# DO NON-COMPETES RESTRICT MOONLIGHTING FOR PHYSICIANS? EVIDENCE FROM POLICY CHANGES

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## Abstract

We study the effects of non-enforcement of non-compete agreements on the regional labor supply of physicians, exploiting statutory changes in Minnesota. We find two temporally distinct increases. The share of physicians moonlighting increased by 2.5 percentage points immediately after the non-enforcement, followed by later increases in the number of within-organization practice arrangements: 5.8 percent among early-career physicians and 7.9 percent among specialists. Overall, the number of healthcare services provided increased by 6.3 percent. Our findings suggest that relaxing regulatory barriers for the highly skilled regulated labor market would raise regional labor supply by increasing output at the intensive margin.

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# 1 Introduction

The regional labor markets for physicians are an important policy priority for the US healthcare system. Previous literature addressed the imbalance of physicians as a mounting issue, as the growth of labor supply does not meet the rapid increase in demand for healthcare services (Kirch and Petelle, 2017; Zhang et al., 2020). While increasing the overall number of physicians is not plausible in the short run, lowering the regulatory barriers to raise their regional labor supply is a viable option that many states have adopted (Deyo et al., 2024; Oh and Kleiner, 2025a).

One of these barriers in the healthcare industry is 'non-compete agreements (NCAs).' NCAs bind between 37% to 45% of physicians, which is substantially higher than other occupations and industries, which is around 18-20%. (McAdams, 2019; Robeznieks, 2023; Sherman et al., 2022). Furthermore, physicians are frequently regulated by other restrictions, such as 'no moonlighting clauses', restricting the practices of working a second job or engaging in freelance work outside one's primary employment. More than half of physicians face full or partial restrictions on moonlighting (Novinson and Kim, 2021). However, because physicians are exempt from the Fair Labor Standards Act – FLSA-exempt, not eligible for overtime pay – these clauses restrict their capacity to moonlight and thereby restrict the regional labor supply of physicians.

This study examines how non-enforcing NCAs increase the regional labor supply of physicians by evaluating a recent state-level policy change. Specifically, during July 2023, Minnesota changed its regulations on NCAs, which also apply to physicians. Using regional labor supply datasets from the Centers for Medicare & Medicaid Services (CMS), we compare Minnesota with Wisconsin, which has similar sociodemographic and economic characteristics. We find two temporally distinct increases in the regional labor supply of physicians after the new statutes are passed: first, by increasing moonlighting, and then by increasing within-organization practice arrangements. Overall, these changes in legislation increased the number of healthcare services provided, indicating an increase in the regional labor supply at an intensive margin.

Our study provides a significant contribution to employment relations and the broader economics literature. This is the first study providing evidence that non-enforcing NCAs can increase the regional labor supply not only by enhancing labor mobility but also by increasing the intensive margin of labor supply through additional employment opportunities. The workers that previous studies examined include those who are not FLSA-exempt. In addition to NCAs,

imposing no moonlighting clauses on FLSA-exempt workers restricts their work hours and reduces the production of goods and services. Our Nash bargaining model provides a theoretical explanation of how prohibiting NCAs – the 'post-job-separation' restrictions – increases employees' bargaining power, leading them to obtain permissions to moonlight: the removal of 'during-employment' restrictions. We also discuss employers' strategic response by 'internalizing' their employees' moonlighting, raising the regional labor supply by increasing the number of within-organization practice arrangements. Both moonlighting and additional within-organization practice arrangements increase the intensive margin of labor supply, and we provide empirical evidence supporting these predictions.

To preview our findings, we show that non-enforcing NCAs increased the share of physicians moonlighting by 2.5 percentage points immediately after the policy change, followed by an increase in the number of within-organization practice arrangements by 5.8 percent among early-career physicians and 7.9 percent among specialists. For both early-career physicians and specialists, we find increases in the overall number of work locations. We also find that the overall number of healthcare services provided increased by 6.3 percent. These results indicate an increase in the regional labor supply of physicians by increasing output at an intensive margin.

The remainder of this paper is organized as follows. In Section 2, we present a background of NCAs and the recent policy changes in Minnesota. In Section 3, we provide theoretical explanations for how prohibiting NCAs increases the regional labor supply. In Section 4, we explain the data, sample selection, and estimation procedures. In Section 5, we outline the results from the analyses and provide the implications of the results. In Section 6, we summarize our findings and policy implications and discuss the limitations and suggestions for future studies.

# 2 Non-Compete Agreements and Regulatory Changes in Minnesota

## 2.1 Influence of Non-Compete Agreements on Labor Market and Consumer Welfare

Non-compete agreements (NCAs) are employment contracts that restrict employees' ability to move to other competing employers or start competing businesses for a certain period of time after separation from employment (Starr, 2026). By restricting the mobility of employees, employers can ensure that the returns for their investment in employees are not given to their competitors, leading to an increase in the investment and thereby contributing to innovation (Marx

and Fleming, 2012). In addition, imposing this restriction helps screen out job applicants who are likely to job-hop, reducing employee turnover and hiring costs (Lavetti, 2021).

However, many studies point out how NCAs reduce labor market efficiency and social welfare. NCAs create a monopsonistic labor market where employers set wages below competitive wages (Gottfries and Jarosch, 2023; Johnson et al., 2025; Rothstein and Starr, 2022). In particular, low-wage workers are more vulnerable to these negative wage effects (Lavetti, 2021; Lipsitz and Starr, 2022). This reduces the production of goods and services and thereby raises the prices, and therefore, employers gain economic rents from both lower wages to their employees and higher prices for providing goods and services (Hausman and Lavetti, 2021; Lamadon et al., 2022; Lipsitz and Tremblay, 2024). Furthermore, some studies point out that the negative impact from reduced labor mobility is greater than the positive impact from increased investment in employees (Marx et al., 2009), and there is no leakage of information after job separations, one of the rationales of imposing NCAs (Cowgill et al., 2024; Greenwood et al., 2025).

Why do the NCAs matter in the healthcare sector? While 18–20% of workers in general are bound by NCAs (Federal Trade Commission, 2023; United States Government Accountability Office, 2023), a substantially larger proportion of physicians, ranging from 37% to 45% depending on surveys, are bound by NCAs (Lavetti et al., 2020; McAdams, 2019; Robeznieks, 2023). This implies that the magnitudes of impacts of NCAs on social welfare are substantially larger in the healthcare sector. Furthermore, NCAs in the sector that provide essential services yet historically suffer from labor scarcity due to other regulatory barriers, such as occupational licensing and scope of practice, would deteriorate consumer welfare by further deteriorating labor market efficiencies and production of services (Kleiner, 2000, 2015; Oh and Kleiner, 2025b). Recent studies provide empirical evidence on the negative impact of NCAs in the healthcare sector. Lavetti et al. (2020) showed that NCAs discouraged physicians from leaving current employers and bringing their patients to new hospitals, reducing consumers' choice. Hausman and Lavetti (2021) showed that higher enforceability of NCAs on physicians raises the prices of healthcare services.

### 2.2 Policy Changes in Minnesota

In May 2023, Minnesota passed Senate File 3035, which makes nearly all NCAs entered into on or after July 1st, 2023, unenforceable (Minnesota Legislature, 2023). In other words, employment contracts that are signed from July 1st, 2023, cannot enforce NCAs against employees. This means that employees who sign or renew their contracts after July 2023 are legally not

restricted from joining other employers after job separations, except for a few circumstances related to the business dissolution (Minnesota Legislature, 2024a). In addition to the non-enforcement of NCAs, Minnesota passed Senate File 3852 in 2024, which bans 'shadow' non-competes, including no-poach agreements that restrict employees' ability to seek or obtain employment with other employers (Minnesota Legislature, 2024b). By banning 'shadow' non-competes, employers' profit maximization strategies are limited to fewer options: at least do not include unlawful practices anymore[1]. Based on the theoretical and empirical evidence from previous literature, the expected impacts of these policy changes include increased labor mobility and wages that increase regional labor supply through hours worked and consumer welfare through higher quality services.

Yet, our study takes one more step to theorize and examine the changes in the regional labor supply of physicians. NCAs are the legal and regulatory barriers that are applied after job separations. However, a significant proportion of physicians are further limited in working for other healthcare providers during their employment due to no moonlighting clauses. Novinson and Kim (2021) show that more than half of physicians face full or partial restrictions on moonlighting. Because of being FLSA-exempt, no moonlighting clauses further limit healthcare practitioners' capacity to increase work hours and earnings during employment. We hypothesize that making NCAs unenforceable increases the regional labor supply of physicians in two ways, which both ways increase the intensive margin of labor supply: by increasing moonlighting through hours worked, and within-organization practices. In the next section, we provide theoretical explanations of our hypotheses.

## 3 Theoretical Framework

In this section, we explain how prohibiting NCAs increases the regional labor supply using theoretical models. We first explain how employees make their decisions on moonlighting. Then, we present the Nash bargaining model explaining how healthcare providers make their decisions on permitting their employees' moonlighting, before and after prohibiting NCAs. Lastly, we

[1] Minnesota strictly regulates employers for unlawful practices after their non-enforcement of NCAs. For instance, the Minnesota Attorney General's office initiated a formal investigation into Aspirus Health's regional hospital in Duluth, MN, for its unlawful pressure on employees to sign the contract that includes non-compete language, and the refusal to sign would be treated as a resignation (Graftaas, 2025). As the state government strictly regulates these actions, unlawful practices do not seem to be plausible strategies for employers, limiting employers' profit-maximizing strategies to lawful options.

discuss employers' strategic responses to the prohibition of NCAs: internalizing employees' moonlighting via increasing within-organization practice arrangements.

### 3.1 Preliminaries

Let employees (i.e., physicians) be indexed by $i = 1,2, \dots I$, and employers (i.e., healthcare providers) be indexed by $j = 1,2, \dots, J$. Each Employee $i$ provides one unit of labor supply if they work for one full-time position, but they can provide $h > 0$ additional labor supply to another employer $j'' \neq j$ via moonlighting if they are permitted and choose to moonlight. For simplicity, assume that $h$ is the same for all employees who moonlight. Thus, Employee $i$'s provision of labor supply is 1 if no moonlighting and is $1 + h$ if moonlighting.

The number of employees that Employer $j$ hires full-time is denoted by $n_j$. Employer $j$'s decisions on permitting moonlighting for its Employee $i$ is denoted by $o_{ij}$ where $o_{ij} = 1$ if permitting and $o_{ij} = 0$ if not permitting. Since the healthcare sector chronically suffers from labor scarcity, we assume the additional labor supply from moonlighting is fully employed by other employers. Therefore, the aggregated regional labor supply in the regional labor market, including both the full-time work schedule and moonlighting, can be denoted by $N = \sum_{j=1}^{J} n_j + \sum_{i=1}^{I} (o_{ij}) h$.

### 3.2 Employee's Problem

There are two sets of choices each employee makes. First, they choose whether to stay in their current positions (*stay*), move to another employer (*move*), or stop working (*stop*). If they choose to *stay* or *move*, then their utility depends on their wage and disutility from working. The wage from working for Employer $j$ is denoted by $w_j$. Disutility from working is denoted by $\delta(1, t)$ where 1 is the unit of labor supply provided by Employee $i$ working full-time and $t$ is the age of the employee. If they choose to *stop*, then their utility is not dependent on wages or disutility from working anymore but is zero. Then, the utilities of staying($u_{stay}$), moving($u_{move}$), and stopping $(u_{stop})$ can be expressed as follows:

$$u_{stay} = w_j - \delta(1, t)$$

$$u_{move} = w_{j' \neq j} - \delta(1, t)$$

$$u_{stop} = 0.$$

Note that $\frac{\partial \delta(1,t)}{\partial t} > 0$, implying that the disutility of working increases as employees get older and get closer to their retirement age, which is also positively correlated with the years of experience.

Second, employees choose whether to *moonlight* or not. The availability of this option is contingent on whether their employers permit it (i.e., $o_{ij} = 1$) or not (i.e., $o_{ij} = 0$). If they choose *moonlighting*, then their overall utility is equal to the sum of the two utilities: the utility from the first choice (*stay* or *move*) and the utility from *moonlighting*, denoted by $u_{moonlight}$, such that

$$u_{moonlight} = w_{j'' \neq j} h - \delta(h, t).$$

As they provide $h$ unit of labor supply from moonlighting, the wage from Employer $j'' \neq j$ is $hw_{j'' \neq j}$, a fraction of their full-time wage, and the disutility from providing $h$ unit of labor supply is $\delta(h, t)$. Assume that $\delta(1, t) + \delta(h, t)$ can be expressed as $\delta(1 + h, t)$.

Before prohibiting NCAs, moving to different employers is not permitted until the legal enforceability of the NCAs expires. Therefore, employees have three options – (a) *staying* without *moonlighting* ($u_{stay}$), (b) *staying* and *moonlighting* ($u_{stay} + u_{moonlight}$), and (c) *stopping* ($u_{stop}$) – and they choose the option that returns the highest utility. $u_{stop}$ can be the optimal utility if the utility gain from wages is less than the disutility of working. However, this is the case among the employees who retire or move to a part-time work schedule only (i.e., $t$ is sufficiently high and therefore does not prefer working full-time), as the disutility from working increases as employees get older (i.e., $\frac{\partial \delta(1,t)}{\partial t} > 0$). Thus, for simplicity, we assume that $u_{stop}$ is always the sub-optimal utility among the employees in this study.

If $o_{ij} = 0$, then $u_{stay}$ is the optimal utility, as employees cannot choose to do *moonlighting*, leading employees to have only one option: *staying* without *moonlighting*. If $o_{ij} = 1$, then the optimal utility is determined by the marginal utility gained from *moonlighting*:

$$\begin{cases} \text{if } w_{j'' \neq j} h > \delta(h, t) \ \rightarrow \ u_{stay} + u_{moonlight} \text{ is the optimal utility} \\ \text{if } w_{j'' \neq j} h < \delta(h, t) \ \rightarrow u_{stay} \text{ is the optimal utility.} \end{cases}$$

In other words, employees are willing to *moonlight* if additional earnings are large enough to compensate for the additional disutility from the increased work hours. As the earnings of healthcare practitioners are generally high, especially those who are more likely to sign NCAs, it is plausible that a substantial number of these employees prefer moonlighting. Furthermore, early-career employees are more likely to *moonlight* than late-career employees, as $\frac{\partial \delta(h,t)}{\partial t} > 0$.

After the prohibition of non-compete agreements, employees are now permitted to move to different employers without legal restrictions. Therefore, they now have two additional options in their utility maximization: (d) *moving* without *moonlighting* ($u_{move}$), (e) *moving* and

*moonlighting* ($u_{move} + u_{moonlight}$). This implies that the first choice (*stay* or *move*) depends on the wages offered by the current employer $j$ and a potential employer $j'$ ($w_j$ and $w_{j'\neq j}$, respectively). Employees choose to *move* if the potential employer offers a higher wage (i.e., $w_{j'\neq j} > w_j$) or the employment negotiation fails. Otherwise, they choose to *stay*.

The decision-making process of the second choice, whether to *moonlight* or not, after the policy change is the same as before the prohibition of NCAs; employees choose *moonlighting* if the utility gain from *moonlighting* is positive, and they do not otherwise. Yet, note that this is also subject to whether the current and/or potential employers permit moonlighting or not.

### 3.3 Nash Bargaining Model: Permitting Moonlighting?

We present a Nash bargaining model explaining how an employer makes decisions on permitting their employees' moonlighting before and after prohibiting NCAs (Rubinstein, 1982; Binmore et al., 1986; Gertler and Trigari, 2009). Our model is of a labor market where employees and employers negotiate wages and moonlighting options. Employees choose the option that maximizes their utilities. Employers choose the wage and permission on moonlighting, depending on which choice yields the maximum profit.

Employer's revenue from hiring one full-time employee is equal to the price of healthcare services produced by this employee, which can be expressed as a function of an aggregated regional labor supply, denoted by $P(N)$. $P(N)$ is also a marginal revenue product, because the employer gains the revenue of $P(N)$ by hiring one additional employee and thereby producing one additional unit of healthcare services. Note that $\frac{\partial P(N)}{\partial N} < 0$; the price of healthcare services decreases as more services are produced by more employees being hired. Also, note that the employer's revenue from hiring one moonlighting employee is $hP(N)$, as this employee provides only $h$ unit of labor supply. The cost of hiring one full-time employee is equal to the wage of hiring one full-time employee. For simplicity, in this model, we assume that employers are perfectly certain about employees' productivity, and therefore the per-unit wage offers for each employee are the same across all employers, including moonlighting (i.e., $w_j = w_{j'\neq j} = w$)[2].

[2] The compensation for moonlighting is usually higher than that for regular clinical work because moonlighting lacks some employee benefits, such as retirement pension and employer-provided health insurance, and is usually done at night and weekends (Bork, 2025; Chelle Law, 2025; CM&F Group, 2024). If we account for this, then our model would show even stronger evidence that prohibiting NCAs increases moonlighting. Yet, for simplicity, we assume an equal per-unit wage.

Employee $i$ and Employer $j$ split the joint surplus by Nash bargaining over the monetary wage/cost $w$. Let $\beta$ denote the Nash bargaining weight for Employee $i$ negotiating with Employer $j$ where $\beta \in (0,1)$, and $b$ be the employee's reservation utility that is equal to $u_{stop}$ before prohibiting NCAs and is equal to $\max\{u_{move}, u_{move} + u_{moonlight}(o_{ij'})\}$ after prohibiting NCAs. Then, the generalized utility function of Employee $i$ employed by Employer $j$ and willing to *moonlight* is denoted by

$$u_{stay} + o_{ij}u_{moonlight} = w\big[1 + h\big(o_{ij}\big)\big] - \delta\big(1 + h\big(o_{ij}\big), t\big),$$

and the employee surplus $S_i$ is denoted by

$$S_i = w\big[1 + h\big(o_{ij}\big)\big] - \delta\big(1 + h\big(o_{ij}\big), t\big) - b.$$

Employer $j$'s revenue from hiring one employee is $P(N)$, and the cost of hiring this employee is $w$. Then, the employer's total payoff from hiring Employee $i$ is denoted by

$$S_j = P(N) - w.$$

Given the payoffs from matching, we can express the Nash bargaining problem as follows.

