Strangulation Laws and Intimate Partner Homicides*

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Abstract

Do strangulation laws save lives? Non-fatal strangulation is a common and dangerous form of intimate partner violence perpetrated by men. It occurs when violence escalates in a relationship, frequently serving as a precursor to homicide. However, non-fatal strangulation has been largely dismissed by the criminal justice system for a long time. We examine the impact on intimate partner homicides of the strangulation laws that have been passed by U.S. state legislatures since 2003 to establish non-fatal strangulation as a serious stand-alone offence. Using FBI Supplementary Homicide Reports (1990–2019) and exploiting the staggered implementation of these laws and TWFE models estimated via OLS and two-stage (2SDID) procedures, we observe a significant decline in intimate partner homicides involving male victims aged 18–34 (-0.12, 95% CI = [-0.17, -0.07]; 46% of the mean male IPH in 2002). In contrast, the effect on female-victim intimate partner homicides is noisy (-0.14, 95% CI = [-0.37, 0.09]; 11% of the mean female IPH in 2002). Our analysis of dynamic effects and several robustness checks reveal no pre-trends or effects on homicides committed by strangers. This gender asymmetry aligns with a stylised model in which a woman who is victim of strangulation decides whether to kill her violent partner, report him to authorities, or take no action. Strangulation laws increase the probability that the perpetrator is incarcerated upon reporting, which decreases the probability that women kill their abuser, but has an ambiguous effect on women-victim intimate partner homicides.

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"If you prosecute a strangler, you can prevent a homicide."
— Casey Gwinn, former City Attorney of San Diego

1 Introduction

Intimate partner violence (IPV) is an alarming and pervasive issue, with many individuals, particularly women, suffering repeat abuse and in extreme cases murder by their intimate partners (in the U.S., one-third of murdered women are killed by an intimate partner, Black et al. (2023)). A critical but historically overlooked aspect of IPV is non-fatal strangulation, a common and gendered form of physical abuse perpetrated by men. Approximately 68% of domestic violence victims are estimated to have been strangled by their partners at some point (Stellpflug et al., 2022). Strangulation often signals an escalation of violence and control within a relationship and is one of the strongest predictors of subsequent homicide in IPV cases (Glass et al., 2008).

Despite the severity of this violent abuse (McGowan, 2024), only in 2003 U.S. state legislatures began passing laws to make non-fatal strangulation a serious stand-alone offence, defining what non-fatal strangulation is, and enlisting it as a specific crime in their statutes. These policies made police and prosecutors aware about it and its life-threatening features and elevated it to warranting serious prosecution (Training Institute for Strangulation Prevention). By 2019, 47 states had passed such laws, and by 2025 all but one did (South Carolina). To date, there is no systematic analysis of the effectiveness of this policy tool in reducing intimate partner homicides (IPH).

In this paper, we evaluate the impact of non-fatal strangulation laws on IPH of men and women. We compile a comprehensive dataset documenting the state legislatures' adoption and timing of these policies across U.S. states and pair it with FBI Supplementary Homicide Reports (1990–2019), which detail the victim's relationship to the perpetrator. Our analysis focuses on homicide rates with women victims and with men victims, aged 18–34, measured per 100,000 population in a state-year, and perpetrated by intimate partners. Our treatment variable of interest is a binary indicator equal to one in the year in which the non-fatal strangulation law becomes effective in a state, and ever since after that.

Before these laws were passed by state legislatures, non-fatal strangulation didn't use to be noticed by law enforcement or was considered as simple assault if recorded at all, due to its frequent lack of visible injuries, lack of weapon, or ignorance about its severe internal injuries. In the words of Gael Strack, one of the nation's leading strangulation experts and former domestic violence prosecutor in California[1]: "Most states treated strangulation about as seriously as if the victim was slapped in the face"; "The lack of physical evidence was causing the criminal justice system to treat many 'choking' cases

[1]CEO of Alliance for HOPE International and of the Alliance's Training Institute on Strangulation Prevention.

as minor incidents when in fact such cases were the most lethal and violent cases in the system".

Strangulation laws may represent an effective policy tool for reducing IPH by increasing the likelihood that abusive partners are incapacitated when the victim reports strangulation. By recognising and recording strangulation as a serious crime, police and prosecutors can take decisive action against violent partners when women report this violent abuse, preventing escalating violence. These laws may reduce the need for battered women to resort to killing their abusive partners to stop the continued abuse, thereby decreasing male-victim intimate partner homicides. However, their impact on female-victim intimate partner homicides critically depends on how effectively they are implemented in terms of incapacitating the abuser to commit a homicide. If incapacitation is limited, this may be offset by the competing risk of retaliation upon reporting. Indeed, Aizer and Dal Bo (2009) showed that a policy designed to alleviate IPV against women may indirectly benefit them only through an unambiguous decline in IPH with male victims.

To explore these channels, we develop a simple theoretical model to examine the dynamics of IPV and non-fatal strangulation. Women may face one of two types of male partners: stranglers or non-stranglers. After a strangulation event, women choose among three actions: killing their partner to stop the escalating violence, reporting him to authorities, or taking no action. Reporting leads to incarceration (and thus incapacitation) with probability p, with probability $(1-p)$ the strangler is not incarcerated, and she will eventually be killed by her abuser, while doing nothing increases the likelihood of being killed by the abuser. Killing the abuser ends the violence but leads to murder prosecution. Women in the population are heterogeneous in how much they value their relationship (economic and sentimental value), so that different women may choose different actions after experiencing strangulation.

This two-period model predicts that strangulation laws, by increasing the incarceration probability p, reduce male-victim IPH by encouraging some women to report their abusers rather than to endure the escalating violence until eventually they kill him to stop it. However, the impact on female-victim IPH is ambiguous, as it depends on the balance between the incapacitation effect (which decreases violence) and the reporting effect (which may increase the risk of a homicide if incarceration is not implemented). Fully effective policies ($p = 1$) would unambiguously reduce female-victim IPH, while partially effective ones ($0 < p < 1$) may yield mixed outcomes.

Our empirical analysis uses a staggered implementation design with two-way fixed effects (TWFE) models estimated via OLS. To address potential biases from heterogeneous treatment effects, we also employ a two-stage difference-in-differences (2SDID) approach (Gardner et al., 2024). We consistently observe that non-fatal strangulation laws significantly reduce male-victim IPH among the 18-34 age group (-0.12, 95% CI = [-0.17, -0.07]; this correspond to 46% of the mean male-victim IPH in 2002, — only about 5-10% of homicides are IPV among male-victim ones). However, their impact on female-victim

IPH among the 18-34 age group is less clear, with noisy estimates (-0.14, 95% CI = [-0.37, 0.09]; although the size of the estimated coefficient is very similar to the male one, this corresponds to only 11% of the mean female-victim IPH in 2002.)

The gendered effects of the policy—a clear sizable reduction in male IPH and noisier estimates for female IPH—are consistent with the model's predictions. Dynamic effects based on 2SDID event studies support the parallel trends assumption and reinforce our findings. No significant impacts are observed among individuals aged 35–49 or 50–70 per 100,000 population. Additionally, placebo tests show no effects on homicides committed by strangers. Mean state characteristics in 1990 or 2002 in income per capita, poverty rate, male to female unemployment rate, and intimate partner homicides do not exhibit significant differences between treated and never-treated states. Our findings are encouraging: enlisting non-fatal strangulation as a serious crime saves many lives by curtailing escalating IPV, thereby improving the wellbeing of the many vulnerable women trapped in violent abusive relationships. The "null" result on women may be evidence of a substantial amount of heterogeneity in how a criminal law is implemented across states and times. We hope that our analysis provides actionable evidence for policymakers worldwide, to design effective policies that address IPV and non-fatal strangulation.[2]

This research contributes to three key strands of literature: the growing body of work on IPV and policy analysis focused on effective judicial and police interventions; the literature on crime, particularly homicides, with an emphasis on gendered effects; and recent scholarship on gender differences and equality of opportunities, as strangulation is a profoundly gendered form of IPV.

The decline in IPH involving male victims is consistent with previous findings on abusive relationship dynamics. Aizer and Dal Bo (2009) demonstrate that no-drop policies in the U.S. significantly reduce only male-victim IPH, while Miller and Segal (2018) find that increases in female police officers reduce male-victim IPH as well as female-victim IPH. Dee (2003) reports an increase in male-victim IPH in states where marital property divisions upon divorce favour husbands. We contribute to this literature by incorporating non-fatal strangulation as an IPV channel potentially leading to IPH, building a two-period model of IPV where the effectiveness of a policy leads to a gender asymmetric IPH prevention, documenting how many lives are saved by these laws. Most IPV models do not consider policy effectiveness, and none incorporates non-fatal strangulation.

More broadly, our findings align with economic research exploring the role of legal changes in shaping abusive relationship dynamics. Cesur et al. (2022) link intimate partner violence reductions to changes in EITC provision, Erten and Keskin (2022) assess the impact of a compulsory schooling reform on IPV in Turkey. The role of stricter police arrest policies remains debated: Chin and Cunningham (2019a) find that mandatory domestic violence arrests do not increase IPH in the U.S., contrasting with Iyengar (2009). Brassiolo (2016) shows that legal reforms easing divorce reduce domestic vio-

[2] The WHO describes IPV as "global public health problem of epidemic proportions".

lence. Similarly, Amaral et al. (2023) highlight that arrests for domestic violence have both incapacitation and deterrence effects, reducing subsequent 911 calls, while Black et al. (2023) estimate that pressing charges decreases recidivism among intimate partner abusers.

