (4.390) [0.799]	0.989 (3.952) [0.802]	9.818 (18.975) [0.605]	-1.888 (2.918) [0.518]	5.254 (1.264) [<0.001]
Subsample	X		X		X	
Dep. Var. Mean	9235.496	11241.954	7231.663	12458.075	7489.915	11786.823
1 <sup>st</sup> Stage F-Stat.	22.246	134.713	93.965	44.128	137.381	60.721
Observations	16,783	18,598	14,677	20,701	12,319	23,059
	Age 65+		Chronic Illness		Female	
	(7)	(8)	(9)	(10)	(11)	(12)
Enrollment	1.015 (3.489) [0.771]	-0.311 (0.552) [0.573]	0.673 (2.931) [0.818]	0.031 (1.039) [0.976]	0.530 (1.367) [0.698]	0.174 (2.638) [0.947]
Subsample	X		X		X	
Dep. Var. Mean	7348.125	2942.198	5778.016	4512.308	4465.767	5824.558
1 <sup>st</sup> Stage F-Stat.	108.086	108.086	108.086	108.086	108.086	108.086
Observations	35,381	35,381	35,381	35,381	35,381	35,381

*Notes:* This table displays estimates of coefficients from regressions of Equation 2. Each column represents a separate regression among a subsample with the dependent variable as indicated in the table. Columns (1-6) reflect aggregate treatment intensity among all incumbent patients for subsets of physicians. Columns (7-12) reflect aggregate treatment intensity among subsets of incumbent patients. For example, Column (1) includes physicians with enrollment consistently less than 99 percent of initial stated capacity, and Column (2) includes all other physicians. Standard errors clustered at the physician level are reported in parentheses, and p-values are reported in brackets. High-fee physicians receive supplementary reimbursement for each visit due to a certificate from additional training. Full-time physicians treat patients for at least 6 hours per weekday, on average, during the six months prior to auto-reassignment. Regressions also include fixed effects for spell, calendar month, and event-month.