*Statement.* The Nash bargaining problem maximizes the Nash product by Employer $j$ choosing wage and *moonlighting* permission:

$$\max_{w, o_{ij}} \big(w\big[1 + h\big(o_{ij}\big)\big] - \delta\big(1 + h\big(o_{ij}\big), t\big) - b\big)^{\beta} (P(N) - w)^{1-\beta}$$

$$\text{s.t.} \begin{cases} w\big[1 + h\big(o_{ij}\big)\big] - \delta\big(1 + h\big(o_{ij}\big), t\big) - b \geq 0 \\ P(N) + w \geq 0 \end{cases} \quad (1)$$

where $w\big[1 + h\big(o_{ij}\big)\big] - \delta\big(1 + h\big(o_{ij}\big), t\big) - b \geq 0$ and $P(N) + w \geq 0$ are the feasibility constraints.

### 3.3.1 Re-defining Surpluses

Assuming that the interior solution exists, we can obtain the function of wage $w$ by log-transforming the Nash product (1) and then solving for $w$:

$$w^* = \frac{\beta P(N) + (1 - \beta)\Big(b + \delta\big(1 + h\big(o_{ij}\big), t\big)\Big)}{1 + (1 - \beta)h\big(o_{ij}\big)}. \quad (2)$$

The derivation of Equation (2) is provided in Appendix A. Then, we can rewrite the employee surplus $S_i$ and employer surplus $S_j$ using Equation (2) as

$$S_i = \frac{\beta\Big[P(N)\Big(1 + h\big(o_{ij}\big)\Big) - \Big(b + \delta\big(1 + h\big(o_{ij}\big), t\big)\Big)\Big]}{1 + (1 - \beta)h\big(o_{ij}\big)} \quad (3)$$

$$S_j = \frac{(1-\beta)\left[P(N)\left(1+h(o_{ij})\right)-\left(b+\delta(1+h(o_{ij}),t)\right)\right]}{1+(1-\beta)h(o_{ij})}. \quad (4)$$

The derivations of these surpluses are provided in Appendix A. Give these surpluses for the employee and employer, the total surplus $S$ is

$$S_{total} = S_i + S_j = \frac{P(N)\left(1+h(o_{ij})\right)-\left(b+\delta(1+h(o_{ij}),t)\right)}{1+(1-\beta)h(o_{ij})}.$$

### 3.3.2. Healthcare Provider's Decision Making: Whether to Permit Moonlighting or Not

Given the total surplus $S_{total}$, suppose Employer 1 tries to maximize the surplus by choosing whether to permit moonlighting or not, denoted by $o_{i1}^*$, with respect to the decisions of competing employers $j' = \{2,3,\dots,\zeta,\zeta+1,\zeta+2,\dots,J\}$:

$$o_{i1}^* \in \underset{o_{i1}}{\operatorname{argmax}} S_{total} = \underset{o_{i1}}{\operatorname{argmax}} \frac{P(N)\left(1+h(o_{i1})\right)-\left(b+\delta(1+h(o_{i1}),t)\right)}{1+(1-\beta)h(o_{i1})}.$$

Suppose, except Employer 1, the employers permitting moonlighting are indexed by $j^1 = \{2,3,\dots,\zeta\}$, and those not permitting moonlighting are indexed by $j^0 = \{\zeta+1,\zeta+2,\dots,J\}$. Then, the aggregated regional labor supply $N$ subject to Employer 1's decision $o_{ij}$ can be expressed as

$$\begin{cases} N_0 = \sum_{j=2}^{J} n_j + \sum_{k=2}^{\zeta} hn_k + n_1 = \sum_{j=1}^{J} n_j + \sum_{k=2}^{\zeta} hn_k & \text{if } o_{ij} = 0 \\ N_1 = \sum_{j=2}^{J} n_j + \sum_{k=2}^{\zeta} hn_k + (1+h)n_1 = \sum_{j=1}^{J} n_j + \sum_{k=1}^{\zeta} hn_k & \text{if } o_{ij} = 1 \end{cases}$$

where $N_0 < N_1$. Because $N_0 < N_1$, $P(N_0) > P(N_1)$ is true as $\frac{\partial P(N)}{\partial N} < 0$. Then, the total surpluses subject to Employer 1's decision $o_{ij}$ are

$$\begin{cases} S_{total}^{o_{i1}=0} = P(N_0) - \left(b+\delta(1,t)\right) & \text{if } o_{i1} = 0 \\ S_{total}^{o_{i1}=1} = \dfrac{P(N_1)(1+h) - \left(b+\delta(1+h,t)\right)}{1+(1-\beta)h} & \text{if } o_{i1} = 1 \end{cases}. \quad (5)$$

Employer 1 does not permit moonlighting if $S_{total}^{o_{i1}=0} > S_{total}^{o_{i1}=1}$. In other words,

$$\frac{1}{(1-\beta)h}\left[(1+h)\left(P(N_0)-P(N_1)\right)-\beta hP(N_0)+\delta(h,t)\right] > b+\delta(1,t), \quad (6)$$

and conversely, Employer 1 permits moonlighting if $S_{total}^{o_{i1}=0} < S_{total}^{o_{i1}=1}$. The derivation of Inequality (6) is provided in Appendix A.

### 3.3.3 Implications: How Do Non-Enforcing Non-Competes Change Employer's Decision?

As Inequality (6) shows, Employer 1's decision on permitting moonlighting is contingent on the sum of reservation utility and disutility from working (i.e., $b + \delta(1,t)$) that depends on the enforceability of NCAs and employee preference. Let the left-hand side of Inequality (6) be denoted by $LHS$. Then, we can use this inequality to express the probability that Employer 1 permits moonlighting (i.e., the probability that $S_{total}^{o_{ij}=0} < S_{total}^{o_{ij}=1}$ is true) as

$$P(o_{i1}^* = 1) = P\left(S_{total}^{o_{ij}=0} < S_{total}^{o_{ij}=1}\right) = P\big(LHS < b + \delta(1,t)\big).$$

Before prohibiting NCAs, the reservation utility $b$ is zero (i.e., $b = u_{stop} = 0$). Therefore,

$$P\big(LHS < b + \delta(1,t)\big) = P\big(LHS < \delta(1,t)\big). \quad (7)$$

After prohibiting NCAs, the reservation utility is determined by an employee's preference for moonlighting and the competing healthcare provider $j'$'s decision on permitting moonlighting. If Employer $j'$ does not permit moonlighting, then the reservation utility $b$ is $u_{move} = w - \delta(1,t)$ where $w > \delta(1,t)$. Therefore, the probability that Employer 1 permits its employees' *moonlighting* after prohibiting NCAs can be expressed as

$$P\big(LHS < b + \delta(1,t)\big) = P(LHS < w),$$

and the comparison with Equation (7) shows that

$$w > \delta(1,t) \Leftrightarrow P(LHS < w) > P\big(LHS < \delta(1,t)\big) \quad (8)$$

If Employer $j'$ permits moonlighting, then the reservation utility $b$ is $u_{move} + u_{moonlight} = w(1+h) - \delta(1+h,t)$ where $w(1+h) > \delta(1+h,t)$. Thus, the probability that Employer 1 permits its employees' *moonlighting* after prohibiting NCAs can be expressed as

$$P\big(LHS < b + \delta(1,t)\big) = P\big(LHS < w(1+h) - \delta(h,t)\big),$$

and the comparison with Equation (7) shows that

$$w(1+h) - \delta(h,t) > \delta(1,t) \Leftrightarrow P\big(LHS < w(1+h) - \delta(h,t)\big) > P\big(LHS < \delta(1,t)\big). \quad (9)$$

Inequalities (8) and (9) show that the probability that Employer 1 permits *moonlighting* increases when NCAs become unenforceable, regardless of whether the competing healthcare provider permits moonlighting or not. Furthermore, this must be true for other employers who did not permit moonlighting to their employees before NCAs were prohibited (i.e., $j^0 = \{\zeta + 1, \zeta + 2, \dots, J\}$). Therefore, more employers would permit their employees' *moonlighting*, leading to an increase in moonlighting and thereby the intensive margin of labor supply of healthcare practitioners.

In summary, our theoretical models illustrate that prohibiting NCAs increases the regional labor supply of healthcare practitioners by increasing moonlighting. Other than negotiating for higher wages, increasing work hours via moonlighting is their only option to raise earnings. Non-enforcement of NCAs increases their negotiating power through having improved alternative options (i.e., the reservation utility $b$, indicating the potential to move to competing employers), leading to obtaining permissions to moonlight that directly increases the regional labor supply.

### 3.4 Employers' Strategic Response: Internalizing Employee Moonlighting

Our Nash bargaining model shows that employers are better off by permitting employees' moonlighting after non-enforcing non-competes regardless of their competing healthcare provider's decisions. On the other hand, we assume that employers hire moonlighting physicians who are working primarily for other healthcare providers, regardless of the policy change, due to the regional scarcity of physicians. Apart from engaging in unlawful practices – such as illegally enforcing NCAs or entering into no-poach agreements with competitors – employers can minimize their costs of hiring moonlighting physicians by 'internalizing' their employees' moonlighting. In other words, employers let their employees spend their moonlighting work hours at their other healthcare facilities, absorbing their employees' moonlighting work hours. From the employers' perspective, this strategy minimizes the cost of searching and hiring moonlighting physicians. From the employees' perspective, this minimizes the cost of searching for moonlighting positions and the loss from the mismatching of organization-specific job skills and knowledge.

Therefore, we theorize that we observe two increases after NCAs become unenforceable: moonlighting (i.e., increase in the number of employers) and within-organization practice arrangements (i.e., increase in the number of work locations affiliated with the same organizations). Because both permitting and internalizing moonlighting allow employees to work more, we hypothesize increases in the total number of work locations and the number of healthcare services provided after non-enforcing NCAs.

## 4 Data and Methods

In this study, we estimate the reduced-form effect of the non-enforcement of NCAs. We

select physicians in Minnesota as the treatment group and those in Wisconsin as the control group[3]. Previous studies have chosen these two states as treatment and control groups to examine the effect of various state-level policy changes. For instance, Fry et al. (2020) compared Hennepin County in Minnesota and Dane County in Wisconsin as a pair to estimate the effect of Medicaid expansion on recidivism. Keele and Minozzi (2013) compared Minnesota and Wisconsin to estimate the effect of Election Day registration on voter turnout. Wexler (2025) evaluated the impact of right-to-work laws on wages, employment, and business activities of union-dense industries by comparing Minnesota and Wisconsin. We carefully select the respondents and conduct robustness checks to obtain the estimates and test parallel trend assumptions.

### 4.1 Regional Labor Supply Measures

We mainly use two datasets from the Centers for Medicare & Medicaid Services (CMS) to examine the changes in the regional labor supply of physicians. First, we use the Doctors and Clinicians National Downloadable File 2022-2025, providing information about where each healthcare practitioner worked each month. Using each physician's unique identifier, the National Provider Identifier (NPI), we obtain three monthly measures: the number of employers in the primary states of practice for each physician, the number of work locations within the primary organizations that each physician works, and the total number of work locations regardless of each physician's primary organization. We identify physicians' main states of practice using Medicare Physician & Other Practitioners by Provider 2022. This data assigns healthcare practitioners to the states with the highest number of their Medicare Part B non-institutional claim line items, and we assume these states to be physicians' main states of practice. Similarly, we identify physicians' primary organizations by the highest number of work locations if they work for two or more employers; note that approximately 80% of physicians work in one location in the first wave of our study time window. Then, these practitioner-month measures are shrunk into practitioner-quarter measures by calculating three quarterly averages: the number of employers that physicians worked for, indicating moonlighting decisions, the (log-transformed) number of within-organization work locations, indicating within-organization practices, and the (log-transformed) total number of work locations, indicating aggregated individual labor supply. For the quarterly

[3] We tried including other nearby US states that have similar regulations related to physicians and healthcare services (e.g., Illinois and Michigan), yet a substantial number of pre-treatment effects are estimated to be statistically significant, indicating the violation of a parallel trend assumption.

averages of the number of employers, we use this measure to create a binary indicator of whether a physician moonlighted (i.e., worked for 2+ employers) or not. Note that we also obtain this binary measure among those who work for only one employer at Time 1 as well.

During the sample selection process, we only include the sample of physicians who appear across all quarterly data from 2022 to 2025. Additionally, when calculating the number of employers, we do not double-count the workplaces that are under the same organization, identified by organization group ID (*org_PAC_id*), because healthcare practitioners can have one employment contract that requires them to work in multiple locations. In other words, we identify the number of employers by the number of affiliations instead of the number of workplaces.

Second, we use the Medicare Physician & Other Practitioners by Provider 2021-2023[4], providing the frequencies of healthcare services each healthcare practitioner provided to the Medicare Part B beneficiaries. Using the NPI, we calculate the (log-transformed) total number of healthcare services each physician provided each year. The main states of practice are pre-identified in the dataset, based on the highest number of their Medicare Part B non-institutional claim line items. However, because the data does not provide the organizations of practice (i.e., which organizations each physician provided the services to), this measure indicates only the overall quantity of labor supply that each physician contributed to each year.

We also calculate the years of experience using the graduation year for subgroup analyses based on years of experience, as our theoretical model predicts that early-career employees are more likely to choose moonlighting (and increase within-organization practices) than late-career employees. For this calculation, we account for the post-graduation training for physicians and surgeons, residency programs, by their primary specialties: 3-4 years for physicians, 5 years for surgeons except neurosurgeons, and 7 years for neurosurgeons (Murphy, 2020). Accounting for these factors, we create three groups, following the definitions provided in Dyrbye et al. (2013): early-career (0-10 years), mid-career (11-20 years), and late-career (21+ years) practitioners. More information about the specialties of healthcare practitioners is provided in Appendix B. The descriptive statistics for the regional labor supply measures are provided in Table 1.

[4] Although our first CMS data covers from 2022-2025, the latest available Medicare Physician & Other Practitioners by Provider data is 2023. Therefore, we use 2021-2023 data to analyze the total number of services provided. We plan to update this measure when the next data is available; it is typically published in every September.

### 4.2 Estimation Procedure

For the estimation of the regional labor supply of physicians, we use a dynamic difference-in-difference (dynamic DiD) model:

$$Y_{ist} = \alpha + \boldsymbol{P}_{ist}\boldsymbol{\gamma} + \theta_{is} + \theta_t + \varepsilon_{ist}, \quad (10)$$

where $i$, $s$ and $t$ denote individual, state, and time, respectively, $Y_{st}$ is the outcome measure – whether a healthcare practitioner $i$ worked for two or more employers (moonlighting), the number of within-organization work locations (within-organization practice arrangements), log-transformed, and the total number of services provided, log-transformed, in the state $s$ in time $t$ – $\boldsymbol{P}_{ist}$ is the vector of event study regressors capturing the pre- and post-treatment effects of non-enforcing NCAs, and $\theta_{is}$ and $\theta_t$ are the individual and time fixed effects. We use this method to track each physician's regional labor supply at each time point before (the first quarter of 2022 to the second quarter of 2023) and after non-enforcing NCAs (the third quarter of 2023 to the last quarter of 2025). We also obtain the standard errors, clustered by the primary specialties in each state (i.e., two sets of specialties for two states), accounting for the potential within-group variations in each specialty in each state. When the number of clusters is not enough to obtain reliable clustered standard errors (i.e., number of clusters less than 30), we use a wild bootstrap, with 10,000 repetitions, using a six-point weight distribution approach to obtain the clustered standard errors (Webb, 2023); this approach produces uneven confidence intervals but is intended to account for the skewness, non-normality, or heteroskedasticity resulted from a small number of clusters.

In addition, as a robustness check, we use the fixed effects counterfactual estimator (FE Counterfactual) model to replicate the results that provide statistically significant post-treatment effects (Liu et al., 2024). Similar to the synthetic controls, this method allows the use of respondent-level panel data to obtain counterfactual estimators under an interactive fixed effects framework by imputing the missing counterfactuals using statistical models fitted exclusively on untreated observations. We obtain the post-treatment effects that are the differences between the actual and counterfactual treatments and the 90% confidence intervals in each time point. Similar to the six-point weight distribution approach, this model produces uneven confidence intervals due to its application of the bootstrap method, with 1,000 repetitions, to obtain the confidence intervals, accommodating heterogeneous treatment effects and non-linear data structure.

### 4.3 Threats to Validity and Solutions

The fundamental assumption of conducting these analyses is the parallel trend assumption. Because Minnesota and Wisconsin have several different regulations and systems related to healthcare services, it is important to conduct a set of validation tests. Across all the estimations, we conduct placebo tests by using the data from pre-treatment periods only and sensitivity analyses by using a different reference time point.

Our main sample includes physicians who already work for two or more employers in the first quarter of 2022, indicating that they moonlight. Yet, our theoretical model explains the decision-making processes of healthcare practitioners whose moonlighting is restricted by their employers. Furthermore, the stringency of NCAs may vary between the two states before Minnesota's policy change in July 2023. Although this is controlled by clustering, stringent regulations further reduce employees' bargaining power and chances of moonlighting. Thus, we conduct the same analyses using the sample of physicians who work for only one employer in the first quarter of 2022: subsampling those who are likely under similar employment contracts and conditions regarding their moonlighting opportunities before Minnesota's policy change.

Regarding the estimation of the total number of services provided, although the time spent on each service varies, we cannot exactly measure the amount of time spent on each service. While some service descriptions provide the approximate time spent on each service provision (e.g., outpatient office visit, 10-19 minutes), the descriptions for the majority of services do not provide the time spent on providing the corresponding services. This introduces heterogeneity into the interpretation of the changes in the intensive margin of labor supply using the total number of services provided. In particular, the time spent on the service provided by general physicians, such as providing medical checks, and that by surgeons, such as performing surgeries, would significantly vary. For instance, Table 1 shows that the total number of services provided substantially varies by primary specialties. To account for this issue, we conduct the subgroup analyses by primary specialties across all analyses to minimize the between-specialty heterogeneity: general physicians, specialists, and surgeons. The detailed categorization of physicians is provided in Appendix B.