The paper proceeds as follows: Section 2 presents our theoretical model; Section 3 describes non-fatal strangulation and the statutory classification of strangulation laws in the U.S.; Section 4 details the homicide data; Section 5 outlines our empirical specification; Section 6 analyses the adoption and timinig of strangulation laws. Section 7 reports the main findings; Section 8 provides robustness checks; and Section 9 concludes.

2 Model

In this section, we present a conceptual framework to understand the consequences of strangulation laws on female and male intimate partner homicides. The model allows us to investigate the impact of strangulation laws through women's behavior and its consequences for the lives of both women and men.

We consider a world where there are two types of male intimate partners: stranglers (S) and non-stranglers (NS). An exogenous fraction $\pi \in (0, 1)$ are stranglers, and $(1-\pi)$ are not. If a woman is strangled, she chooses among: killing the man to stop violence escalation (K), reporting the man to the authorities (R), or doing nothing (N). If a woman is not strangled, she does not make any decision.

If the woman kills the man, she incurs a total cost of $m + c$, where $c > 0$ is the cost of being prosecuted for killing the man, and m is the value of the relationship (economic and sentimental). Here, $m > 0$ and follows a cumulative distribution function (cdf) F with probability density function (pdf) f, which reflects heterogeneity in the population of women regarding how much they value their relationship. This may depend on a host of factors, including the woman's personality, socioeconomic status, etc.

If the woman reports the strangulation episode, with probability $p \in [0, 1]$ the man gets incarcerated and the relationship dissolves, so the woman incurs a cost of m. With probability $(1 - p)$, the man does not get incarcerated, and the woman eventually gets killed by him due to the escalation of violence, incurring a cost of d, the expected disutility of dying.

If the woman does nothing, she eventually gets killed for sure by her abuser, incurring a cost of d, the expected disutility of dying.

The model allows us to assess the effect of the strangulation law based on its effectiveness, which we measure with p, the probability that the man gets incarcerated when the woman reports him to the authorities. If there is no law, or if the law is completely ineffective, $p = 0$; if the law is implemented and fully effective, $p = 1$; and if the law is partially effective, $0 < p < 1$.

2.1 Woman's behavior

If the man strangles (S) the woman, she will choose to kill him (K) if K is preferable to both reporting him to the authorities (R) and doing nothing (N):

- K is preferable to R if:

$$m \leq d - \frac{c}{1 - p}.$$

- K is preferable to N if:

$$m \leq d - c.$$

Note that $m \leq d - \frac{c}{1-p}$ implies $m \leq d - c$. Thus, the woman will choose K if

$$m \leq d - \frac{c}{1-p}.$$

If the man strangles (S) the woman, she will choose to report him to the authorities (R) if R is preferable to both doing nothing (N) and killing him (K):

- R is preferable to N if:
$$p(m-d) \leq 0.$$
Since $p \geq 0$, this requires $m \leq d$.
- R is preferable to K if:
$$m \geq d - \frac{c}{1-p}.$$

Thus, the woman will choose R if

$$d - \frac{c}{1-p} \leq m \leq d.$$

Finally, if the man strangles (S) the woman, she will choose to do nothing (N) if N is preferable to both killing him (K) and reporting him to the authorities (R):

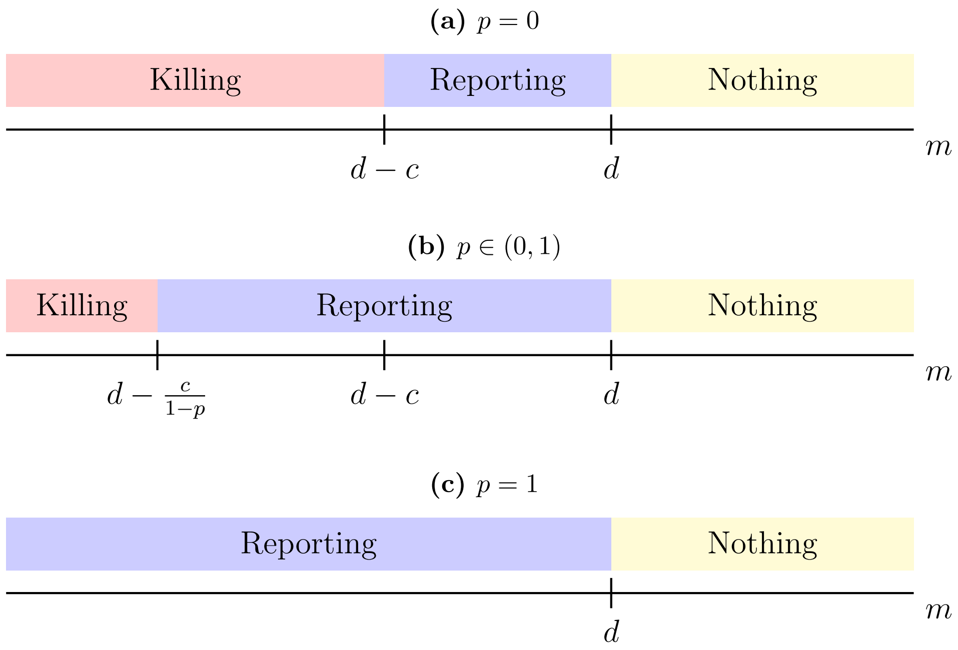
- N is preferable to K if:
$$m \geq d - c.$$
- N is preferable to R if:
$$m \geq d.$$

Note that $m \geq d$ implies $m \geq d - c$. Thus, the woman will choose N if

$$m \geq d.$$

The woman's behavior for different values of p is summarized in Figure 1.

Figure 1: Woman's behavior under different values of p



2.2 Predictions in the population of strangled women

Different women have different values of m. Given the cumulative distribution function of m in the population, F, we can compute the proportion of women among those who have been strangled who will kill their abuser, $P(K|S)$, report him $P(R|S)$, or do nothing $P(N|S)$ as:

$$P(K|S) = F\left(d - \frac{c}{1-p}\right).$$

$$P(R|S) = F(d) - F\left(d - \frac{c}{1-p}\right).$$

$$P(N|S) = 1 - F(d).$$

We can also compute the probability that a woman who has been strangled will be eventually killed by her abuser due to escalating violence, $P(WK|S)$, noting that the woman will be eventually killed when doing nothing (N), while she is eventually killed with probability $(1-p)$ after she decides to report her abuser to the authorities (R):

$$P(WK|S) = P(N|S) + (1-p)P(R|S) =$$

$$= (1 - F(d)) + (1-p)\left[F(d) - F\left(d - \frac{c}{1-p}\right)\right].$$

We interpret the strangulation law as an increase in p: it increases the probability that the abuser is incarcerated after strangling his partner upon her reporting him. In practice, the law elevates strangulation to stand-alone crime that becomes a serious misdemeanor or a felony, so that police and prosecutors can record and prosecute this violent abuse, increasing the probability that the abuser is incarcerated.

The following propositions follow from the model:

Proposition 1. A strangulation law **reduces** the probability that a man who has strangled his woman is killed by her. Specifically, a marginal increase in p decreases the probability of the man getting killed by:

$$\frac{\partial P(K|S)}{\partial p} = -\frac{c}{(1-p)^2} f\Big(d - \frac{c}{1-p}\Big) \leq 0.$$

Proposition 2. A strangulation law **increases** the probability that a woman reports the man who strangles her to the authorities. Specifically, a marginal increase in p increases the probability of reporting by:

$$\frac{\partial P(R|S)}{\partial p} = \frac{c}{(1-p)^2} f\Big(d - \frac{c}{1-p}\Big) \geq 0.$$

Proposition 3. A strangulation law has **no effect** on the probability that a woman who has been strangled by her partner does nothing. Specifically, a marginal increase in p has no effect on the probability of doing nothing:

$$\frac{\partial P(N|S)}{\partial p} = 0.$$

Proposition 4. A strangulation law has an **ambiguous** effect on the probability that a woman who has been strangled is eventually killed. On the one hand, the probability of her being killed may decrease as the man is more likely to be incarcerated and less likely to harm her (incapacitation effect). On the other hand, the probability may increase because she is more likely to report rather than kill him (reporting effect). Specifically, a marginal increase in p has the following effect on the probability of a woman being killed:

$$\frac{\partial P(WK|S)}{\partial p} = \underbrace{-\Big[F(d) - F\Big(d - \frac{c}{1-p}\Big)\Big]}_{\text{incapacitation effect}<0} + \underbrace{\frac{c}{(1-p)} f\Big(d - \frac{c}{1-p}\Big)}_{\text{reporting effect}>0}.$$

Figure 2 simulates $P(K|S)$, $P(R|S)$, $P(N|S)$, and $P(WK|S)$ for different values of p, using 1000 draws under the assumption that F is a standard normal cdf, and with costs assumed to be $d = 3$ and $c = 2$.