# 5 Result

We provide the results from the analyses of the regional labor supply of physicians, including the proportion of physicians moonlighting, the number of within-organization practice arrangements, the total number of work locations, and the total number of healthcare services provided. We interpret the results from the analyses that pass both the placebo tests and sensitivity analyses only, reported in Appendices C and D. We also provide the replications of the results with statistically significant post-treatment effects using the FE Counterfactual method in Appendix E. Note that the sensitivity analyses and robustness checks in Appendices D and E provide 90% confidence intervals.

## 5.1 Changes in Moonlighting

Figure 1 shows the results from the dynamic DiD of Equation (10), using the data of physicians' moonlighting decisions in each quarter. There are four sub-figures, each presenting the pre- and post-treatment effects of non-enforcing NCAs on the regional labor supply of physicians at corresponding career levels. The first (upper left) sub-figure illustrates that the share of physicians, at all career levels, moonlighting increased by 2.5 percentage points after non-enforcing NCAs. The other sub-figures illustrate the changes in the engagements in moonlighting among physicians with different career levels. Although these sub-figures show statistically significant post-treatment effects, these results are not supported by sensitivity analyses. Similarly, Figure 2 shows the results of the subgroup analyses by categorizing physicians into their specialties: general physicians, specialists, and surgeons. Although the second sub-figure shows that the share of specialists moonlighting increased by 1.1 percentage points after non-enforcing NCAs, this result is not supported by sensitivity analyses.

However, once we focus on the physicians who work for only one employer at the beginning of our study time window (i.e., those who are more likely to be bound by NCAs), we observe meaningful changes. Figure 3 shows the results from the dynamic DiD of Equation (10), using the data of physicians who worked for only one employer (i.e., no moonlighting) in Time 1. The results are consistent with our baseline findings and further strengthen our theoretical predictions. The first sub-figure shows that the share of physician moonlighting increased by 2.7 percentage points in general. Furthermore, the share of early-career physicians moonlighting increases by 3.2 percentage points after non-enforcing NCAs. Similarly, Figure 4 also presents

meaningful changes; the second sub-figure shows that the share of specialists moonlighting increased by 1.5 percentage points.

Overall, we observe the increases in the share of physicians moonlighting, particularly among those who worked for one employer only in Time 1. However, we observe these increases only from the earlier post-treatment periods. Furthermore, the estimated effects from the later post-treatment periods are often negative and nearly statistically significant at 95% confidence level. This pattern is consistent in sensitivity analyses and robustness checks (see Appendices D and E). In summary, these results indicate an increase in physicians' moonlighting only in the earlier periods after the non-enforcement of NCAs.

### 5.2 Changes in Within-Organization Practice Arrangements

Figure 5 shows the results from the dynamic DiD of Equation (10), using data on the log-transformed number of physicians' within-organization practice arrangements in each quarter. Other than the result for early-career physicians (Figure 5B), the parallel trend assumptions are mostly not met. This possibly indicates that mid- and late-career physicians are likely not to change the number of within-organization practice arrangements, as they may already have optimized this number before the non-enforcement of NCAs. Table 1 shows that mid- and late-career physicians have a greater number of within-organization work locations than early-career physicians. On the other hand, the upper-right sub-figure illustrates the changes in the number of within-organization practice arrangements among early-career physicians, showing that this number increased by $(e^{0.056} - 1) \approx 5.8\%$. In addition, the statistically significant effects are observed from the later post-treatment periods only: the first and second quarters of 2025.

Figure 6 shows the results of the subgroup analyses by physicians' specialties. The first sub-figure shows no statistically significant effect, and the last sub-figure shows that the parallel trend assumptions are not met. On the other hand, the second sub-figure (Figure 6B) shows that the number of within-organization practice arrangements among specialists increased by $(e^{0.076} - 1) \approx 7.9\%$. In addition, although the first two post-treatment effects are also positive and statistically significant, we observe the effects that are greater in magnitude and statistically more significant from the last four post-treatment periods.

Overall, we observe an increase in within-organization practice arrangements among early-career physicians and specialists. However, we also observe that these increases are mostly from the later post-treatment periods. This pattern is also observed in Appendix E.3: the actual treatment

effects are greater in magnitude than the counterfactual effects, mostly in the later post-treatment periods.

Why do the increases in moonlighting and within-organization practice arrangement exhibit different timing? We predict that employers made a strategic transition – from hiring moonlighting physicians from outside to absorbing moonlighting work hours from inside – which takes time. In addition to no moonlighting clauses, employers' preexisting profit-maximization strategies included the hiring of moonlighting physicians primarily working for other healthcare providers. Given Minnesota's policy change timeline – non-enforcing NCAs in July 2023 and then banning 'shadow' non-competes in July 2024 – employers' initial strategic responses after July 2023 could be to keep employing moonlighting physicians or illegally enforce 'shadow' non-competes and then discard the latter option after July 2024. Once hiring moonlighting physicians becomes the only strategy, employers find 'internalizing' moonlighting to be more profitable by minimizing the costs of searching and hiring. This leads to observing two distinct phases of the increase in the regional labor supply of physicians: initially by moonlighting and then by within-organization practice arrangements. Nevertheless, both increases allow employees to work more, and therefore, the intensive margin of labor supply of physicians would increase. We examine this prediction in the next sub-section.

### 5.3 Changes in Labor Supply at Intensive Margin

There are two ways we can validate the hypothesis in the previous sub-section: testing the increase in the total number of work locations, regardless of within- or outside-organization practice arrangements, and the total number of healthcare services provided. For both the increases in moonlighting and within-organization practices, physicians spend more work hours in various work locations, and therefore, the number of work locations would increase. Similarly, for both increases, the quantity of healthcare services provided would increase, as physicians spend more work hours providing more services. We examine these changes in this sub-section.

Figure 7 shows the results from the dynamic DiD of Equation (10), using data on the total number of work locations in each quarter for the two subgroups: early-career physicians and specialists, the subgroups that provided statistically significant post-treatment effects from the estimations of moonlighting and within-organization practice arrangements. The results are consistent with our hypothesis; for both sub-figures, there are statistically significant effects in the earlier – $(e^{0.019} - 1) \approx 1.9\%$ increase for both early-career physicians and specialists – and later

– $(e^{0.054} - 1) \approx 5.5\%$ increase for early-career physicians and $(e^{0.0549} - 1) \approx 6.1\%$ increase for specialists – post-treatment periods. Yet, the sensitivity analysis and robustness check show that the later-period treatment effect for specialists is not statistically significant.

Table 2 shows the results from the dynamic DiD of Equation (10), using the data of the log-transformed number of healthcare services provided in each year. Each set of two rows presents the estimated coefficients indicating the pre-treatment (Minnesota × 2022) and post-treatment (Minnesota × 2023) effects, respectively. The first two rows, the estimation using the data of physicians across all career levels and specialties, show that the total number of services provided increased by $(e^{0.061} - 1) \approx 6.30\%$ after non-enforcing NCAs. The next six rows present the results from subgroup analyses by career level, showing that the total number of services provided by mid-career physicians increased by $(e^{0.062} - 1) \approx 6.40\%$. The last six rows present the results from subgroup analyses by specialty, showing that the total number of services provided by general physicians increased by $(e^{0.076} - 1) \approx 7.90\%$. In addition, although not statistically significant at 95% confidence level, the estimated post-treatment effects for late-career physicians and specialists are also positive and nearly statistically significant. These results indicate an increase in the intensive margin of labor supply after non-enforcing NCAs[5]; the overall quantity of services provided per physician increased.

## 6 Conclusions

We examine how non-enforcing non-compete agreements increase the regional labor supply of physicians by evaluating the impacts of Minnesota's recent policy changes. Using a Nash bargaining model, we explain how non-enforcing non-compete agreements leads employees to get permissions for moonlighting and leads employers to absorb their employees' moonlighting, both of which increase the intensive margin of labor supply. Then, we examine the changes in the regional labor supply of physicians by tracking the changes in the share of physicians moonlighting, the number of within-organization practice arrangements, the total number of work locations, and the number of healthcare services provided.

The results are consistent with our theoretical predictions. First, physicians' moonlighting increased after non-enforcing non-competes, which was observed during the earlier periods of

[5] Due to the data availability, our estimation time frame includes only until 2023. This will be updated once the data is published. We expect to find an increase in the total number of services in the later periods as well.

post-non-enforcement. Second, within-organization practice arrangements increased after non-enforcing non-competes, which was observed during the later periods of post-non-enforcement. Third, the total number of work locations increased after non-enforcing non-competes, and the timing of statistically significant increases overlaps with increases in moonlighting and within-organization practice arrangements. Lastly, the number of healthcare services provided by physicians increased after the non-enforcement. Based on these findings, we conclude that non-enforcing non-compete agreements increase the regional labor supply of physicians at the intensive margin.

Despite some benefits of imposing non-compete agreements for employers, the labor market inefficiency and the consumer welfare loss are significant, especially in the sectors with a highly skilled regulated labor market. Imposing non-competes harms both workers by reducing wages and mobility and consumers by reducing the supplies and raising the prices, as well as putting entering firms that should compete against preexisting firms at more disadvantageous positions (Starr, 2023). Furthermore, such as the healthcare sector, imposing non-competes adds another stringent regulatory barrier on top of the preexisting regulatory barriers that have restricted the labor supply, such as occupational licensing and scope of practices, further reducing regional labor supply and consumer welfare without improving the quality of services (Bae and Timmons, 2023; Kleiner, 2015; Oh, 2025; Oh and Kleiner, 2025a). If these regulations incapacitate economies from achieving a state or local equilibrium, policies that reduce the stringency of these regulations could enhance both worker and consumer welfare.

We want to point out several limitations of this study. First, we possibly underestimated the policy effects because our data does not include a portion of healthcare services provided via concierge and direct primary care (DPC) services. There has been an increase in the healthcare practitioners' participation in concierge and DPC services, where typical DPC providers opt out of Medicare to avoid regulatory risks of charging membership fees (Zhu et al., 2025; Reynolds, 2024). Nevertheless, our estimations still provide enough empirical evidence that prohibiting non-competes increases regional labor supply. Second, although it covers a significant portion of the US healthcare sector, our regional labor supply datasets cover only the physicians who submit Medicare Part B non-institutional claims.

Therefore, future research should extend our findings to obtain more robust estimates by utilizing larger and more comprehensive, and possibly panel datasets with consecutive time points

to obtain the short- and long-term effects of prohibiting non-competes on the regional labor supply, and possibly, consumer welfare. Also, future research should estimate the long-term changes in the out-of-state practices of physicians, because some employers restrict their employees' moonlighting by geographical boundaries; the removal of such restrictions makes these practitioners prefer in-state moonlighting more than out-of-state practices. Furthermore, the use of a staggered approach to analyze the impact of prohibiting non-competes on social welfare after more states prohibit non-competes would provide more robust and comprehensive results. Lastly, it would be fruitful to examine the changes in social welfare from other sectors with similar or different preexisting regulatory barriers, which would strengthen theoretical and empirical evidence related to the impact of non-compete agreements on regional labor supplies.

Nevertheless, our study innovates literature by providing evidence that prohibiting non-compete agreements can increase the regional labor supply not only by enhancing labor mobility but also by increasing the intensive margin of labor supply.

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**Table 1. Descriptive Statistics of Physicians and Their Services**

| | Minnesota | | Wisconsin | |
|---|---|---|---|---|
| | Prop/ Mean | SD | Prop/ Mean | SD |
| Physicians and Surgeons – Doctors and Clinicians National Downloadable File, January-March 2022 | | | | |
| Early Career (0-10 years) | .223 | .416 | .221 | .415 |
| Number of Employers | 1.279 | .756 | 1.225 | .546 |
| Number of Within-Organization Practice Arrangements | 1.865 | 1.938 | 1.841 | 2.007 |
| Mid Career (11-20 years) | .201 | .400 | .194 | .396 |
| Number of Employers | 1.332 | .861 | 1.279 | .660 |
| Number of Within-Organization Practices Arrangements | 2.699 | 2.815 | 2.842 | 4.490 |
| Late Career (21+ years) | .240 | .427 | .260 | .438 |
| Number of Employers | 1.295 | .805 | 1.267 | .604 |
| Number of Within-Organization Practices Arrangements | 2.770 | 3.029 | 3.014 | 4.625 |
| N | 14,417 | | 12,935 | |
| Total Number of Healthcare Services Provided – Medicare Physician & Other Practitioners by Provider, 2021 | | | | |
| Overall | 2,502.3 | 9,377.4 | 1,864.3 | 9,200.5 |
| By Career Level | | | | |
| Early Career (0-10 years) | 1,745.8 | 6,763.4 | 1,183.9 | 4,256.3 |
| Mid Career (11-20 years) | 2,733.1 | 9,560.9 | 2,285.3 | 12,356.6 |
| Late Career (21+ years) | 3,085.9 | 11,213.3 | 2,180.4 | 9,707.3 |
| By Specialty | | | | |
| General Physicians | 1,336.8 | 4,864.9 | 1,410.0 | 8,343.2 |
| Specialists | 3,806.8 | 12,3383.1 | 2,534.7 | 11,019.0 |
| Surgeons | 735.8 | 2,017.6 | 818.8 | 2,291.0 |
| N | 11,398 | | 10,247 | |

**Note:** Prop – proportion; SD – standard deviation. The above descriptive statistics are from the Centers for Medicare & Medicaid Services (CMS): Doctors and Clinicians National Downloadable File and Medicare Physician & Other Practitioners by Provider.

**Figure 1. Proportion of Physicians Working for Two or More Employers, By Career Level**

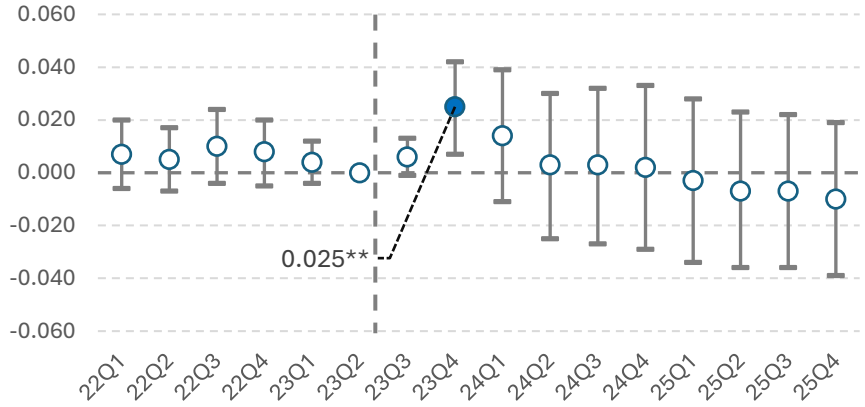



Figure 1A. Overall (N = 275,456)

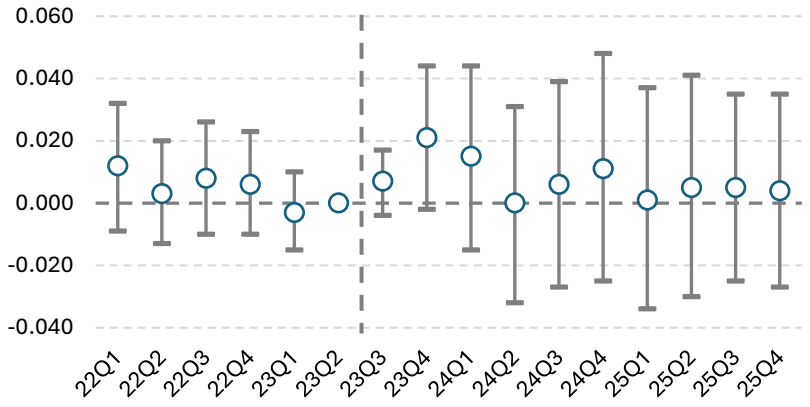



Figure 1B. Early-Career (N = 91,968)

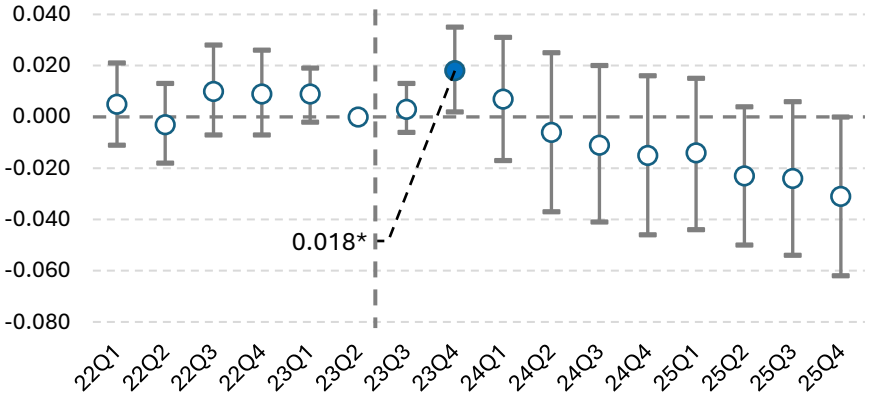



Figure 1C. Mid-Career (N = 83,024)

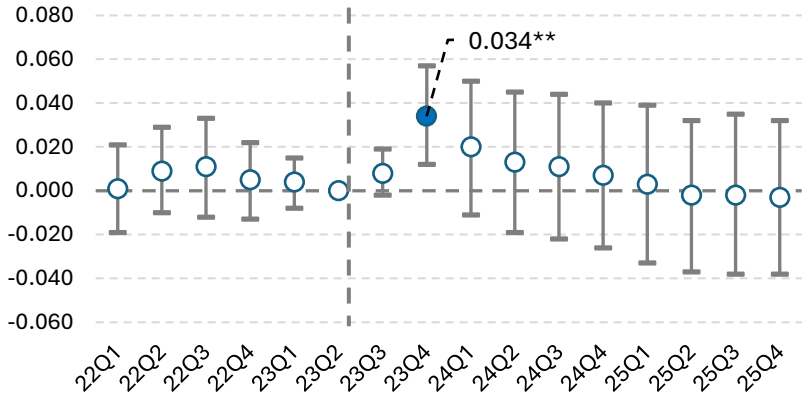



Figure 1D. Late-Career (N = 97,472)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state. The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 2. Proportion of Physicians Working for Two or More Employers, By Specialty**

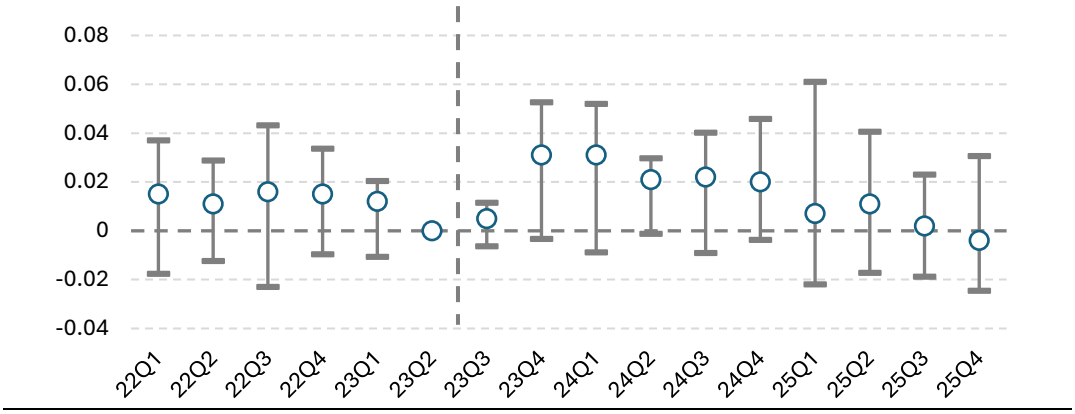



Figure 2A. General Physicians (N = 97,280)

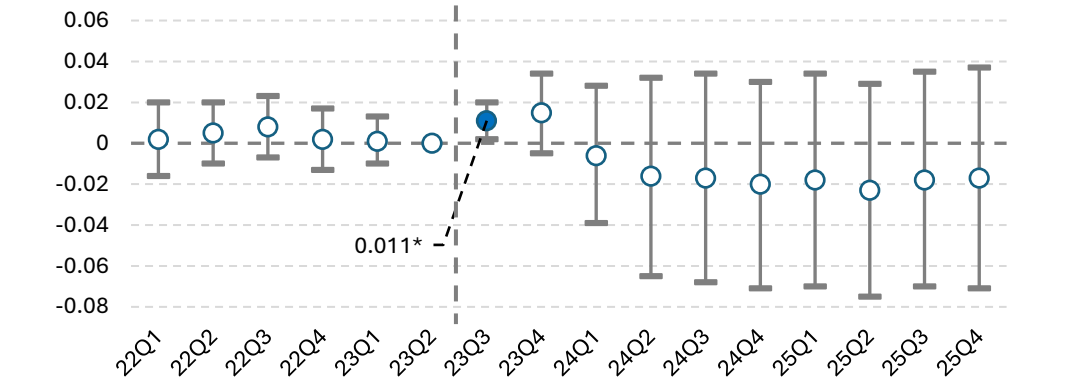



Figure 2B. Specialists (N = 130,800)

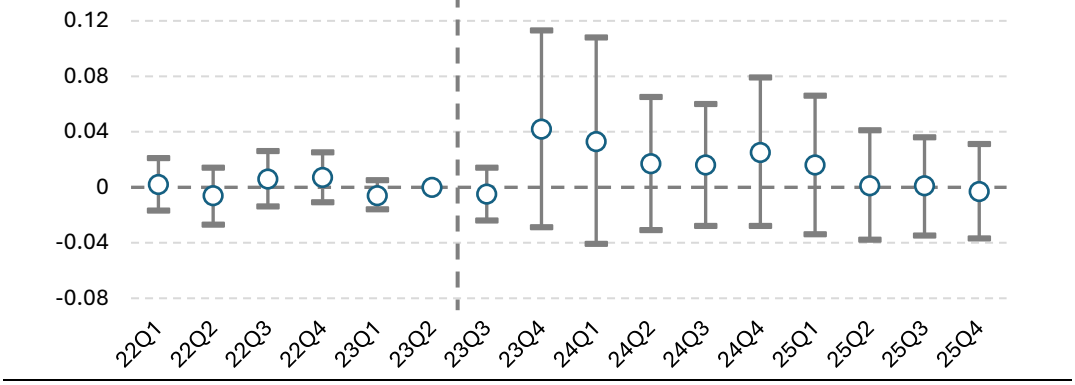



Figure 2C. Surgeons (N = 47,376)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals for Specialists and Surgeons are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state, and those for General Physicians are calculated using a wild bootstrap using a six-point weight distribution with 10,000 repetitions, clustered by two sets of healthcare practitioners' specialties for each state, due to insufficient number of clusters (= 14). The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 3. Proportion of Physicians Working for Two or More Employers, Working for One Employer in Time 1 Only, By Career Level**

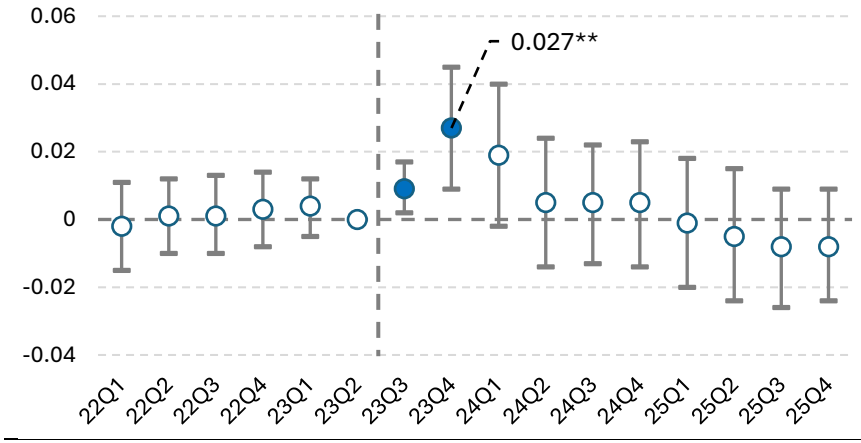



Figure 3A. Overall (N = 216,288)

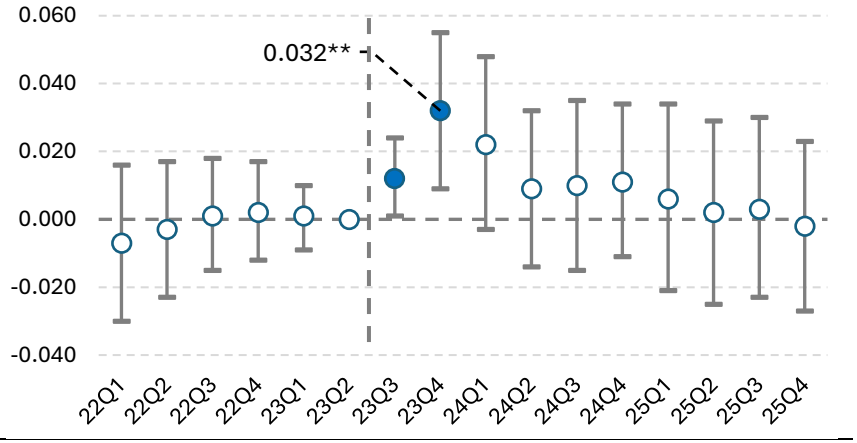



Figure 3B. Early-Career (N = 73,776)

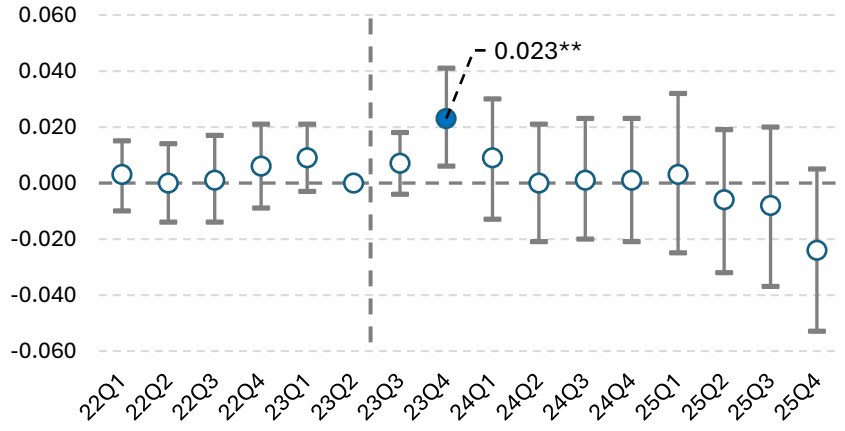



Figure 3C. Mid-Career (N = 64,000)

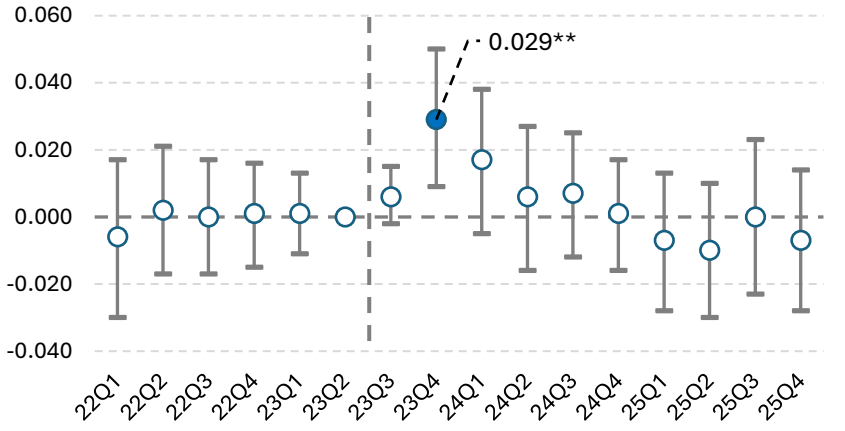



Figure 3D. Late-Career (N = 76,080)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state. The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 4. Proportion of Physicians Working for Two or More Employers, Working for One Employer in Time 1 Only, By Specialty**

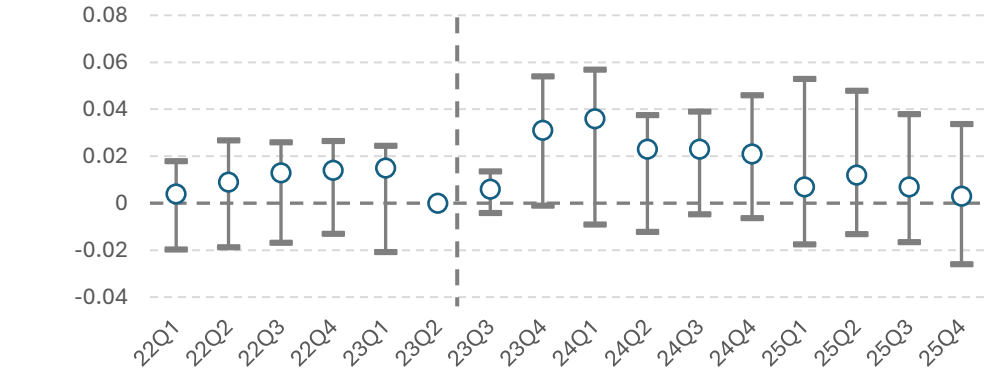



Figure 2A. General Physicians (N = 82,880)

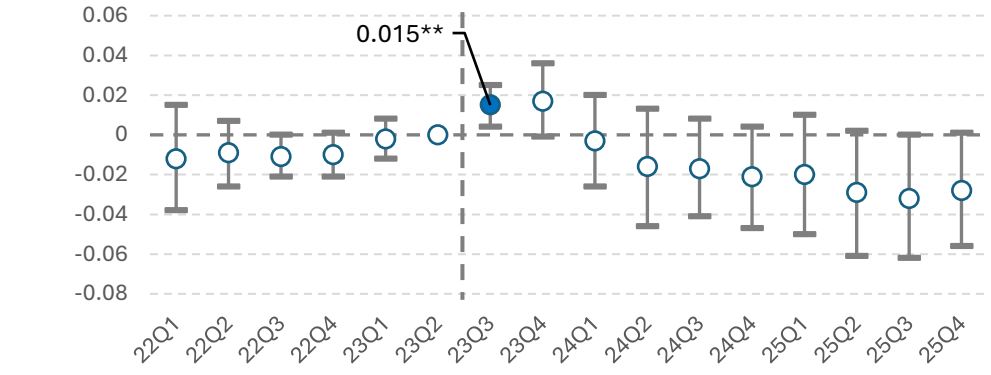



Figure 2B. Specialists (N = 95,200)

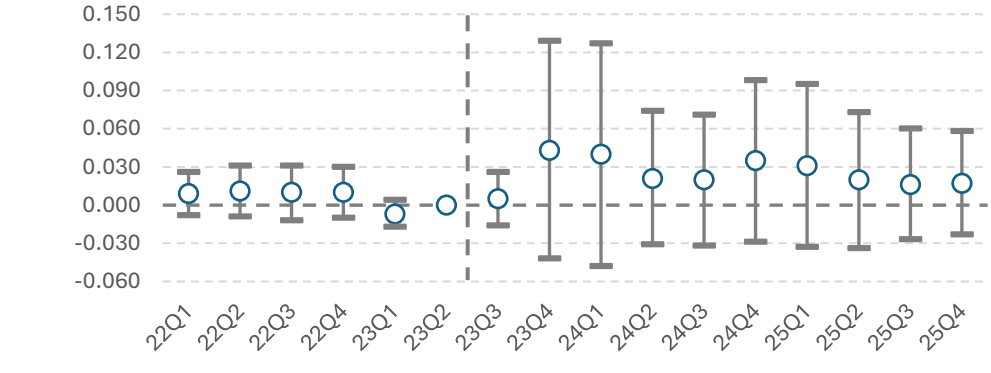



Figure 2C. Surgeons (N = 38,208)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals for Specialists and Surgeons are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state, and those for General Physicians are calculated using a wild bootstrap using a six-point weight distribution with 10,000 repetitions, clustered by two sets of healthcare practitioners' specialties for each state, due to insufficient number of clusters (= 14). The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 5. Number of Within-Organization Practice Arrangements, By Career Level**

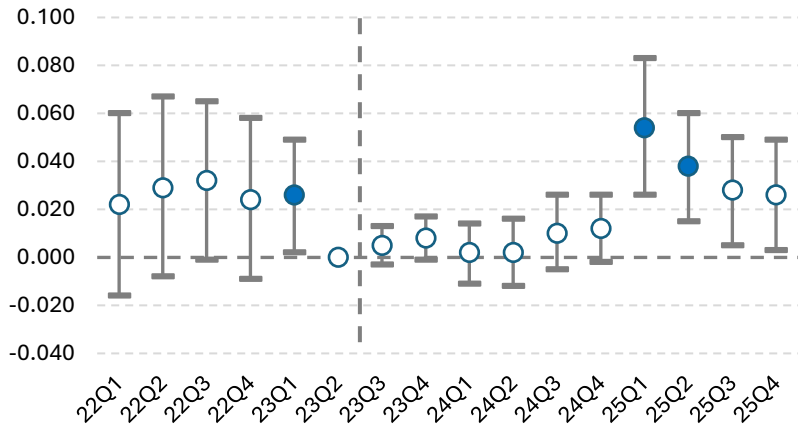



Figure 5A. Overall (N = 275,456)

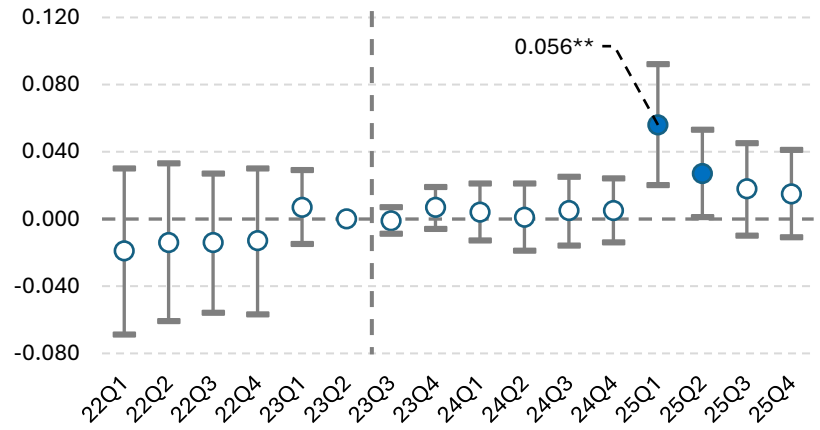



Figure 5B. Early-Career (N = 91,968)

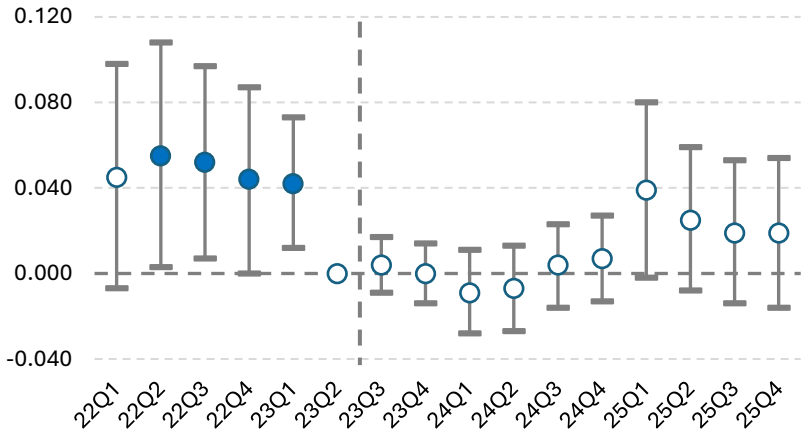



Figure 5C. Mid-Career (N = 83,024)