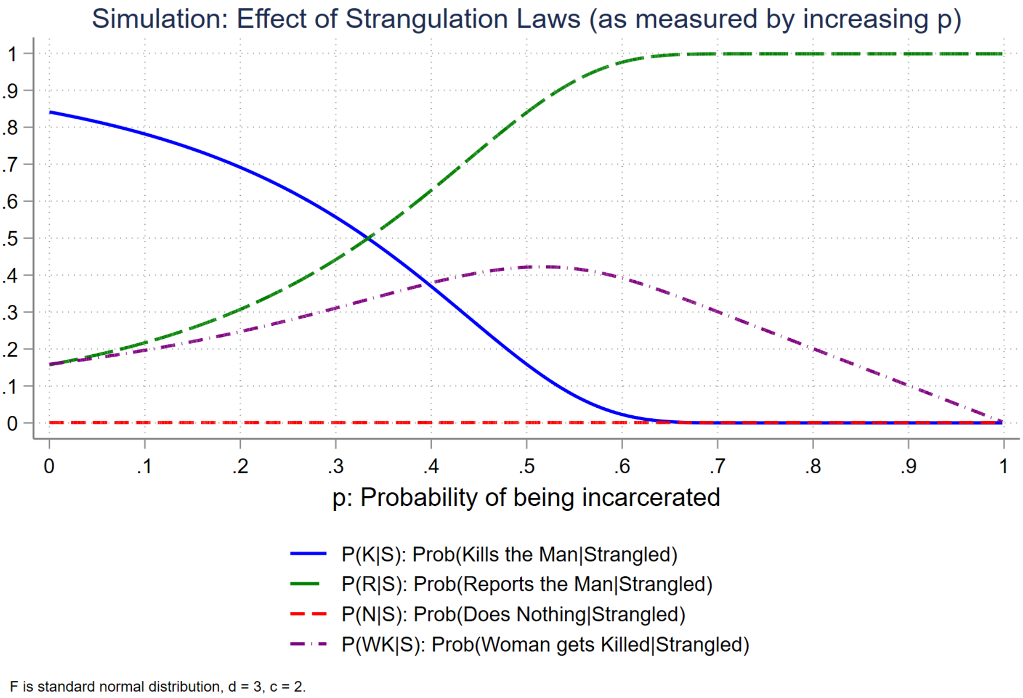


Figure 2: Simulation of the predictions in the population of strangled women.

The simulation shows the following: $P(K|S)$ decreases with p (Proposition 1), $P(R|S)$ increases with p (Proposition 2), $P(N|S)$ is independent of p (Proposition 3), and $P(WK|S)$ is a non-monotonic function of p: it increases with p when $p < 0.5$, but decreases with p when $p > 0.5$. Therefore, the effect of p on $P(WK|S)$ is ambiguous (Proposition 4).

2.3 Testable Predictions

Our propositions pertain to the population of women who are victims of non-fatal strangulation, while our data encompass the entire population of men and women. Furthermore, our outcome of interest is whether strangulation laws save lives, that is, decrease the incidence of intimate partner homicides of men and women. To derive testable predictions, we compute the unconditional probabilities that a woman kills her intimate male partner in the population and that a man kills his intimate female partner in the population:

$$P(K) = P(S)P(K \mid S) = \pi F\left(d - \frac{c}{1-p}\right),$$

$$P(WK) = P(S)P(KW \mid S) = \pi\left[(1 - F(d)) + (1-p)\left(F(d) - F\left(d - \frac{c}{1-p}\right)\right)\right],$$

where π denotes the fraction of stranglers in the population, and $P(K)$ and $P(WK)$ are proxied by the male and female intimate partner homicide incidence rates, respectively.

Testable prediction 1. A strangulation law reduces the probability that a man is killed by his intimate female partner:

$$\frac{\partial P(K)}{\partial p} = -\pi\frac{c}{(1-p)^2} f\left(d - \frac{c}{1-p}\right) \leq 0.$$

Testable prediction 2. A strangulation law has an ambiguous effect on the probability that a woman is killed by her intimate male partner:

$$\frac{\partial P(WK)}{\partial p} = \pi\left[\underbrace{-\left[F(d) - F\left(d - \frac{c}{1-p}\right)\right]}_{\text{incapacitation effect}<0} + \underbrace{\frac{c}{(1-p)} f\left(d - \frac{c}{1-p}\right)}_{\text{reporting effect}>0}\right].$$

In other words, we expect that strangulation laws decrease male intimate partner homicides, and if the incapacitation effect outweighs the reporting effect, strangulation laws are also expected to decrease female intimate partner homicides.

2.4 Discussion on the effectiveness of the law and its effects

If the implementation of the strangulation law causes p to shift from 0 to 1, the predictions of the model are unambiguous. In this extreme case, a strangulation law will reduce both the probability that a man is killed by his intimate female partner and the probability that a woman is killed by her intimate male partner. Specifically, the comparison of these polar cases shows that as p increases from 0 to 1:

- $P(K)$ decreases from $\pi F(d-c)$ to 0.[3]
- $P(WK)$ decreases from $\pi(1-F(d-c))$ to $\pi(1-F(d))$.

However, there are several reasons why the effectiveness of the strangulation law (p) may fall between 0 and 1, including:

- **Partial enforcement:** Police may not consistently respond effectively to reports of strangulation, or prosecutors may not prioritize such cases.
- **Limited awareness:** Victims may not realize that strangulation is now a criminal offense with serious consequences.
- **Limited resources:** Enforcement agencies may lack the resources to fully implement the law, such as trained personnel, forensic tools to investigate strangulation, or shelters and support for victims who report the crime.

Finally, we note that our model neglects the behavior of men, but strategic behavior by offenders could further complicate outcomes. For example, offenders might adapt their behavior in response to the law, avoiding strangulation specifically but engaging in other forms of violence, thereby diluting the law's direct impact.[4]

[3] When $p = 1$, $P(K) \to \pi F(-\infty) = 0$.

[4] One could endogenize π by modeling the man's behavior in choosing whether to strangle or not. However, if π is independent of p in equilibrium due to competing forces, the implications remain unchanged.

3 Institutional Background

We provide here a brief explanation of what non-fatal strangulation consists of, along with an overview of the institutional background surrounding the non-fatal strangulation laws. The recently emerging dating trend of "sexual choking", a form of strangulation during casual sex, is not under analysis in this study.

3.1 Non-Fatal Strangulation

Our focus is on non-fatal strangulation, a near-lethal manifestation of gendered IPV that has already escalated to violent attacks and coercive control. Strangulation is an intentional physical attack that not only blocks airways but also impedes blood circulation, potentially causing severe brain damage that manifests later. The only weapon needed are the attacker's hands. Only 11 pounds of pressure for 6.8 seconds on the carotid artery and 4.4 pounds on jugular vein required to produce unconsciousness: this is less than the pressure used to open a can of soda. Brain death may occur within 4-5 minutes if strangulation persists. However, if the pressure is immediately released, consciousness will be regained within 10 seconds, but brain damage might have already occurred (Strack and Gwinn, 2011).

Strangulation does not usually cause visible external injuries on the victim (as frequently as in 50% of cases there are no visible symptoms) but may result in a wide range of mostly internal injuries, such as fracture of the hyoid bone, larynx, tracheal rings, carotid tears and occlusions, blood clots, pain, swelling, voice changes, anoxic brain trauma, and altered mental state with slow processing of information, forgetfulness, breathing difficulties, dizziness, etc.

Despite this severity and near-death features, the perception and knowledge of the public and professionals about the dangers of strangulation was totally inadequate. Strangulation was often referred to as choking or attempted strangulation and downgraded to a minor incident or totally dismissed. It was minimized or unreported by the victims themselves, by police officers attending the scene, and by prosecutors (McKay, 2014). Contrary to stabbing which can be charged as a very serious crime even with superficial wounds, strangulation can go easily undetected due to lack of awareness among police and prosecutors, which led the entire criminal justice system to overlook non-fatal strangulation. This exposed victims to escalating intimate partner violence and potentially death, as strangulation is usually one of the last types of violent abuses committed by an intimate partner before murder ("when a victim is strangled, she is at the edge of a homicide": Strack and Gwinn (2011).). Indeed, there is a high risk of being killed by your IP if you've been strangled: the victim is 750% more likely to be killed by their abuser if non-fatal strangulation happened (Glass et al., 2008).

3.2 Statutory Classification and US State Legislatures' Bills

Strangulation statutes are a recent criminal justice phenomenon. Historically, until the 1990s, IPV was often dismissed by law enforcement as a private family matter; it was not until the aftermath of two teenage mothers' deaths in 1995 in San Diego that the criminal justice system started to notice strangulation, its severity and high frequency in IPV. However, it took until 2003 for the first state legislature to pass a bill that enlisted strangulation as a stand-alone crime, describing the act of strangulation in detail and the offence associated to it (Oregon, law effective since 2004). Many states legislatures followed suit implementing strangulation laws across the US in the next twenty years. By 2019, 47 states had passed such laws, and by 2025 all but one did (South Carolina).

These bills specifically identified strangulation in statute, defining it and identifying it as a crime for the first time. The fact that they explicitly spelt out strangulation in the Statutes, elevating it to a specific well-defined serious crime, provided law enforcement with the necessary tool to investigate it, encouraging them to prosecute this crime with the seriousness it deserves. By including strangulation into the state criminal law and elevating it to a serious offense liable for arrest (felony or class A misdemeanor), police officers, prosecutors and courts were empowered to recognize and combat this very lethal form of violent domestic abuse.