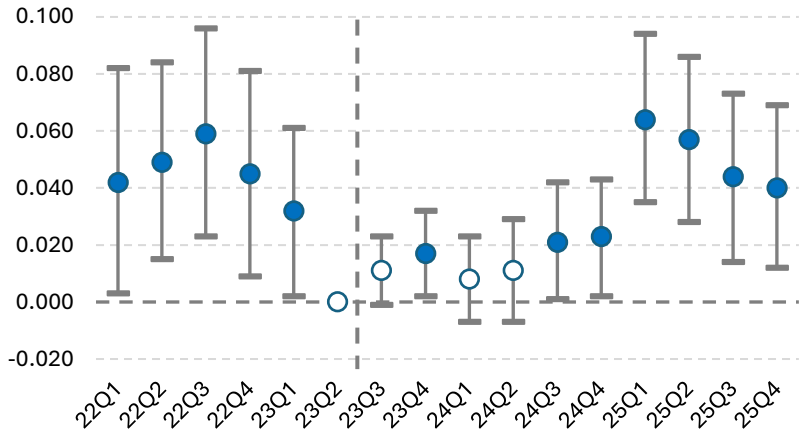



Figure 5D. Late-Career (N = 97,472)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state. The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 6. Number of Within-Organization Practice Arrangements, By Specialty**

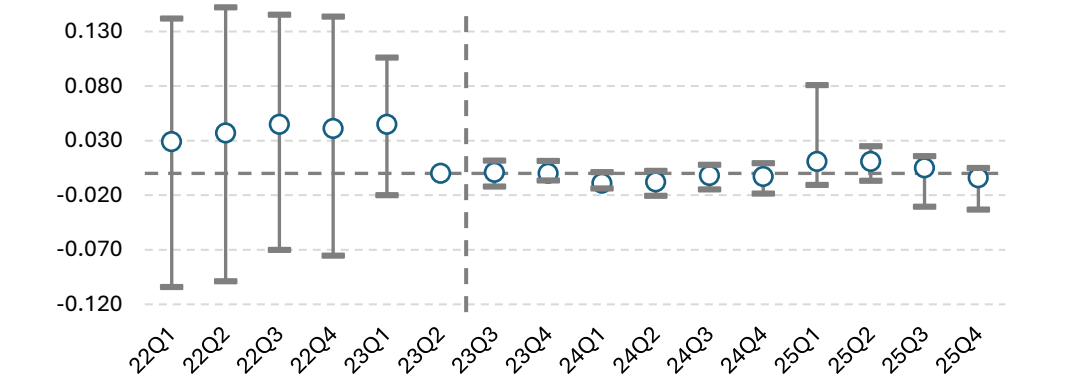



Figure 6A. General Physicians (N = 97,280)

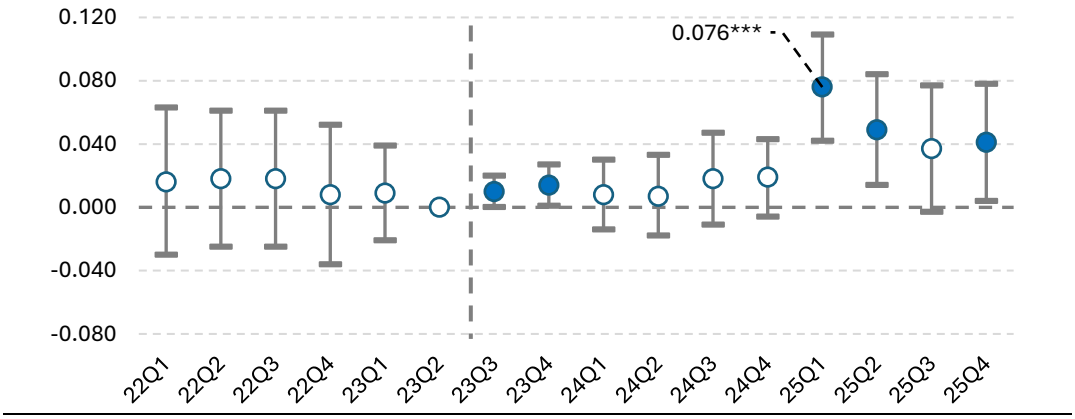



Figure 6B. Specialists (N = 130,800)

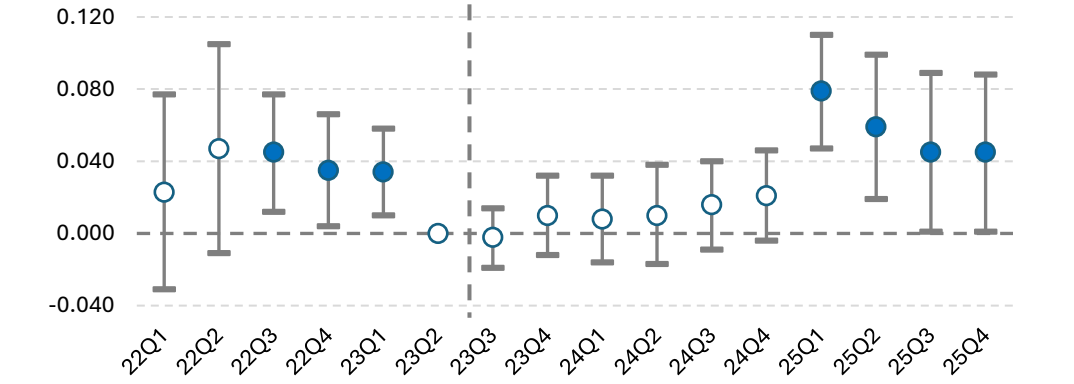



Figure 6C. Surgeons (N = 47,376)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals for Specialists and Surgeons are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state, and those for General Physicians are calculated using a wild bootstrap using a six-point weight distribution with 10,000 repetitions, clustered by two sets of healthcare practitioners' specialties for each state, due to insufficient number of clusters (= 14). The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Figure 7. Total Number of Work Locations**

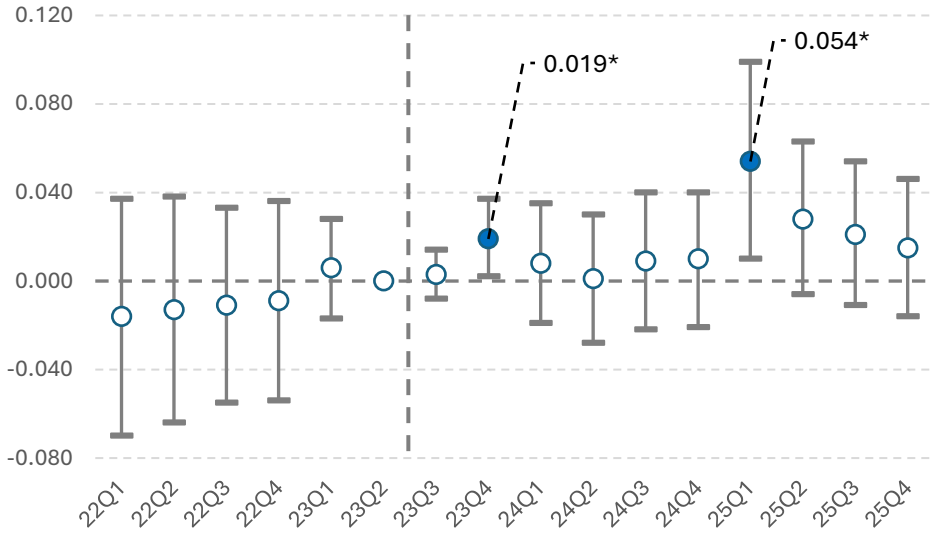



Figure 7A. Early-Career (N = 91,96888)

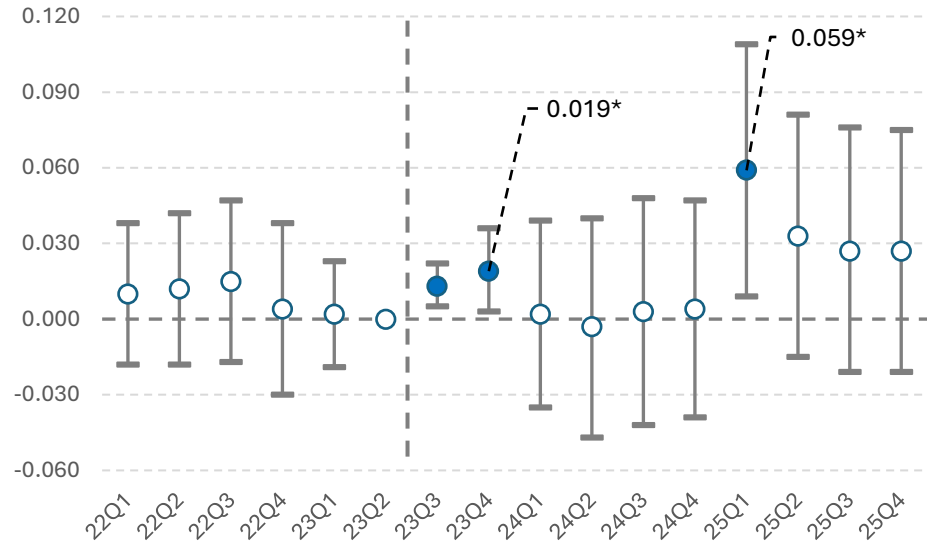



Figure 7B. Specialists (N = 130,800)

**Note:** Q – quarter. Each sub-figure presents the estimated coefficients (dots) and 95% confidence intervals (vertical intervals) from the dynamic difference-in-difference estimations using the sample of physicians and surgeons from the Centers for Medicare & Medicaid Services Doctors and Clinicians National Downloadable Files 2022-2025. The 95% confidence intervals are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state. The estimated coefficients that are statistically significant are color-filled, and their estimated coefficients are presented with asterisks, indicating their p-values. The vertical long dash line between "2023Q2" and "2023Q3" indicates the pre- and post-treatment periods. *** p<.001, ** p<.01, * p<.05.

**Table 2. Changes in the Total Number of Healthcare Services Provided**

| Outcome = Log(Number of Services) | EST | 95% CI | | F-Stat | $R^2$ |
|---|---|---|---|---|---|
| Overall (N = 64,935) | | | | | |
| Minnesota × 2022 | .005 | -.018 | .028 | 33.22 | .011 |
| Minnesota × 2023 | .061* | .007 | .116 | | |
| By Career Level | | | | | |
| Early Career (N = 21,486) | | | | | |
| Minnesota × 2022 | -.020 | -.077 | .038 | 47.91 | .019 |
| Minnesota × 2023 | .039 | -.059 | .138 | | |
| Mid Career (N = 18,396) | | | | | |
| Minnesota × 2022 | .006 | -.024 | .035 | 18.09 | .023 |
| Minnesota × 2023 | .062* | .005 | .120 | | |
| Late Career (N = 24,315) | | | | | |
| Minnesota × 2022 | .015 | -.016 | .046 | 65.26 | .070 |
| Minnesota × 2023 | .064 | -.007 | .135 | | |
| By Specialty | | | | | |
| General Physicians (N = 21,792) | | | | | |
| Minnesota × 2022 | .034 | -.018 | .052 | 873.29 | .027 |
| Minnesota × 2023 | .076*** | .014 | .100 | | |
| Specialists (N = 32,601) | | | | | |
| Minnesota × 2022 | .010 | -.022 | .041 | 11.00 | .005 |
| Minnesota × 2023 | .075 | -.004 | .153 | | |
| Surgeons (N = 10,542) | | | | | |
| Minnesota × 2022 | -.071* | -.128 | -.010 | 17.54 | .015 |
| Minnesota × 2023 | -.014 | -.101 | .074 | | |

**Note:** The above table presents the estimated coefficients (EST) and 95% confidence intervals (95% CI) from the dynamic difference-in-difference estimations using the sample of physicians from the Centers for Medicare & Medicaid Services Medicare Physician & Other Practitioners by Provider data 2021-2023. Year 2021 is used as a reference period for the dynamic DiD. The 95% confidence intervals are calculated based on the clustered standard errors, clustered by two sets of healthcare practitioners' specialties for each state, except for the estimation of General Physicians; due to the insufficient number of clusters (= 14) for the calculation of reliable clustered standard errors, a wild bootstrap using a six-point weight distribution with 10,000 repetitions was used, clustered by two sets of healthcare practitioners' specialties for each state. *** p<.001, ** p<.01, * p<.05.

# Appendix A

## Appendix A.1 Derivation of Equation (2)

Given the Nash product (1) and assuming that the interior solution exists, log-transform the product and then differentiate by $w$:

$$\frac{\beta}{w\left[1+h\left(o_{ij}\right)\right]-\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right)}-\frac{1-\beta}{P(N)+w}=0.$$

Solve this equation for $w$, then

$$w^{*}=\frac{\beta P(N)+(1-\beta)\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right)}{1+(1-\beta)h\left(o_{ij}\right)}.$$

## Appendix A.2 Derivation of Equation (3)

For conciseness, let $1+(1-\beta)h\left(o_{ij}\right)=A$. Plugging the wage derived in Equation (4) into the employee surplus $S_i$, then

$$S_i=\frac{\beta P(N)+(1-\beta)\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right)}{A}\left[1+h\left(o_{ij}\right)\right]-\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right).$$

First, $(1-\beta)b\left(1+h\left(o_{ij}\right)\right)=b-\beta b+(1-\beta)bh\left(o_{ij}\right)=-\beta b+bA$. Therefore,

$$\frac{\beta P(N)+(1-\beta)b}{A}\left[1+h\left(o_{ij}\right)\right]=\frac{\beta\left[P(N)\left(1+h\left(o_{ij}\right)\right)-b\right]}{A}+b.$$

Second, $(1-\beta)\delta\left(1+h\left(o_{ij}\right),t\right)\left(1+h\left(o_{ij}\right)\right)$ can be re-written as

$$\frac{\delta\left(1+h\left(o_{ij}\right),t\right)-\beta\delta\left(1+h\left(o_{ij}\right),t\right)+\delta\left(1+h\left(o_{ij}\right),t\right)(1-\beta)h\left(o_{ij}\right)}{A}$$

$$=\frac{-\beta\delta\left(1+h\left(o_{ij}\right),t\right)}{A}+\frac{\delta\left(1+h\left(o_{ij}\right),t\right)A}{A}=\frac{-\beta\delta\left(1+h\left(o_{ij}\right),t\right)}{A}+\delta\left(1+h\left(o_{ij}\right),t\right).$$

Therefore, $S_i$ can be re-written as

$$S_i=\frac{\beta\left[P(N)\left(1+h\left(o_{ij}\right)\right)-b\right]}{A}-\frac{\beta\delta\left(1+h\left(o_{ij}\right),t\right)}{A}$$

$$+b+\delta\left(1+h\left(o_{ij}\right),t\right)-\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right)$$

$$=\frac{\beta\left[P(N)\left(1+h\left(o_{ij}\right)\right)-\left(b+\delta\left(1+h\left(o_{ij}\right),t\right)\right)\right]}{A}.$$

Plugging $1+(1-\beta)h\left(o_{ij}\right)$ back to $A$, then

$$S_i = \frac{\beta\left[P(N)\left(1+h(o_{ij})\right)-\left(b+\delta(1+h(o_{ij}),t)\right)\right]}{1+(1-\beta)h(o_{ij})}.$$

**Appendix A.3 Derivation of Equation (4)**

The employer surplus $S_j$ is

$$S_j = P(N) - w.$$

Plugging the wage derived in Equation (2) into this equation,

$$S_j = P(N) - \frac{\beta P(N) + (1-\beta)\left(b+\delta(1+h(o_{ij}),t)\right)}{1+(1-\beta)h(o_{ij})}$$

$$= \frac{(1-\beta)\left[P(N)\left(1+h(o_{ij})\right)-\left(b+\delta(1+h(o_{ij}),t)\right)\right]}{1+(1-\beta)h(o_{ij})}.$$

**Appendix A.4 Derivation of Inequality (6)**

Condition (5) provides two total surpluses based on Employer 1's decisions on permitting moonlighting: $S_{total}^{o_{i1}=0}$ and $S_{total}^{o_{i1}=1}$. Comparing the two surpluses when $S_{total}^{o_{i1}=0}$ is greater than $S_{total}^{o_{i1}=1}$,

$$S_{total}^{o_{i1}=0} > S_{total}^{o_{i1}=1} \Leftrightarrow P(N_0) - \left(b+\delta(1,t)\right) > \frac{P(N_1)(1+h) - \left(b+\delta(1+h,t)\right)}{1+(1-\beta)h}$$

Multiplying both sides by $1+(1-\beta)h$,

$$P(N_0) + hP(N_0) - \beta hP(N_0) - [1+(1-\beta)h]\left(b+\delta(1,t)\right) >$$

$$P(N_1)(1+h) - \left(b+\delta(1+h,t)\right)$$

that can be re-written as

$$(1+h)P(N_0) - (1+h)P(N_1) >$$

$$\beta hP(N_0) + [1+(1-\beta)h]\left(b+\delta(1,t)\right) - \left(b+\delta(1+h,t)\right).$$

Simplifying the above system,

$$(1+h)[P(N_0) - P(N_1)] > \beta hP(N_0) + (1-\beta)h\left(b+\delta(1,t)\right) - \delta(h,t).$$

Solve for $b+\delta(1,t)$, then

$$\frac{1}{(1-\beta)h}[(1+h)[P(N_0) - P(N_1)] - \beta hP(N_0) + \delta(h,t)] > b+\delta(1,t).$$

## Appendix B. Categorization of Physicians

From the CMS National Downloadable File, we identified the types of physicians by checking their primary specialties (variable name: *pri_spec*). The categorization and the list of specialties for each group are provided below.

1. Primary Carer & Generalists: Family medicine, General practice, Internal medicine, Pediatric medicine, Geriatric medicine, Hospitalist, Preventive medicine, and Family practice

2. Specialists: Addiction medicine, Allergy/immunology, Endocrinology, Gastroenterology, Hematology, Infectious disease, Advanced heart failure and transplant cardiology, Nephrology, Pulmonary disease, Rheumatology, Sleep medicine, Undersea and hyperbaric medicine, Medical oncology, Medical toxicology, Medical genetics and genomics, Osteopathic manipulative medicine, Interventional pain management, Peripheral vascular disease, Sports medicine, Hematopoietic cell transplantation and cellular therapy, Hospice/palliative care, Pain management, Ophthalmology, Adult congenital heart disease (ACHD), Advanced heart failure and transplant cardiology, Cardiac electrophysiology, Cardiovascular disease (Cardiology), Interventional cardiology, Neurology, Neuropsychiatry, Psychiatry, Geriatric psychiatry, Diagnostic radiology, Interventional radiology, Nuclear medicine, Pathology, Radiation oncology, Anesthesiology, Critical care (intensivists), Dermatology, Emergency medicine, Micrographic dermatologic surgery (MDS), and Physical medicine and rehabilitation

3. Surgeons: Cardiac surgery, Colorectal surgery (Proctology), General surgery, Hand surgery, Maxillofacial surgery, Neurosurgery, Oral surgery, Orthopedic surgery, Otolaryngology, Plastic and reconstructive surgery, Surgical oncology, Thoracic surgery, Urology, Vascular surgery, Gynecological oncology, and Obstetrics/gynecology

# Appendix C. Placebo Test: Pre-Trend Analysis

## Appendix C.1. Proportion of Physicians Working for Two or More Employers

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | .007 | .012 | .005 | .001 | .015 | .002 | .002 |
| | (.007) | (.011) | (.008) | (.010) | (.012) | (.009) | (.009) |
| 22Q2 | .005 | .003 | -.003 | .009 | .011 | .005 | -.006 |
| | (.006) | (.008) | (.008) | (.010) | (.009) | (.008) | (.010) |
| 22Q3 | .010 | .008 | .010 | .011 | .016 | .008 | .006 |
| | (.007) | (.009) | (.009) | (.012) | (.011) | (.007) | (.010) |
| 22Q4 | .008 | .006 | .009 | .005 | .015 | .002 | .007 |
| | (.006) | (.008) | (.008) | (.009) | (.007) | (.007) | (.009) |
| 23Q1 | .004 | -.003 | .009 | .004 | .012** | .001 | -.006 |
| | (.004) | (.006) | (.005) | (.006) | (.004) | (.006) | (.005) |
| $R^2$ | .000 | .001 | .001 | .001 | .001 | .001 | .001 |
| Observations | 103,296 | 34,488 | 31,134 | 36,552 | 36,480 | 49,050 | 17,766 |

**Note:** The above tables present the estimated coefficients and the clustered standard errors in parentheses from the placebo tests by using pre-treatment periods only to validate the results presented in Figures 1 and 2. *** p<.001, ** p<.01, * p<.05.

## Appendix C.2. Proportion of Physicians Working for Two or More Employers, Working for One Employer in Time 1 Only

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | -.002 | -.008 | .002 | -.001 | .004 | -.012 | .009 |
| | (.007) | (.010) | (.007) | (.010) | (.005) | (.013) | (.008) |
| 22Q2 | .001 | -.003 | -.003 | .007 | .009 | -.009 | .011 |
| | (.006) | (.008) | (.007) | (.008) | (.007) | (.008) | (.010) |
| 22Q3 | .001 | .001 | .002 | .000 | .013 | -.011* | .010 |
| | (.006) | (.008) | (.008) | (.010) | (.007) | (.005) | (.010) |
| 22Q4 | .003 | .003 | .006 | -.002 | .014* | -.010 | .010 |
| | (.005) | (.008) | (.008) | (.008) | (.006) | (.005) | (.010) |
| 23Q1 | .004 | .002 | .009 | -.001 | .015** | -.002 | -.007 |
| | (.004) | (.006) | (.006) | (.006) | (.005) | (.005) | (.005) |
| $R^2$ | .023 | .027 | .021 | .020 | .024 | .025 | .020 |
| Observations | 81,108 | 27,666 | 24,000 | 28,530 | 31,080 | 35,700 | 14,328 |

**Note:** The above tables present the estimated coefficients and the clustered standard errors in parentheses from the placebo tests by using pre-treatment periods only to validate the results presented in Figures 3 and 4. *** p<.001, ** p<.01, * p<.05.

## Appendix C.3. Number of Within-Organization Practice Arrangements

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | .022 | -.019 | .045 | .042* | .029 | .016 | .023 |
| | (.019) | (.025) | (.026) | (.020) | (.040) | (.023) | (.026) |
| 22Q2 | .029 | -.014 | .055* | .049** | .037 | .018 | .047 |
| | (.019) | (.024) | (.027) | (.017) | (.041) | (.022) | (.028) |
| 22Q3 | .032 | -.014 | .052* | .059** | .045 | .018 | .045** |
| | (.017) | (.021) | (.023) | (.018) | (.035) | (.022) | (.016) |
| 22Q4 | .024 | -.013 | .044* | .045* | .041 | .008 | .035* |
| | (.017) | (.022) | (.022) | (.018) | (.035) | (.022) | (.015) |
| 23Q1 | .026* | .007 | .042** | .032* | .045* | .009 | .034** |
| | (.012) | (.011) | (.016) | (.015) | (.020) | (.015) | (.012) |
| $R^2$ | .005 | .002 | .009 | .014 | .008 | .003 | .010 |
| Observations | 103,296 | 34,488 | 31,134 | 36,552 | 36,480 | 49,050 | 17,766 |

**Note:** The above tables present the estimated coefficients and the clustered standard errors in parentheses from the placebo tests by using pre-treatment periods only to validate the results presented in Figures 5 and 6. *** p<.001, ** p<.01, * p<.05.

## Appendix C.4. Total Number of Work Locations

| Time | Early Career | Specialists |
|---|---|---|
| 22Q1 | -.016 | .010 |
| | (.027) | (.014) |
| 22Q2 | -.013 | .012 |
| | (.026) | (.015) |
| 22Q3 | -.011 | .015 |
| | (.022) | (.016) |
| 22Q4 | -.009 | .004 |
| | (.023) | (.017) |
| 23Q1 | .006 | .002 |
| | (.011) | (.011) |
| $R^2$ | .002 | .003 |
| Observations | 34,488 | 49,050 |

**Note:** The above tables present the estimated coefficients and the clustered standard errors in parentheses from the placebo tests by using pre-treatment periods only to validate the results presented in Figure 7. *** p<.001, ** p<.01, * p<.05.

# Appendix D. Sensitivity Analysis – Robustness to Reference Period Choice

## Appendix D.1. Proportion of Physicians Working for Two or More Employers

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | .002 | .008 | .007** | -.008* | .005 | -.003 | .008 |
| | (.003) | (.005) | (.004) | (.005) | (.004) | (.006) | (.005) |
| 22Q3 | .005 | .004 | .013** | .001 | .005 | .003 | .012 |
| | (.004) | (.006) | (.005) | (.006) | (.006) | (.004) | (.008) |
| 22Q4 | .003 | .003 | .012* | -.004 | .005 | -.003 | .014* |
| | (.004) | (.007) | (.007) | (.006) | (.005) | (.005) | (.007) |
| 23Q1 | -.001 | -.006 | .011 | -.006 | .001 | -.004 | .001 |
| | (.004) | (.008) | (.007) | (.008) | (.006) | (.006) | (.009) |
| 23Q2 | -.005 | -.003 | .003 | -.009 | -.011 | -.005 | .006 |
| | (.006) | (.008) | (.008) | (.010) | (.009) | (.008) | (.010) |
| 23Q3 | .001 | .003 | .006 | -.001 | -.006 | .006 | .001 |
| | (.006) | (.009) | (.008) | (.010) | (.009) | (.010) | (.012) |
| 23Q4 | .020* | .018 | .021* | .025 | .020 | .010 | .048 |
| | (.011) | (.015) | (.011) | (.016) | (.013) | (.013) | (.036) |
| 24Q1 | .009 | .011 | .009 | .010 | .020** | -.011 | .040 |
| | (.015) | (.018) | (.014) | (.019) | (.009) | (.020) | (.037) |
| 24Q2 | -.002 | -.004 | -.003 | .004 | .010 | -.021 | .023 |
| | (.016) | (.018) | (.017) | (.019) | (.007) | (.028) | (.023) |
| 24Q3 | -.002 | .002 | -.008 | .002 | .012 | -.022 | .022 |
| | (.017) | (.019) | (.017) | (.021) | (.012) | (.029) | (.022) |
| 24Q4 | -.003 | .008 | -.012 | -.002 | .009 | -.025 | .032 |
| | (.018) | (.021) | (.018) | (.022) | (.012) | (.029) | (.028) |
| 25Q1 | -.008 | -.002 | -.012 | -.006 | -.003 | -.023 | .022 |
| | (.019) | (.020) | (.017) | (.024) | (.018) | (.030) | (.029) |
| 25Q2 | -.012 | .002 | -.020 | -.012 | .000 | -.028 | .007 |
| | (.018) | (.020) | (.017) | (.023) | (.015) | (.030) | (.023) |
| 25Q3 | -.012 | .001 | -.022 | -.011 | -.008 | -.023 | .007 |
| | (.018) | (.017) | (.017) | (.024) | (.011) | (.030) | (.022) |
| 25Q4 | -.015 | .000 | -.028 | -.012 | -.015 | -.022 | .003 |
| | (.018) | (.017) | (.018) | (.023) | (.009) | (.031) | (.021) |
| $R^2$ | .002 | .002 | .003 | .003 | .004 | .003 | .004 |
| Observations | 275,456 | 91,968 | 83,024 | 97,472 | 97,280 | 130,800 | 47,376 |

**Note:** The above table presents estimated coefficients and clustered standard errors in parentheses, from the sensitivity analyses by setting a different reference time point (22Q2) to validate the results presented in Figures 1 and 2. *** p<.01, ** p<.05, * p<.10.

**Appendix D.2. Proportion of Physicians Working for Two or More Employers, Working for One Employer in Time 1 Only**

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | -.003 | -.005 | .005 | -.009 | -.005** | -.003 | -.002 |
| | (.003) | (.004) | (.004) | (.006) | (.002) | (.007) | (.004) |
| 22Q3 | .000 | .004 | .006 | -.007 | .003 | -.002 | -.001 |
| | (.004) | (.006) | (.006) | (.005) | (.006) | (.006) | (.006) |
| 22Q4 | .002 | .007 | .009 | -.009* | .005 | -.001 | -.001 |
| | (.004) | (.008) | (.006) | (.005) | (.004) | (.008) | (.008) |
| 23Q1 | .002 | .006 | .012* | -.008 | .006 | .007 | -.018** |
| | (.005) | (.010) | (.007) | (.007) | (.006) | (.010) | (.009) |
| 23Q2 | -.001 | .003 | .003 | -.007 | -.009 | .009 | -.011 |
| | (.006) | (.008) | (.007) | (.008) | (.007) | (.008) | (.010) |
| 23Q3 | .008 | .012 | .010 | .004 | -.003 | .024** | -.006 |
| | (.007) | (.010) | (.008) | (.009) | (.008) | (.011) | (.008) |
| 23Q4 | .026** | .031** | .027** | .021* | .022*** | .026* | .032 |
| | (.010) | (.013) | (.012) | (.012) | (.005) | (.014) | (.042) |
| 24Q1 | .018 | .026* | .018 | .011 | .026*** | .006 | .029 |
| | (.011) | (.014) | (.013) | (.012) | (.008) | (.015) | (.043) |
| 24Q2 | .004 | .008 | .006 | .001 | .014** | -.007 | .010 |
| | (.009) | (.012) | (.012) | (.010) | (.006) | (.018) | (.025) |
| 24Q3 | .003 | .009 | .002 | -.000 | .014*** | -.008 | .009 |
| | (.008) | (.011) | (.011) | (.008) | (.004) | (.014) | (.023) |
| 24Q4 | .003 | .016 | .004 | -.009 | .012** | -.012 | .024 |
| | (.009) | (.012) | (.013) | (.010) | (.005) | (.014) | (.031) |
| 25Q1 | -.002 | .002 | .006 | -.010 | -.002 | -.011 | .020 |
| | (.010) | (.013) | (.014) | (.012) | (.006) | (.016) | (.032) |
| 25Q2 | -.006 | .004 | -.004 | -.015 | .003 | -.020 | .009 |
| | (.010) | (.013) | (.012) | (.011) | (.006) | (.018) | (.027) |
| 25Q3 | -.009 | -.001 | -.008 | -.016 | -.002 | -.023 | .005 |
| | (.009) | (.011) | (.013) | (.012) | (.006) | (.018) | (.023) |
| 25Q4 | -.009 | .003 | -.010 | -.017 | -.006 | -.019 | .006 |
| | (.009) | (.011) | (.012) | (.012) | (.006) | (.017) | (.020) |
| $R^2$ | .023 | .027 | .022 | .021 | .026 | .022 | .025 |
| Observations | 216,288 | 73,776 | 64,000 | 76,080 | 82,880 | 95,200 | 38,208 |

**Note:** The above table presents estimated coefficients and clustered standard errors in parentheses, from the sensitivity analyses by setting a different reference time point (22Q2) to validate the results presented in Figures 3 and 4. *** p<.01, ** p<.05, * p<.10.

## Appendix D.3. Number of Within-Organization Practice Arrangements

| | By Career Level | | | | By Specialty | | |
|---|---|---|---|---|---|---|---|
| Time | Overall | Early Career | Mid Career | Late Career | General Physicians | Specialists | Surgeons |
| 22Q1 | -.007** | -.005 | -.010 | -.007 | -.008** | -.001 | -.024** |
| | (.004) | (.004) | (.006) | (.006) | (.003) | (.004) | (.009) |
| 22Q3 | .003 | -.000 | -.003 | .010 | .009 | -.000 | -.002 |
| | (.005) | (.005) | (.008) | (.006) | (.007) | (.005) | (.015) |
| 22Q4 | -.005 | .000 | -.011 | -.004 | .004 | -.010 | -.012 |
| | (.005) | (.008) | (.009) | (.007) | (.006) | (.007) | (.017) |
| 23Q1 | -.003 | .021 | -.013 | -.018*** | .008 | -.009 | -.013 |
| | (.009) | (.015) | (.014) | (.007) | (.021) | (.009) | (.020) |
| 23Q2 | -.029 | .014 | -.055** | -.049*** | -.037 | -.018 | -.047 |
| | (.019) | (.024) | (.027) | (.017) | (.041) | (.022) | (.028) |
| 23Q3 | -.024 | .013 | -.051* | -.038* | -.035 | -.007 | -.049 |
| | (.020) | (.023) | (.028) | (.020) | (.041) | (.020) | (.030) |
| 23Q4 | -.021 | .021 | -.055* | -.032 | -.037 | -.004 | -.037 |
| | (.020) | (.024) | (.029) | (.020) | (.042) | (.024) | (.030) |
| 24Q1 | -.028 | .018 | -.064** | -.041** | -.046 | -.010 | -.039 |
| | (.021) | (.025) | (.030) | (.020) | (.041) | (.030) | (.028) |
| 24Q2 | -.027 | .015 | -.062** | -.038* | -.045 | -.010 | -.037 |
| | (.021) | (.024) | (.029) | (.021) | (.037) | (.031) | (.025) |
| 24Q3 | -.019 | .019 | -.052* | -.028 | -.039 | -.000 | -.031 |
| | (.021) | (.025) | (.028) | (.020) | (.038) | (.030) | (.027) |
| 24Q4 | -.017 | .019 | -.048* | -.027 | -.039 | .001 | -.026 |
| | (.020) | (.025) | (.028) | (.019) | (.037) | (.028) | (.029) |
| 25Q1 | .025 | .070** | -.017 | .015 | -.025 | .058** | .032 |
| | (.022) | (.027) | (.032) | (.020) | (.038) | (.025) | (.035) |
| 25Q2 | .008 | .041 | -.030 | .008 | -.026 | .031 | .012 |
| | (.021) | (.026) | (.029) | (.020) | (.040) | (.026) | (.035) |
| 25Q3 | -.002 | .032 | -.036 | -.005 | -.031 | .019 | -.002 |
| | (.021) | (.026) | (.029) | (.021) | (.039) | (.030) | (.032) |
| 25Q4 | -.003 | .029 | -.036 | -.009 | -.041 | .023 | -.002 |
| | (.022) | (.026) | (.031) | (.022) | (.039) | (.029) | (.034) |
| $R^2$ | .019 | .013 | .020 | .030 | .017 | .018 | .032 |
| Observations | 275,456 | 91,968 | 83,024 | 97,472 | 97,280 | 130,800 | 47,376 |

**Note:** The above table presents estimated coefficients and clustered standard errors in parentheses, from the sensitivity analyses by setting a different reference time point (22Q2) to validate the results presented in Figures 5 and 6. *** p<.01, ** p<.05, * p<.10.

## Appendix D.4. Total Number of Work Locations

| Time | Early Career | Specialists |
|---|---|---|
| 22Q1 | -.003 | -.002 |
| | (.005) | (.005) |
| 22Q3 | .003 | .003 |
| | (.007) | (.005) |
| 22Q4 | .004 | -.008 |
| | (.010) | (.008) |
| 23Q1 | .019 | -.010 |
| | (.017) | (.009) |
| 23Q2 | .013 | -.012 |
| | (.026) | (.015) |
| 23Q3 | .016 | .001 |
| | (.025) | (.014) |
| 23Q4 | .033 | .007 |
| | (.025) | (.019) |
| 24Q1 | .021 | -.010 |
| | (.027) | (.030) |
| 24Q2 | .014 | -.016 |
| | (.026) | (.033) |
| 24Q3 | .022 | -.009 |
| | (.027) | (.034) |
| 24Q4 | .023 | -.008 |
| | (.027) | (.033) |
| 25Q1 | .067** | .046 |
| | (.031) | (.033) |
| 25Q2 | .042 | .021 |
| | (.029) | (.033) |
| 25Q3 | .035 | .015 |
| | (.026) | (.033) |
| 25Q4 | .028 | .015 |
| | (.027) | (.034) |
| $R^2$ | .008 | .015 |
| Observations | 91,968 | 130,800 |

**Note:** The above table presents estimated coefficients and clustered standard errors in parentheses, from the sensitivity analyses by setting a different reference time point (22Q2) to validate the results presented in Figure 7. *** p<.01, ** p<.05, * p<.10.