These bills changed the perception and knowledge about strangulation, because prior to them it went often unprosecuted, at best categorized as simple assault, or even unrecorded by law enforcement: often it does not bear visible injuries, and the previous statutes did not mention it or characterize it at all when referring to aggravated assaults or (serious) bodily injury. Law enforcement's testimonies to state legislators debating these bills emphasize exactly these pitfalls: for instance, among the testimonies contained in the state legislature hearings and proceedings for state bill SB2185 of North Dakota in 2007, Dan Draovitch, a retired police chief writes "Please, on behalf of our Law Enforcement folks - please modify this law to specifically add Strangulation, and strengthen our laws and give us a well defined law to better protect the victims of Domestic Violence....", while from the State's Attorney Office they ask the legislators whether they know "how hard it is to explain to a victim of strangulation that the person who about ended their life could only be charged with a "simple assault" because the victim only had a red mark on their neck and no other visible injury. Imagine having to explain to this person that the maximum penalty for this offense is only 30 days in jail. Does that seem like the punishment fits the crime?"

There is sparse literature on state strangulation laws and no taxonomy collating complete or consistent information on the state legislature bills (Pritchard et al., 2017). We collect data on strangulation statutes directly at the source, by reading the state legislatures' archives and proceedings, manually identifying the specific bill that adds non-fatal strangulation to the statutes and its legislative passage history. In some instances, these bills are very short and deal only with the strangulation offense, in other states the strangulation provision is added to the statutes among a long list of amendments concerning other topics.

We pay specific attention to the description of the offense and to the dates in which the bill was passed (approved by governor) and the law became effective (if different from the approval date), thus retrieving the exact years in which the state strangulation laws were implemented for all the US states until 2025. The treatment variable in our analysis is a binary indicator equal to one in the year in which the non-fatal strangulation law becomes effective in a state, and ever since after that.

Figure 3 categorizes states by their treatment cohorts from 2004 to 2019, covering 49 states and excluding Alaska and Hawaii, dividing them into various cohorts based on the year of treatment. Oregon was the first state to pass a strangulation bill in 2003 (law became effective in 2004), followed by North Carolina, Nebraska, and Oklahoma in 2004. The most recent states to pass such laws until 2019 were New Mexico in 2018 and Kentucky in 2019. Throughout the period from 1990 to 2019, there are four states that did not pass any strangulation law: Washington D.C., Maryland, Ohio, and South Carolina. These are the never-treated states in our analysis, since our empirical analysis focuses on laws implemented until the year 2019, discarding later years because of the COVID-19 pandemic's disruptions.

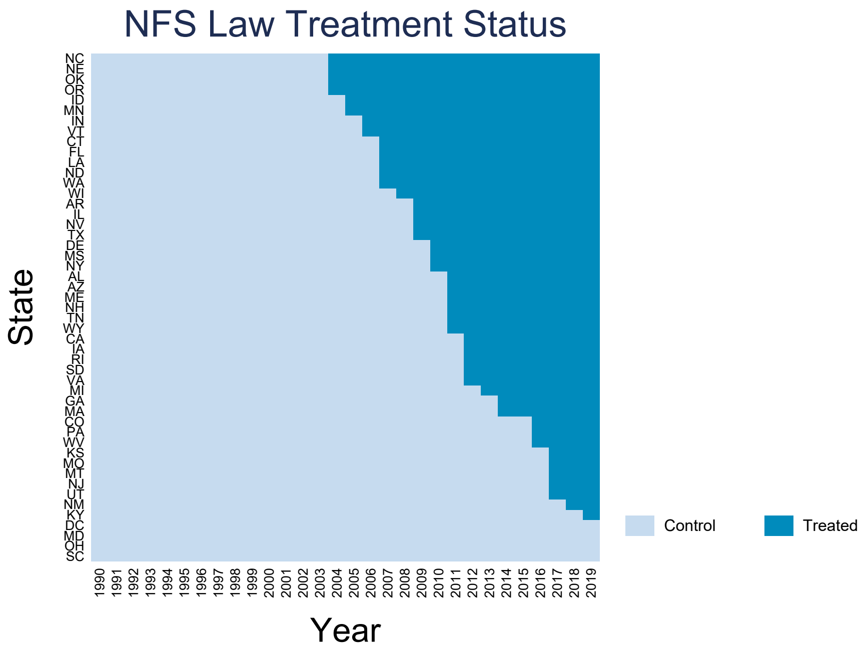


Figure 3: Staggered implementation of Non-Fatal Strangulation Laws

Table 1 provides the complete taxonomy until 2019 listing the number of states and their percentage within each cohort. The largest cohort is 2011, with six states (12.24%), and the smallest cohort is 2015 (0%). Each cohort represents a different year of intervention, reflecting the progression and distribution of treatment over time.[5]

[5] Alaska's NFS law dates back to 2005, while Hawaii's was enacted in 2006. After 2019, other states followed suit: Maryland (2020), Washington, D.C. (2023), and Ohio (2023). As of January 2025, South Carolina has yet to pass a law.

Table 1: State Treatment Cohorts (2004-2019)

Treatment Cohort	**States**	**Number of States**	**% of States**
Never treated	DC, MD, OH, SC	4	8.16%
2004 cohort	NE, NC, OK, OR	4	8.16%
2005 cohort	ID, MN	2	4.08%
2006 cohort	IN, VT	2	4.08%
2007 cohort	CT, FL, LA, ND, WA	5	10.20%
2008 cohort	WI	1	2.04%
2009 cohort	AR, IL, NV, TX	4	8.16%
2010 cohort	DE, MS, NY	3	6.12%
2011 cohort	AL, AZ, ME, NH, TN, WY	6	12.24%
2012 cohort	CA, IA, RI, SD, VA	5	10.20%
2013 cohort	MI	1	2.04%
2014 cohort	GA, MA	2	4.08%
2015 cohort	–	0	0.00%
2016 cohort	CO, PA, WV	3	6.12%
2017 cohort	KS, MI, MT, NJ, UT	5	10.20%
2018 cohort	NM	1	2.04%
2019 cohort	KY	1	2.04%
Total		**49**	**100%**

Globally, there is still a lack of legal recognition and perception of non-fatal strangulation as a serious violent crime: for instance, Scotland or Singapore do not have any specific provision, while in England and Wales a non-fatal strangulation law became effective only as recently as 2022 and in Victoria (Australia) in late 2024. IPV charities and victims' families across the globe continue to advocate for non-fatal strangulation to be elevated to a severe offence for a violent crime.

4 Data Description

Our main outcome of interest is female and male homicides committed by intimate partners. Intimate Partner (IP) is defined as relationships like current spouse, ex-spouse, girlfriend/boyfriend, and common-law wife/husband, while non-IP is defined as all other relationships. We omit same-sex relationships from the sample due to their extremely small numbers among IP homicides. We focus our analysis where in an incident of IP homicide (IPH hereafter) the victim is 18-34 years old, expressed as a rate per 100,000 population. We supplement this outcome with female-victim and male-victim IPH in the age groups 35-49 and 50-70. We use these data from the Supplementary Homicide Reports (SHR) of the Federal Bureau of Investigation (FBI) (which is part of the Uniform Crime Reporting (UCR) series) provided by Fox and Swatt (2023). The FBI-SHR data are among the most comprehensive datasets on homicides in the United States. These data provides information on victim and offender age, sex, race, weapon type and location. The unit of analysis in the SHR is the incident of homicide (not the victim) and contains one record per homicide incident.

There are two sources for using homicide data in the US, the SHR, as mentioned above and National Incident-Based Reporting System (NIBRS); both of which records the relationship between victims and offender. Whereas NIBRS includes detailed data for each offenses, including property involved in the crimes, known offenders, linkages to other crimes committed at the same time etc; the biggest concern with NIBRS is the sparse coverage it has geographically for the time frame used in this analysis (1990-2019). Literature records that in 2018, only 30% of the US population and 28% of all crimes reported to UCR was captured in NIBRS (Fegadel and Heide, 2018). As of 2020, only about 49% of the law enforcement agencies were reporting to the NIBRS, whereas UCR is more widely used providing information on nearly all law enforcement agencies in the US.[6] As a result, we use this data for our outcomes in this paper.[7]

As described above, The SHR records detailed voluntary monthly submissions from local law enforcement agencies, collating information on the victim's characteristics such as age, sex, and race, as well as the offender's characteristics, victim-offender relationship, and type of weapon used, among others. These detailed data on homicides cover a period of over thirty years. Even though submissions to the FBI-SHR are voluntary, the reporting level is generally high (Fox and Swatt, 2009). One drawback of these data is potential under-reporting since submission is voluntary, as well as the fact that law enforcement agencies are required to log a record in the month when the homicides are discovered rather than when they occurred, which might result in measurement error:

[6] However, FBI has transitioned to NIBRS only data in 2021 and in future NIBRS will be useful to complement analysis done with SHR data.

[7] Research in Economics and other disciplines involving homicide data tend to use FBI-SHR data for outcomes as well, among others, Pampel and Williams (2000); Jennings and Piquero (2008); Aizer and Dal Bo (2009); Chin and Cunningham (2019b).

however, we pool the data at the annual level. Despite this, the SHR data are the most comprehensive and reliable dataset on homicides in the US at the state and county level, and this data source is widely used in the literature (Cunningham et al., 2017; Garrett et al., 2017).