# Appendix E. Fixed Effects Counterfactual Estimator Model

## Appendix E.1. Comparison: Proportion of Physicians Working for Two or More Employers

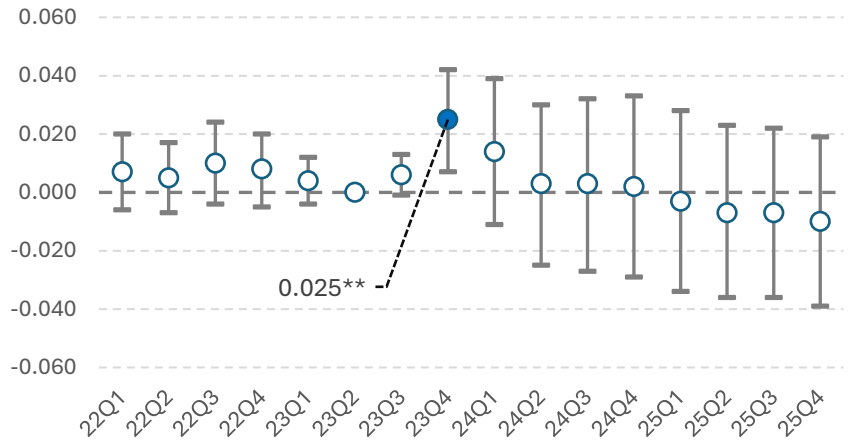



Figure E.1.A. Overall, Dynamic DiD (N = 275,456)

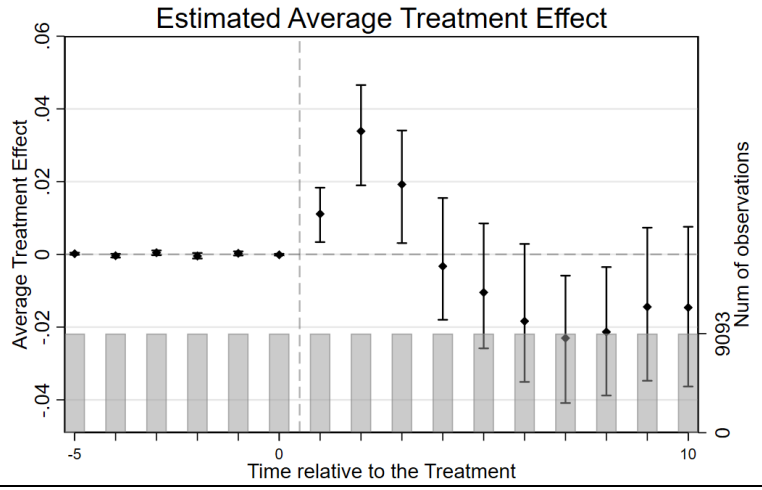



Figure E.1.B. Overall, FE Counterfactual (N = 275,456)

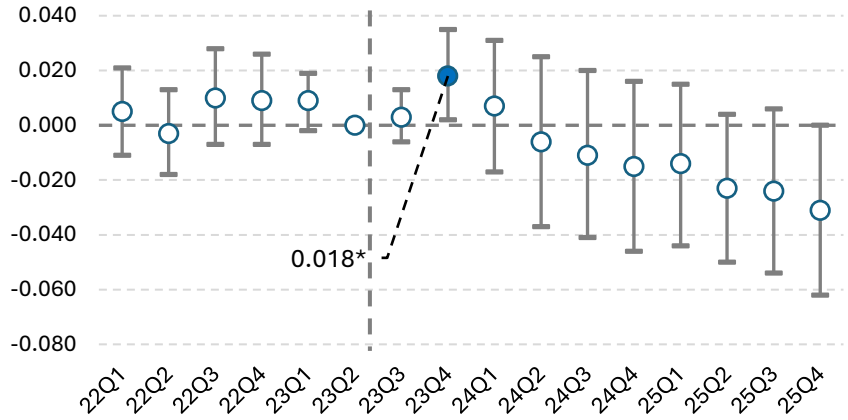



Figure E.1.C Mid-Career, Dynamic DiD (N = 83,024)

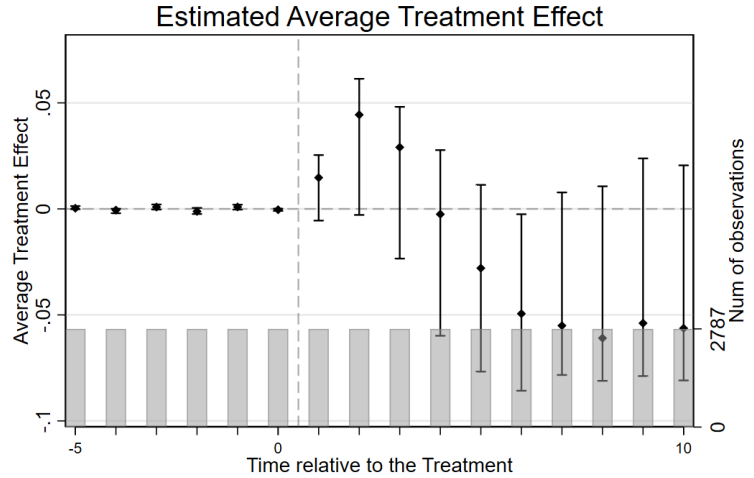



Figure E.1.D. Mid-Career, FE Counterfactual (N = 83,024)

**Appendix E.1. Continued**

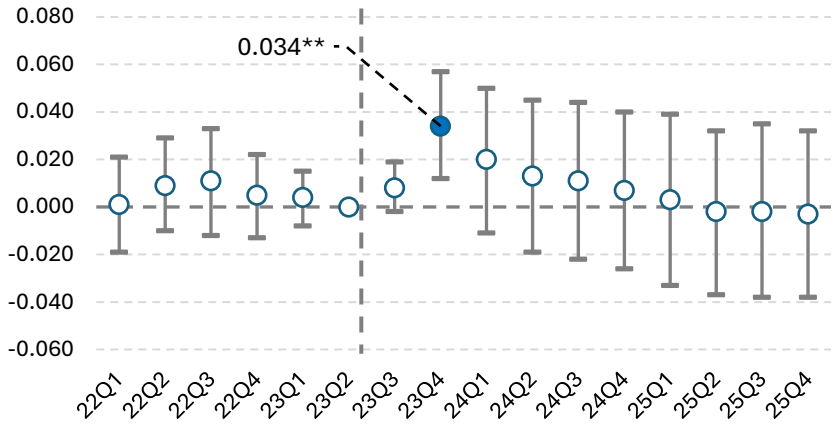



Figure E.1.E. Late-Career, Dynamic DiD (N = 97,472)

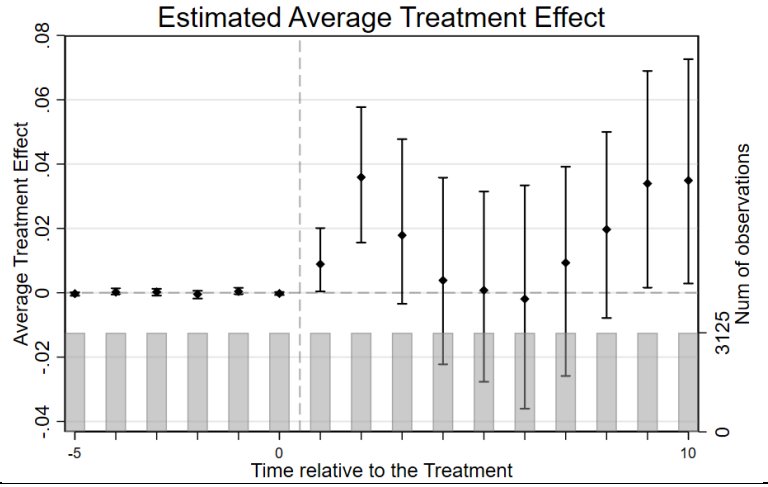



Figure E.1.F. Late-Career, FE Counterfactual (N = 97,472)

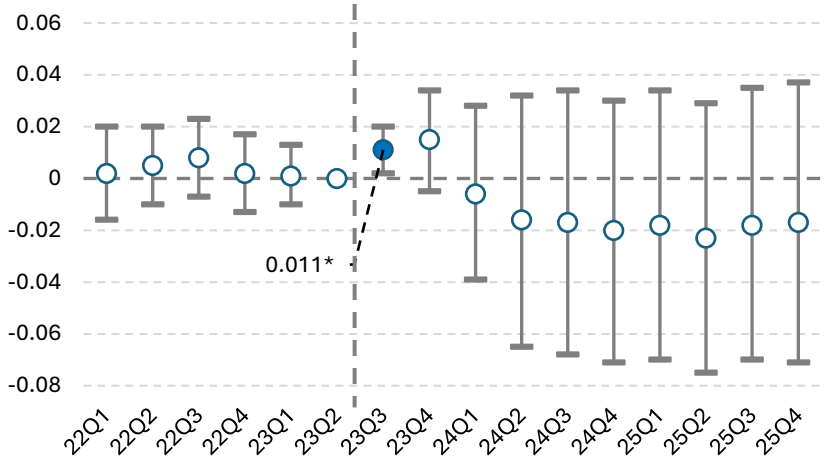



Figure E.1.G. Specialists, Dynamic DiD (N = 130,800)

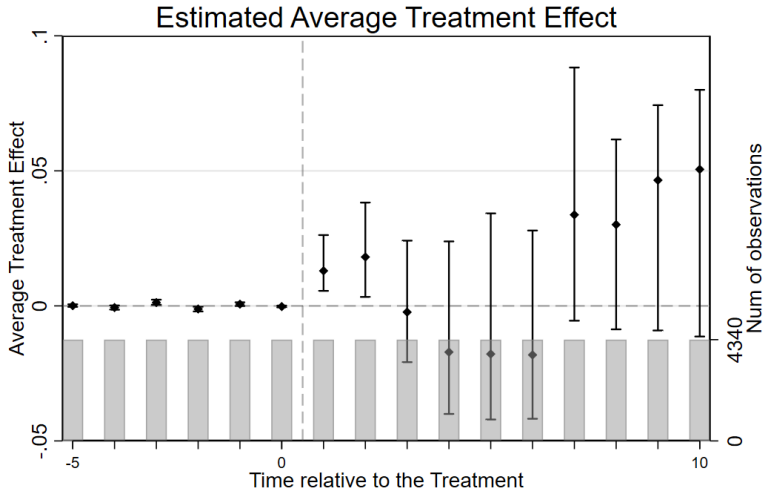



Figure E.1.H. Specialists, FE Counterfactual (N = 130,800)

**Note:** DiD – Dynamic difference-in-difference; FE – Fixed effects. The figures on the left present the results from the dynamic difference-in-difference, and those on the right present the results from the fixed effects counterfactual estimator method: estimated coefficients and 90% confidence intervals. The sub-figures on the right present the robustness checks using the fixed effects counterfactual estimator method to replicate the statistically significant results in Figures 1 and 2.

**Appendix E.2. Comparison: Proportion of Physicians Working for Two or More Employers, Working for One Employer in Time 1 Only**

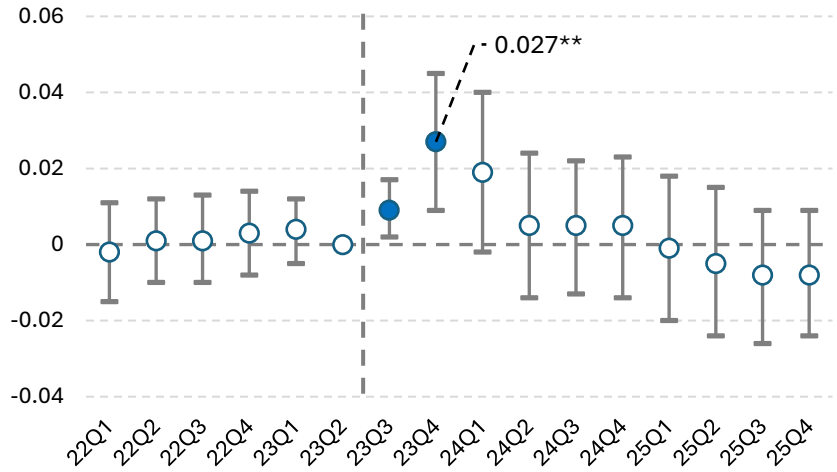



Figure E.2.A. Overall, Dynamic DiD (N = 216,288)

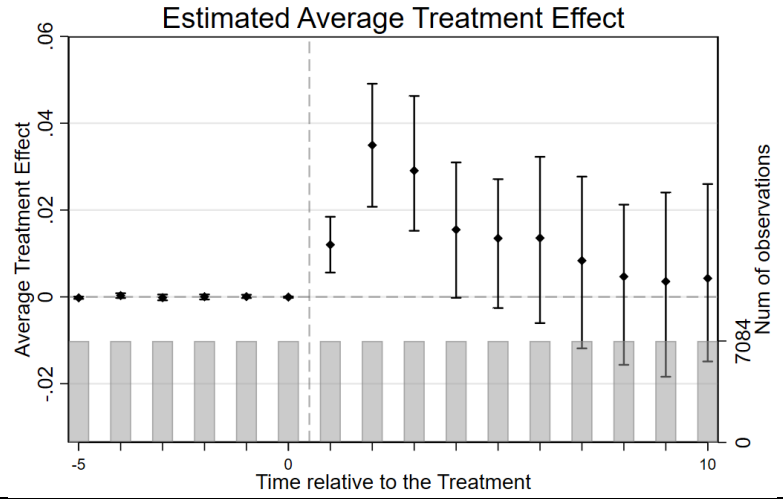



Figure E.2.B. Overall, FE Counterfactual

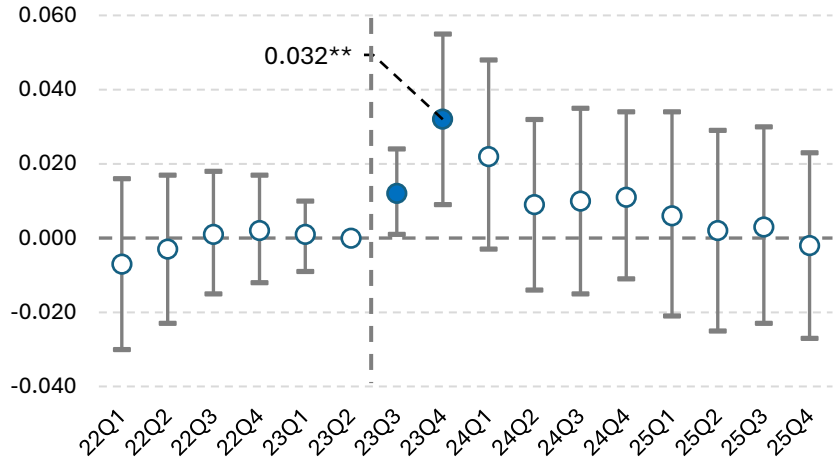



Figure E.2.C. Early-Career, Dynamic DiD (N = 73,776)

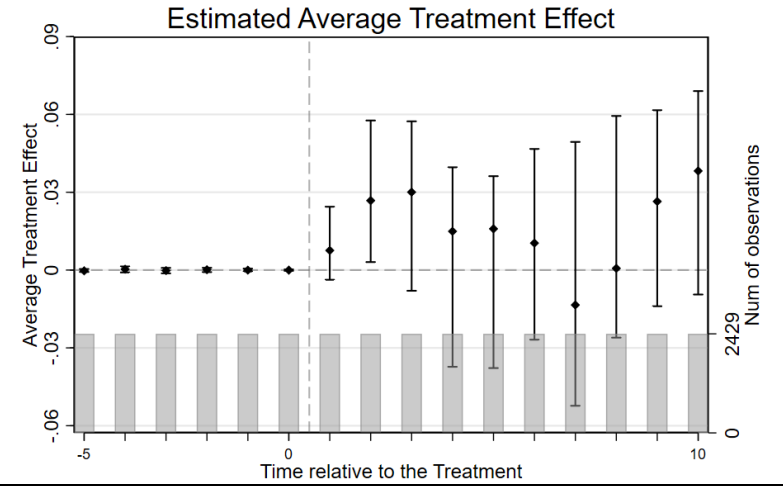



Figure E.2.D. Early-Career, FE Counterfactual

**Appendix E.2. Continued**

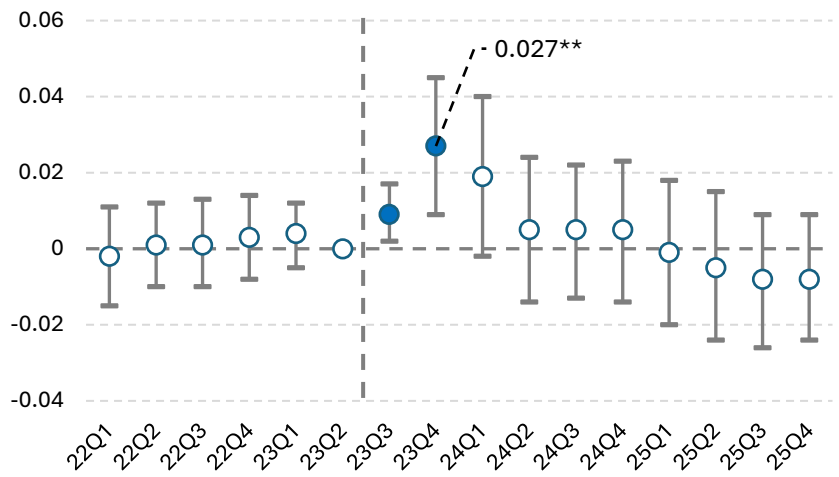



Figure E.2.E. Mid-Career, Dynamic DiD (N = 64,000)