We focus on homicides with a single victim and a single offender. It is important to note that homicides are the most extreme form of violence and, therefore, their prevalence per 100,000 population will appear small in terms of average numbers, although they are unfortunately less rare among intimate partner violence victims.

In the robustness checks section, we consider several control variables such as (log) income per capita, poverty rate and unemployment rate, all at the state level, to control for resources in a state. Specifically, we use age-specific female and male unemployment, educational attainments for both gender by age groups, and age-gender specific wages at the state level, computed from the Current Population Survey (Flood et al., 2022). Female (male) unemployment in a particular age group is calculated from CPS data as the number of unemployed females (males) over the number of females (males) in that age group in state s and year t. These range from 0.8% to 8% for females and 0.7% to 14% for males in age group 18-70 for example. The percentage of females with college or higher education among the female population aged 18-70 is approximately 25% to 77%, whereas that of males range from 26-74%. We compute and merge in these controls for each age groups used in our study, that is 18-49, 18-34, 35-49, and 50-70. Moreover, we use the state policy correlates database collated by IPPSR (2023), which is based on the research of Grossmann et al. (2021), and use some state specific characteristics like per-capita income, poverty rate etc. We also add a variable proxying for gender power balance, as customary in the domestic violence literature (Aizer, 2010): male-to-female unemployment ratio (constructed from the variables above) at the state level.

We complement our analysis by considering two additional outcome variables from the FBI data: the number of homicides of men and women committed by strangers per state and year per 100,000 population in the same age ranges as in our IPH analysis, and the number of property crimes per state and year per 100,000 population.

5 Empirical Specification

5.1 Overall ATT estimates

TWFE via OLS estimation. Our main empirical specification relies on a static two-way fixed-effects (TWFE) regression model estimated by OLS:

$$IPH_{st} = \beta NFSLaw_{st} + \alpha_s + \gamma_t + \varepsilon_{st} \tag{5.1}$$

where IPH_{st} is the main outcome variable of interest, a measure of the male-victim / female-victim homicide rate (per 100,000 inhabitants) committed by intimate partners in state s during year t. Law_{st} is an indicator equal to one for years after state s introduced a non-fatal strangulation law at time t. α_s, a vector of time-invariant state fixed effects, accounts for time-invariant state characteristics that may be correlated with the adoption of non-fatal strangulation laws and with IPH_{st}. γ_t, a vector of shocks in a given time period experienced equally by all states, accounts for possible national trends in IPH_{st}. ε_{st} captures any unobservable factors that affect IPH_{st}. Standard errors are clustered at the state level to allow for correlation in the residuals.

The parameter of interest β is the (constant) average effect of the treatment on the treated (ATT), in our context, the effect of introducing strangulation legislation on the prevalence of intimate partner homicides amongst states that introduced a strangulation law. If the treatment effect is constant across states and over time, then the OLS estimate of equation (5.1) will be consistent for β under a parallel trends assumption on the error term (Butts and Gardner, 2022; Roth et al., 2023).

TWFE via Two-Stage Estimation (2SDID). As highlighted by Goodman-Bacon (2021), the estimation of TWFE via OLS is problematic under the presence of heterogeneous effects. We complement our OLS estimation procedure with a heterogeneity-robust analysis based on the two-stage procedured derived by Gardner et al. (2024). This is a two-stage difference-in-difference (2SDID) estimator which will provide a consistent estimate as long as three assumptions are satisfied, namely, parallel trends, limited anticipation, and correct specification of the potential outcome without treatment (i.e., without passing the NFS law). The two-stage difference-in-differences (2SDID) estimator, proposed by Gardner et al. (2024), addresses issues with the OLS estimator of the TWFE model. It first estimates state and time effects using only untreated or not-yet-treated observations. Then, it uses these estimated effects to adjust the outcomes and regress the adjusted outcomes on treatment status to estimate the average treatment effect. This method ensures the treatment effect is consistently estimated by leveraging the parallel trends assumption, with adjustments made for standard errors to account for first-stage estimation uncertainty.

5.2 Dynamic ATT estimates

The 2SDID approach can also be extended to dynamic models for evaluating treatment effects over time. As discussed by (Butts and Gardner, 2022), researchers sometimes estimate dynamic (event-study) TWFE via OLS, allowing treatment effects to change over time, to deal with heterogeneity:

$$IPH_{st} = \sum_{k=L}^{-2} \beta_k Law_{st}^k + \sum_{k=0}^{M} \beta_k Law_{st}^k + X_{st}'\theta + \alpha_s + \gamma_t + \eta_{st} \tag{5.2}$$

where the treatment indicator Law_{st} in Equation 5.1 is replaced with a sequence of event-study year indicators Law_{st}^k. We allow k to index the years before and after treatment, with the year just before treatment left out as the comparison year. For $k \geq 0$, β_k represents the average effect of being treated for k periods. For $k \geq 0$, β_k is known as "pre-trend." Unfortunately, Sun and Abraham (2021) show that the need for a robust difference-in-differences estimator may remain even in the event-study model, hence we provide event-study estimates using the 2SDID.

5.3 Control variables?

In the robustness checks section, we consider control variables such as (log) income per capita, poverty rate and unemployment rate, all at the state level, to control for resources in a state. We also add a variable proxying for gender power balance, as customary in the domestic violence literature (Aizer, 2010): male-to-female unemployment ratio at the state level. While the intuition for adding covariates is that parallel trends only hold conditional on some variables, the inclusion of time-varying controls imposes some statistical problems (Huntington-Klein, 2022). With this caveat in mind, we proceed in two different ways: adding controls that are purely time-varying (meaning the control measured at year t in state s) and time-trend varying (meaning the control measured at baseline (1990) interacted with linear time trend (Bailey and Goodman-Bacon, 2015; Conti and Ginja, 2020; Mora-García et al., 2024).

6 Adoption and Timing of NFS Laws

Is Adoption Random? Tables 2-4 examine pre-existing differences between treated and never-treated (by 2019) states in their characteristics, including the outcomes of interest and their changes over time.

For both male and female Intimate Partner Homicides, as well as resources and gender inequality measures, we find no evidence of differences between these groups of states in 1990 and 2002, nor in their changes between 1990 and 2002.

Table 2: Mean characteristics in 1990 (weighted): Treated vs Never-treated by 2019

Variable	Treated	Never-Treated	Difference (SE)
Income per capita	19376.73	19396.08	19.35 (1743.4)
Log income per capita	9.86	9.86	0.00 (0.09)
UR (unemployment rate)	5.62	5.20	-0.42 (0.549)
Poverty rate	13.57	12.25	-1.32 (1.57)
Male-to-Female UR	1.6	1.3	-0.3 (0.2)
Male-victim IPH 18-34	0.78	0.76	-0.02 (0.17)
Female-victim IPH 18-34	1.88	2.35	0.47 (0.93)
Male-victim IPH 35-49	1.00	2.22	1.22 (1.01)
Female-victim IPH 35-49	1.47	1.22	-0.25 (0.72)

Note: Robust HC3 standard errors in parentheses
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

Table 3: Mean characteristics in 2002 (weighted): Treated vs Never-treated by 2019

Variable	Treated	Never-Treated	Difference (SE)
Income per capita	31502.35	31436.58	-65.77 (3033.466)
Log income per capita	10.35	10.35	0.00 (0.09)
UR (Unemployment rate)	5.84	5.41	-0.43 (0.512)
Poverty rate	12.29	10.26	-2.03 (1.56)
Male-to-Female UR	1.5	1.3	-0.2 (0.3)
Male-victim IPH 18-34	0.27	0.33	0.06 (0.13)
Female-victim IPH 18-34	1.32	1.42	0.10 (0.74)
Male-victim IPH 35-49	0.33	0.41	0.08 (0.08)
Female-victim IPH 35-49	1.14	1.17	0.03 (0.24)

Note: Robust HC3 standard errors in parentheses
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

Table 4: Mean change in characteristics between 1990 and 2002 (weighted): Treated vs Never-treated by 2019

Variable	Treated	Never-Treated	Difference (SE)
Δ Income per capita	12227.65	12094.89	-132.75 (1377.65)
Δ Log income per capita	0.49	0.48	-0.01 (0.02)
Δ UR (Unemployment rate)	0.19	0.22	0.03 (0.31)
Δ Poverty rate	-1.37	-2.01	-0.64 (0.49)
Δ Male-to-Female UR	-0.025	-0.022	-0.003 (0.29)
Δ Male-victim IPH 18-34	-0.49	-0.45	0.04 (0.10)
Δ Female-victim IPH 18-34	-0.49	-0.96	-0.47 (0.30)
Δ Male-victim IPH 35-49	-0.63	-1.83	-1.20 (0.96)
Δ Female-victim IPH 35-49	-0.28	-0.08	0.20 (0.56)

Note: Robust HC3 standard errors in parentheses
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

Is the Timing of Adoption Random? In Figures A1-A18 (Appendix), we examine whether the timing of adoption is related to pre-existing differences between treated and never-treated (by 2019) states in their outcomes of interest and their changes over time. No clear pattern emerges from these figures, supporting the absence of a systematic relationship between the timing of the law and pre-existing differences or changes in Intimate Partner Homicides.

7 Results

7.1 Overall ATT Estimates of NFS Law on IPH

Table 5 displays the OLS and 2SDID estimates of the overall ATT effects of the NFS laws on intimate partner homicides by gender and age group. We find evidence that these laws reduced male-victim intimate partner homicides in the 18-34 age group by -0.123 [95% CI: -0.174, -0.071], representing a 46% decline relative to the average IPH rate in 2002. This finding is consistent with testable prediction 1.

For female-victim intimate partner homicides, in the same age group, our estimate is more uncertain: -0.142 [95% CI: -0.372, 0.088]. The wide confidence interval suggests that the effect varies across states and over time, depending on how effectively the law is implemented, consistent with testable prediction 2.

For the remaining age groups, we do not find much evidence of an effect of the law, perhaps with the exception of the impact on female-victim intimate partner homicides among individuals aged 35-49.

Table 5: Effects of NFS Law on Male and Female IPH (per 100,000)

	OLS	2SDID	Mean in 2002
Male-victim IPH 18-34	-0.095***	-0.123***	0.27
	(0.031)	(0.033)	
Female-victim IPH 18-34	-0.120	-0.142	1.32
	(0.083)	(0.124)	
Male-victim IPH 35-49	-0.025	0.005	0.34
	(0.055)	(0.074)	
Female-victim IPH 35-49	-0.073	-0.140*	1.14
	(0.064)	(0.082)	
Male-victim IPH 50-70	-0.012	-0.012	0.20
	(0.020)	(0.022)	
Female-victim IPH 50-70	-0.049	-0.047	0.40
	(0.030)	(0.032)	

Note: Clustered standard errors in parentheses (49 clusters).
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

7.2 Dynamic ATT Estimates of NFS Law on IPH

In this section, we examine dynamic effects and assess the validity of the parallel trends assumption. Overall, Figures 4-5 provide support for the parallel trends assumption. Figure 4 illustrates the negative dynamic effect of the laws on male-victim intimate partner homicides in the post-intervention period, while the pre-intervention coefficients remain centered around or close to zero. Figure 5 highlights the substantial variability in the estimated effects on female-victim intimate partner homicides, with this variability increasing after the intervention.