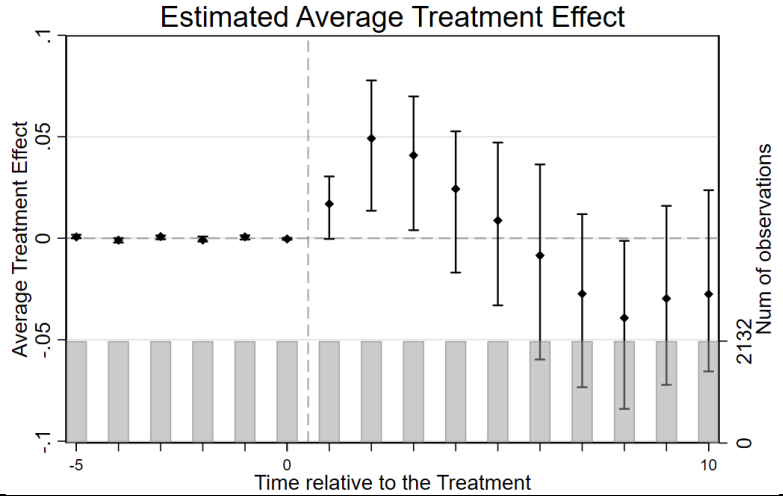



Figure E.2.F. Mid-Career, FE Counterfactual

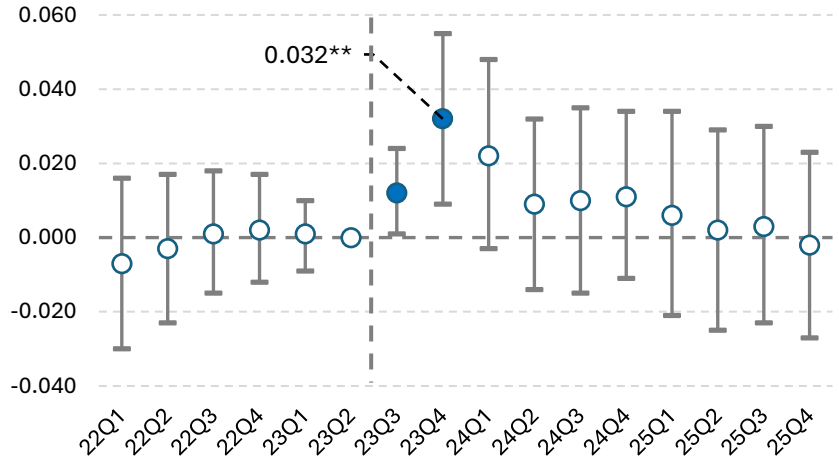



Figure E.2.G. Late-Career, Dynamic DiD (N = 76,080)

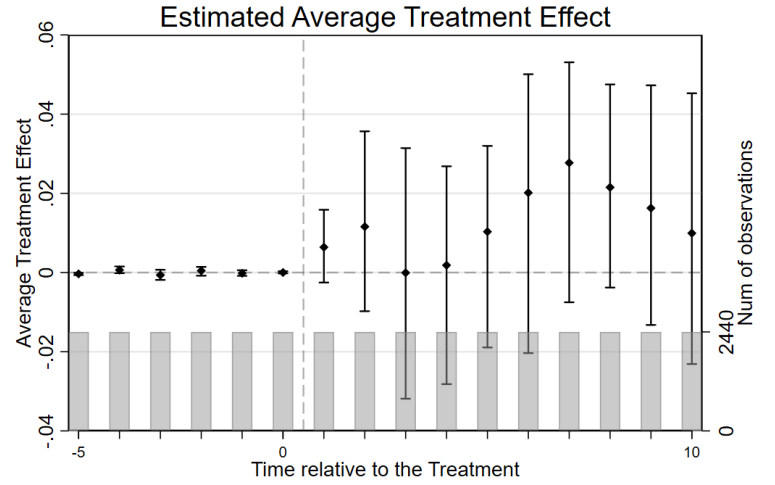



Figure E.2.H. Late-Career, FE Counterfactual

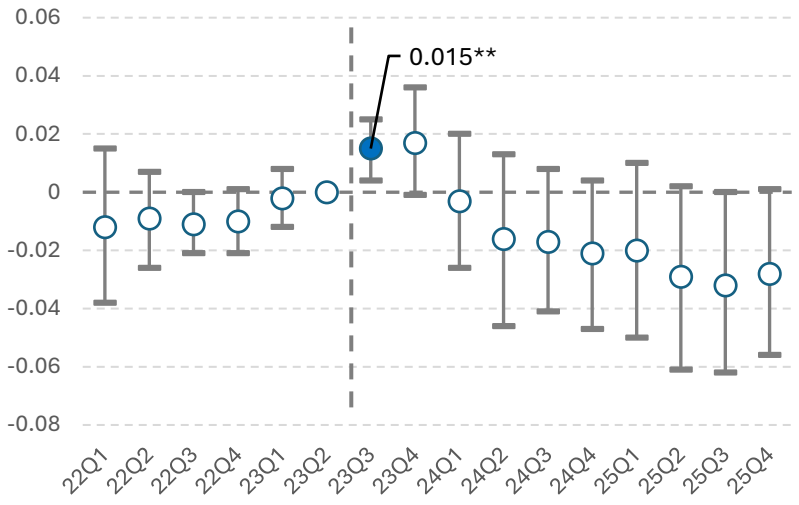



Figure E.2.I. Specialist, Dynamic DiD (N = 95,200)

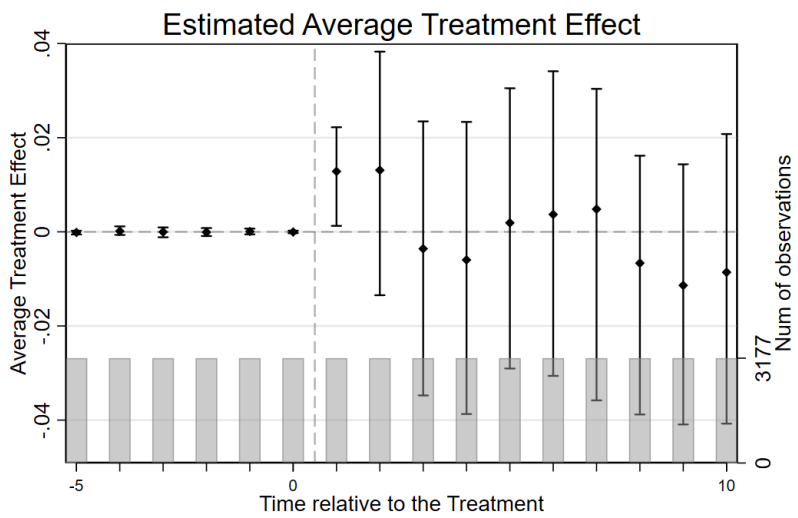



Figure E.2.J. Specialists, FE Counterfactual

**Note:** DiD – Dynamic difference-in-difference; FE – Fixed effects. The figures on the left present the results from the dynamic difference-in-difference, and those on the right present the results from the fixed effects counterfactual estimator method: estimated coefficients and 950% confidence intervals. The sub-figures on the right present the robustness checks using the fixed effects counterfactual estimator method to replicate the statistically significant results in Figures 3 and 4.

## Appendix E.3. Comparison: Number of Within-Organization Practices

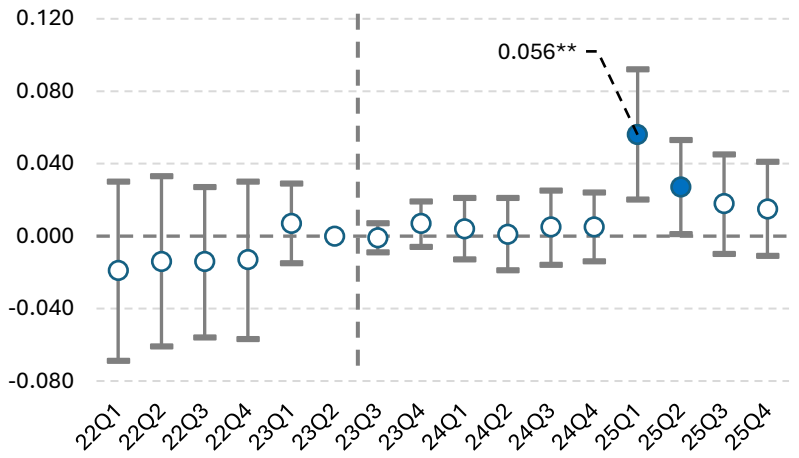



Figure E.3.A. Early-Career, Dynamic DiD (N = 91,968)

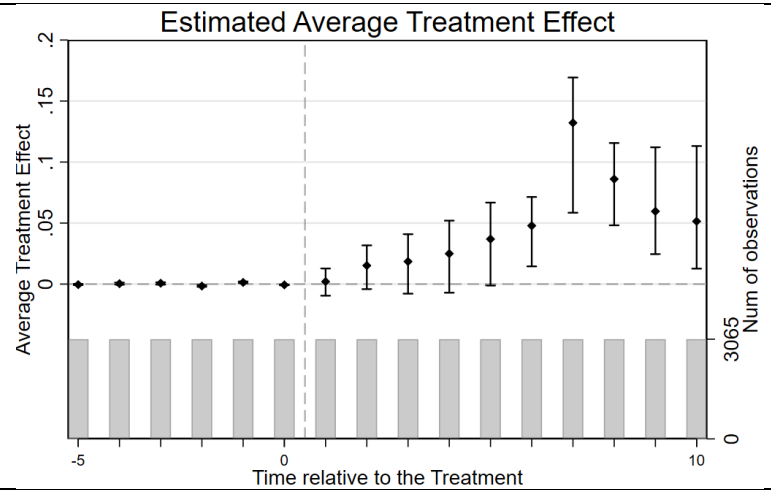



Figure E.3.B. Early-Career, FE Counterfactual

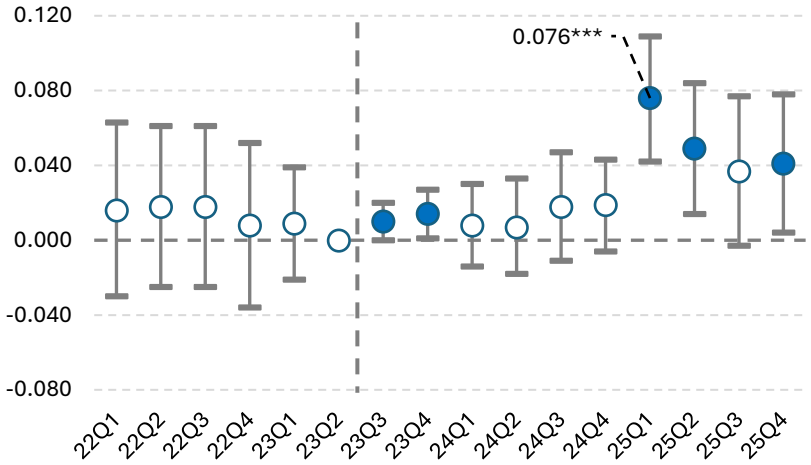



Figure E.3.C. Specialists, Dynamic DiD (N = 130,800)

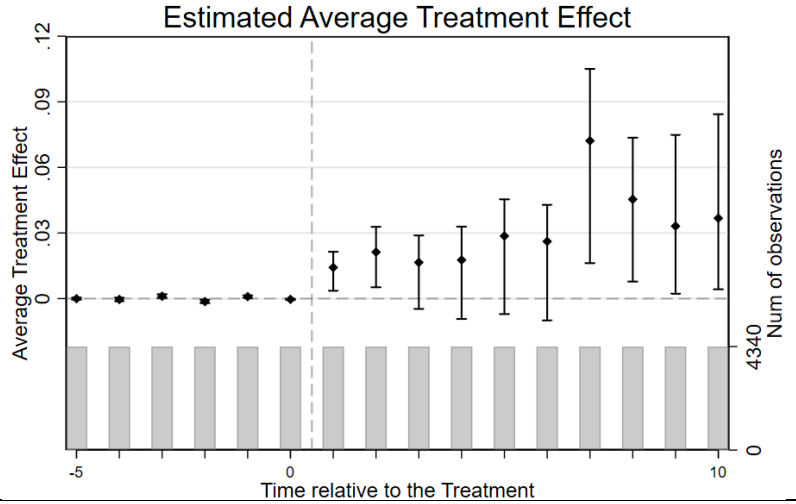



Figure E.3.D. Specialists, FE Counterfactual

**Note:** DiD – Dynamic difference-in-difference; FE – Fixed effects. The figures on the left present the results from the dynamic difference-in-difference, and those on the right present the results from the fixed effects counterfactual estimator method: estimated coefficients and 95% confidence intervals. The sub-figures on the right present the robustness checks using the fixed effects counterfactual estimator method to replicate the statistically significant results in Figures 5 and 6.

## Appendix E.4. Comparison: Total Number of Practices

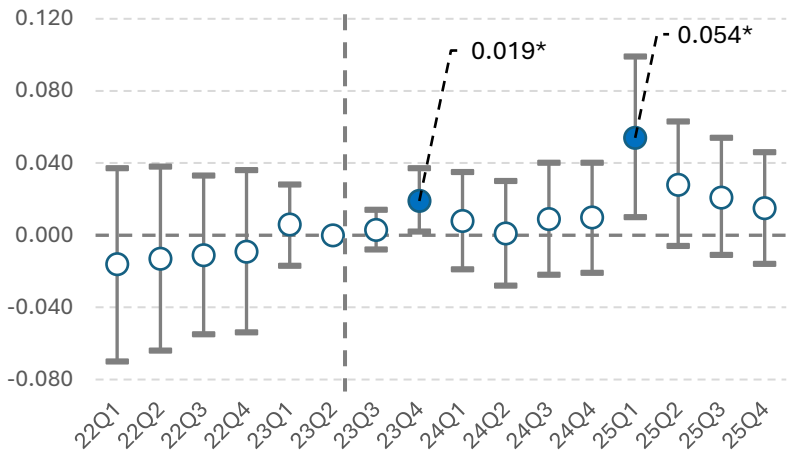



Figure E.4.A. Early-Career, Dynamic DiD (N = 91,968)

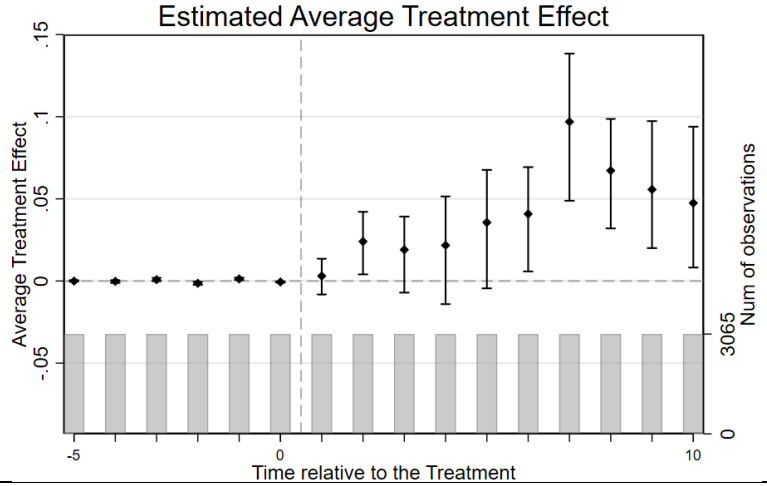



Figure E.4.B. Early-Career, FE Counterfactual

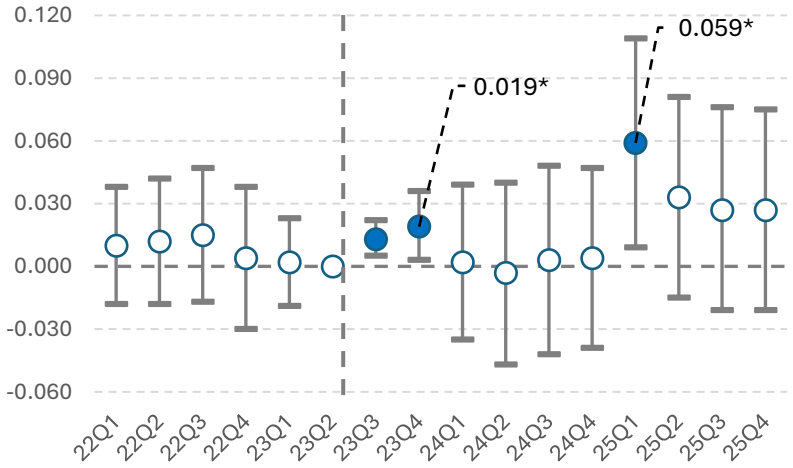



Figure E.4.C. Specialists, Dynamic DiD (N = 130,800)

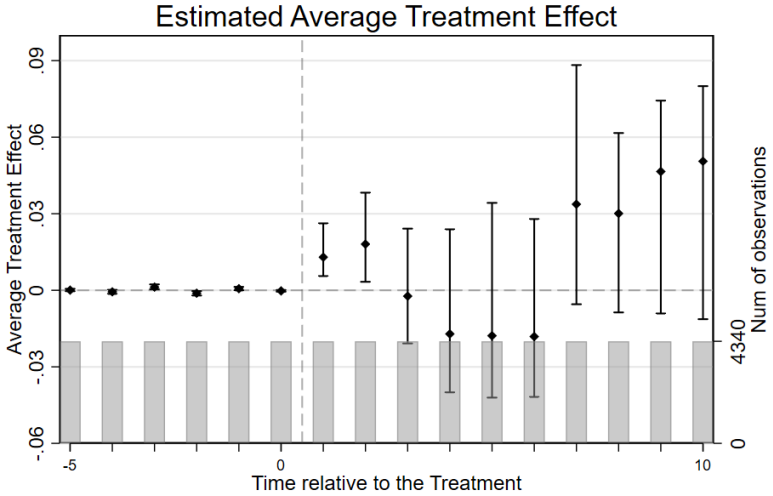



Figure E.4.D. Specialists, FE Counterfactual

**Note:** DiD – Dynamic difference-in-difference; FE – Fixed effects. The figures on the left present the results from the dynamic difference-in-difference, and those on the right present the results from the fixed effects counterfactual estimator method: estimated coefficients and 90% confidence intervals. The sub-figures on the right present the robustness checks using the fixed effects counterfactual estimator method to replicate the statistically significant results in Figure 7.