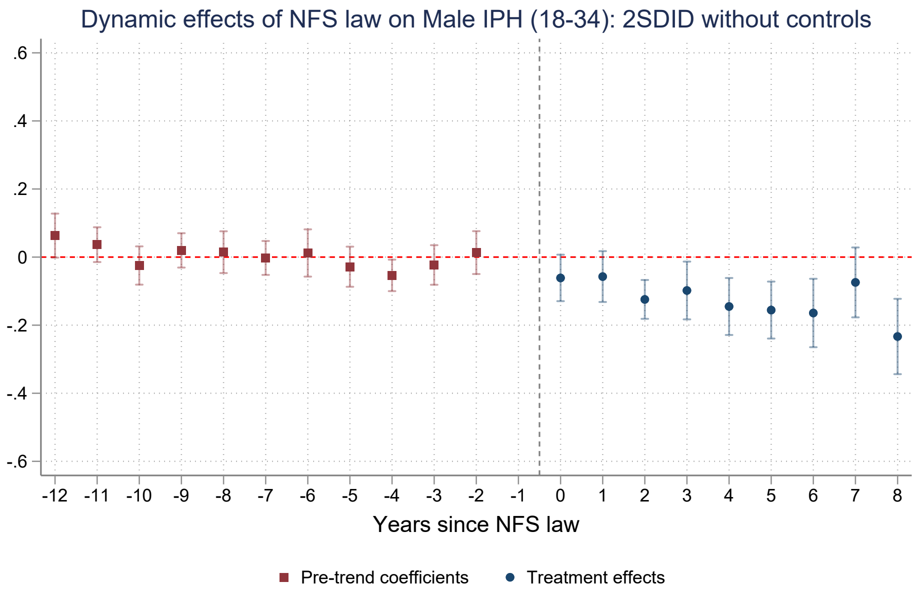


Figure 4: 2SDID Dynamic Effects of NFS Laws on Male IPH 18-34 per 100,000

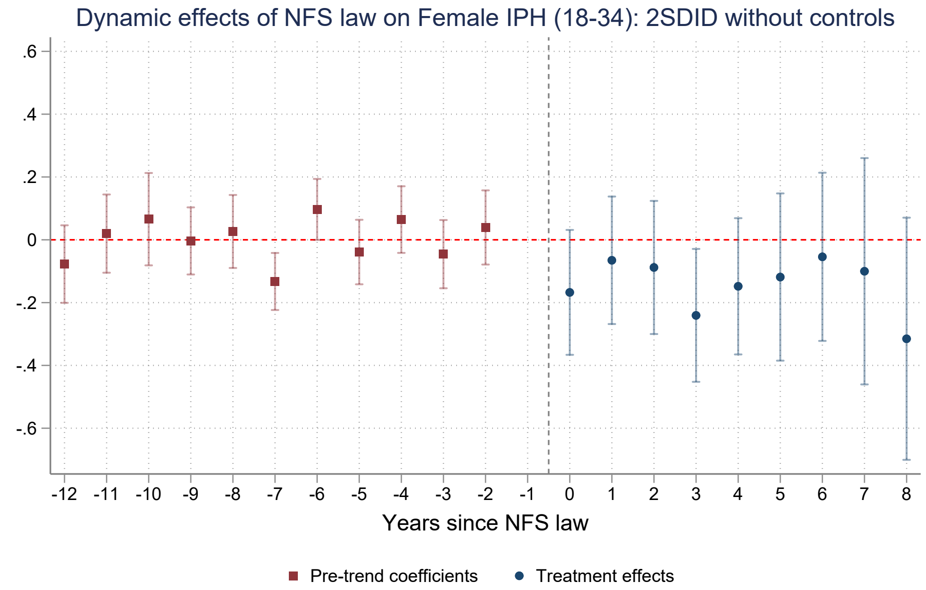


Figure 5: 2SDID Dynamic Effects of NFS Laws on Female IPH 18-34 per 100,000

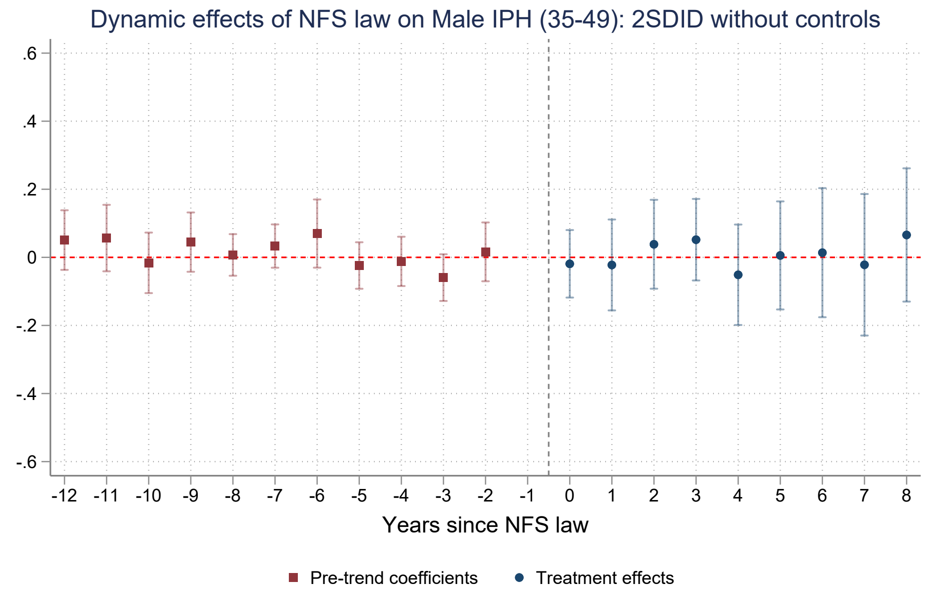


Figure 6: 2SDID Dynamic Effects of NFS Laws on Male IPH 35-49 per 100,000

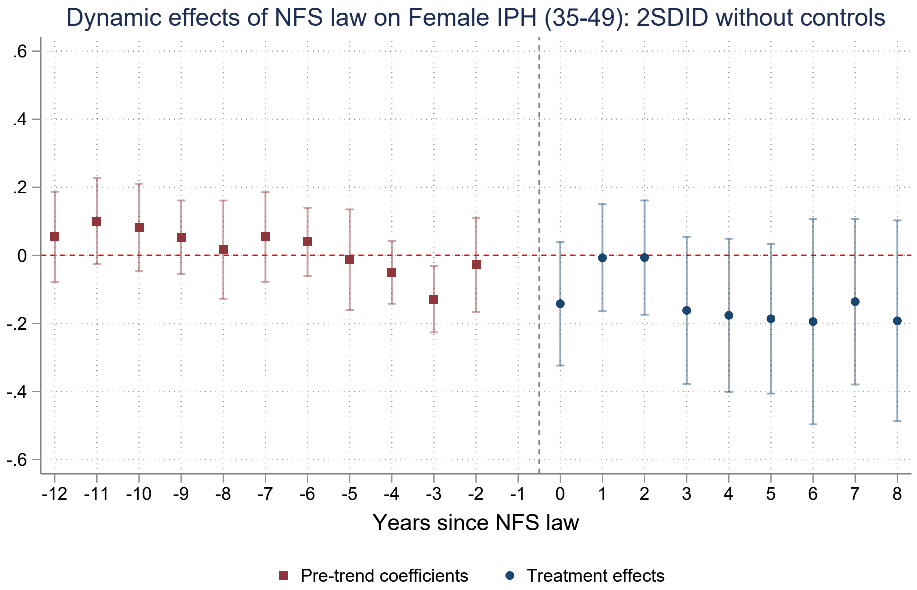


Figure 7: 2SDID Dynamic Effects of NFS Laws on Female IPH 35-49 per 100,000

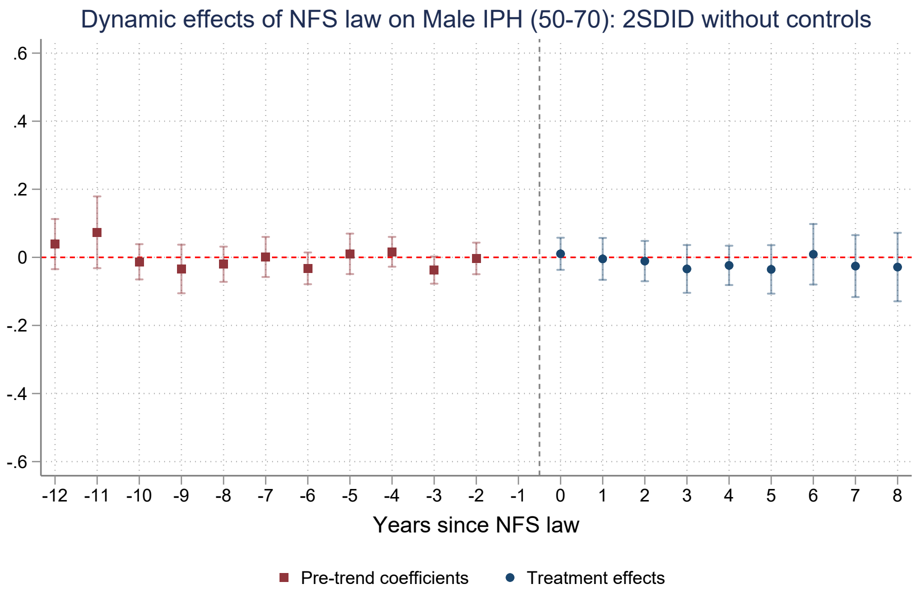


Figure 8: 2SDID Dynamic Effects of NFS Laws on Male IPH 50-70 per 100,000

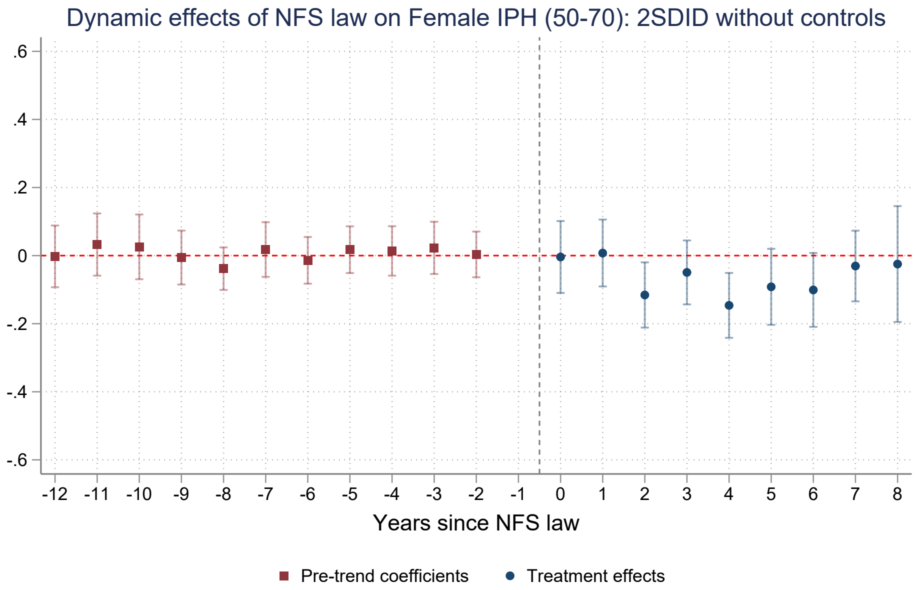


Figure 9: 2SDID Dynamic Effects of NFS Laws on Female IPH 50-70 per 100,000

8 Robustness Checks

In this section, we perform a series of robustness checks. We first investigate compositional changes along resources (income per capita, unemployment rate, poverty rate) and gender-inequality (male-to-female unemployment rate) measures. Second, we re-run our analysis with control variables. Third, we perform a series of placebo checks investigating the absence of effects of the law on female and male homicide rates committed by strangers. Finally, we treat homicides as count data and run Poisson and Negative Binomial regressions.

8.1 Compositional effects

Table 6 estimates the effects of the NFS law on resources and gender inequality measures using TWFE models estimated via OLS and the 2SDID procedure in Gardner et al. (2024). While we do not find much of an effect on these measures, except for small differences in log income per capita and the poverty rate, we will re-estimate the overall ATT effects and the dynamic ATT effects after adding these control variables.

Table 6: Effects of NFS Law on Resources and Gender Inequality Measures

	OLS	2SDID	Mean in 2002
Income per capita	626.12	1126.71	31502.66
	(728.66)	(1124.12)	[403.96]
Log Income per capita	0.013	0.020*	10.35
	(0.010)	(0.012)	[0.126]
UR (unemployment rate)	-0.092	-0.166	5.80
	(0.242)	(0.206)	[0.82]
Poverty rate	-0.374	-0.580*	12.13
	(0.257)	(0.310)	[2.74]
Male-to-Female UR	0.040	-0.003	1.49
	(0.054)	(0.064)	[0.36]

Note: Clustered standard errors in parentheses (49 clusters).
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

8.2 Adding controls

We re-estimate the overall ATT effects and the dynamic ATT effects after adding control variables in two different ways: (1) purely time-varying (meaning the control measured at year t in state s) and (2) time-trend varying (meaning the control measured at baseline

(1990) interacted with linear time trend (Bailey and Goodman-Bacon, 2015; Conti and Ginja, 2020; Mora-García et al., 2024).

The strongest correlations (in absolute value) are found between the poverty rate and the unemployment rate (0.4992), followed by the correlation between the poverty rate and log income per capita (-0.2624). The smallest correlations (in absolute value) are observed between the unemployment rate and log income per capita (-0.0569), as well as between the male-to-female unemployment rate and log income per capita (-0.0607). A regression of NFS law on these variables, accounting for year and state fixed effects, reveals neither individually significant predictors nor jointly significant predictors. The F-statistic is 0.96 (p-value = 0.4356).

Table 7 presents estimates after controlling for time-varying factors—log income per capita, unemployment rate, poverty rate, and the male-to-female unemployment rate ratio. Table 8, on the other hand, includes time-trend varying controls, which consist of the same variables measured in 1990 and interacted with a linear time trend. Figures A19–A24 (Appendix) displays the estimated dynamic effects after adding time-trend varying controls. Reassuringly, we find similar effects than without controls.

Table 7: Effects of NFS Law on Male and Female IPH (per 100,000) with time-varying controls

	OLS	2SDID	Mean in 2002
Male-victim IPH 18-34	-0.097***	-0.120***	0.27
	(0.030)	(0.033)	
Female-victim IPH 18-34	-0.123	-0.144	1.32
	(0.082)	(0.118)	
Male-victim IPH 35-49	-0.020	0.017	0.34
	(0.055)	(0.074)	
Female-victim IPH 35-49	-0.081	-0.137*	1.14
	(0.065)	(0.078)	
Male-victim IPH 50-70	-0.014	-0.010	0.20
	(0.019)	(0.022)	
Female-victim IPH 50-70	-0.046	-0.030	0.40
	(0.030)	(0.031)	

Note: Clustered standard errors in parentheses (49 clusters).
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

Table 8: Effects of NFS Law on Male and Female IPH (per 100,000) with trend-varying controls

	OLS	2SDID	Mean in 2002
Male-victim IPH 18-34	-0.079***	-0.109***	0.27
	(0.029)	(0.038)	
Female-victim IPH 18-34	-0.091	-0.113	1.32
	(0.077)	(0.121)	
Male-victim IPH 35-49	0.000	0.039	0.34
	(0.048)	(0.065)	
Female-victim IPH 35-49	-0.060	-0.114	1.14
	(0.069)	(0.091)	
Male-victim IPH 50-70	-0.003	0.000	0.20
	(0.022)	(0.027)	
Female-victim IPH 50-70	-0.043	-0.032	0.40
	(0.027)	(0.032)	

Note: Clustered standard errors in parentheses (49 clusters).
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

8.3 Placebos

To validate the causal interpretation of our findings on male-victim intimate partner homicides (IPH), we conduct a placebo test by examining the effect of the Non-Fatal Strangulation (NFS) Law on homicides committed by strangers. If the observed decline in male-victim IPH is truly attributable to the NFS law rather than broader trends in homicide reduction, we should expect no systematic effect of the law on homicides committed by strangers. Table 9 presents estimates for male and female homicide victims across two age groups (18-34 and 35-49) when the perpetrator is a stranger.

The results support the validity of our identification strategy. Across all categories, the estimated effects of the NFS law on stranger-perpetrated homicides are small in magnitude and statistically indistinguishable from zero. Specifically, for male victims aged 18-34, the OLS estimate is -0.092 (SE: 0.157), and the 2SDID estimate is -0.246 (SE: 0.220), relative to a baseline mean of 1.86 per 100,000 in 2002. These findings suggest no meaningful impact of the law on male homicides committed by strangers.

For female victims, the estimated effects are also negligible. The OLS estimate for female-victim homicides (18-34) is 0.008 (SE: 0.083), and the 2SDID estimate is -0.016 (SE: 0.124), relative to a baseline mean of 0.23.

Similarly, no significant effects are found for the 35-49 age group. For male victims aged 35-49, the estimated effects are -0.014 (OLS) and -0.084 (2SDID), both with tight standard errors and far from conventional levels of statistical significance. For female victims aged 35-49, the estimated effects are similarly small, with an OLS estimate of 0.019 (SE: 0.017) and a 2SDID estimate of 0.009 (SE: 0.022).

Taken together, these results indicate no systematic reduction in homicides committed by strangers following the implementation of the NFS law. If the reduction in male-victim IPH for the 18-34 age group were driven by broader changes in violent crime or policing, we might expect to observe similar reductions in homicides committed by strangers. However, the absence of any significant effect in this category suggests that the observed decline in male-victim IPH is indeed attributable to the NFS law, strengthening our causal interpretation.

Table 9: Effects of NFS Law on Male-Victim and Female-Victim Homicides committed by strangers (per 100,000)

	OLS	2SDID	Mean in 2002
Male-victim homicides 18-34	-0.092	-0.246	1.86
	(0.157)	(0.220)	
Female-victim homicides 18-34	0.008	-0.016	0.23
	(0.083)	(0.124)	
Male-victim homicides 35-49	-0.014	-0.084	0.81
	(0.078)	(0.080)	
Female-victim homicides 35-49	0.019	0.009	0.14
	(0.017)	(0.022)	

Note: Clustered standard errors in parentheses (49 clusters).
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

8.4 Count data

Table 10 examines the effects of the NFS Law using Poisson and Negative Binomial models, shifting from a per-100,000 rate to raw counts of intimate partner homicides (IPHs). The findings indicate that the effect on male IPH (ages 18–34) remains significant. Additionally, we now find evidence of a negative effect on female IPH (ages 18–34) and female IPH (ages 50–70).

Table 10: Effects of NFS Law on Male and Female IPH using Poisson and NB Models (counts)

	Poisson	NB	Mean in 2002
Male-victim IPH 18-34	-0.238**	-0.238**	3.7
	(0.095)	(0.095)	
Female-victim IPH 18-34	-0.095**	-0.098**	20.8
	(0.046)	(0.047)	
Male-victim IPH 35-49	-0.047	-0.044	4.6
	(0.064)	(0.064)	
Female-victim IPH 35-49	0.036	0.024	17.1
	(0.053)	(0.056)	
Male-victim IPH 50-70	0.084	0.084	2.2
	(0.081)	(0.081)	
Female-victim IPH 50-70	-0.097**	-0.097**	4.6
	(0.046)	(0.046)	

Note: Clustered standard errors in parentheses.
*p-value<0.1, **p-value<0.05, ***p-value<0.01.

9 Conclusion

Strangulation statutes are a relatively new criminal justice phenomenon, while strangulation is a common and very gendered form of intimate partner abuse committed when violence is escalating and heading toward murder. In this paper, we provide the first systematic analysis of the impact of non-fatal strangulation laws on IPH of men and women in the US, exploiting state-level variation in their timing of implementation and the FBI Supplementary Homicide Reports from 1990-2019, which record the victim's relationship to their murderer.

We build an IPV model focusing on abuse dynamics that have already reached a violent and coercive stage, as is the case for non-fatal strangulation, and develop the testable predictions that strangulation laws reduce male-victim IPH by encouraging some women to report their abusers rather than to endure the escalating violence until eventually they kill him to stop it (prediction 1). However, the impact on female-victim IPH is ambiguous (prediction 2), as it depends on the balance between the incapacitation effect (which decreases violence) and the reporting effect (which may increase the risk of a homicide if incarceration is not implemented).

We assess the benefits of this policy tool by determining whether and to what extent strangulation laws save lives, and whether they can help the vulnerable women subject to violent intimate partner abuse. Using TWFE models estimated via OLS and 2SDID, we find evidence that these laws reduced male-victim intimate partner homicides in the 18-34 age group by -0.123 [95% CI: -0.174, -0.071], representing a 46% decline relative to the average IPH rate in 2002. This finding is consistent with testable prediction 1. For female-victim intimate partner homicides, in the same age group, our estimate is more uncertain: -0.142 [95% CI: -0.372, 0.088]. The wide confidence interval suggests that the effect varies across states and over time, depending on how effectively the law is implemented, consistent with testable prediction 2.

This comprehensive nationwide analysis can help the police, prosecutors, and advocates against strangulation and IPV to evaluate the effectiveness and reach of non-fatal strangulation laws and specifically the channels through which they can save lives.

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Appendix

A. Timing of Adoption

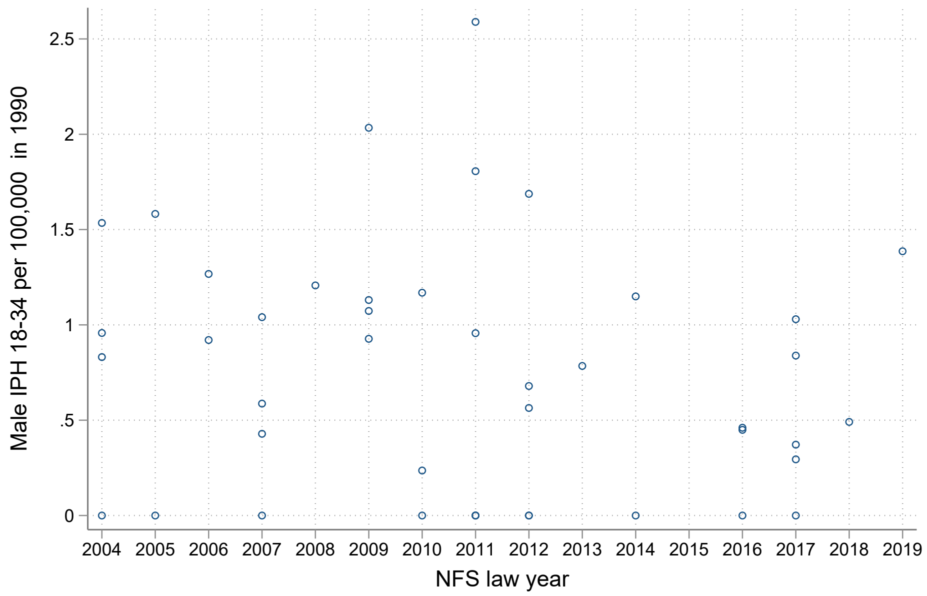

Figure A1: Male IPH 18-34 per 100,000 in 1990

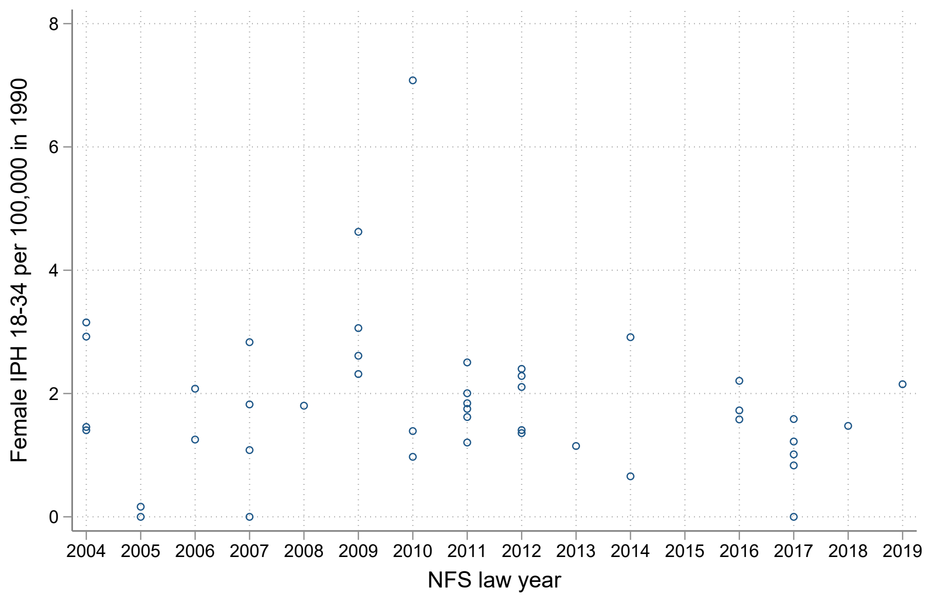

Figure A2: Female IPH 18-34 per 100,000 in 1990

Figure A3: Male IPH 35-49 per 100,000 in 1990

Figure A4: Female IPH 35-49 per 100,000 in 1990

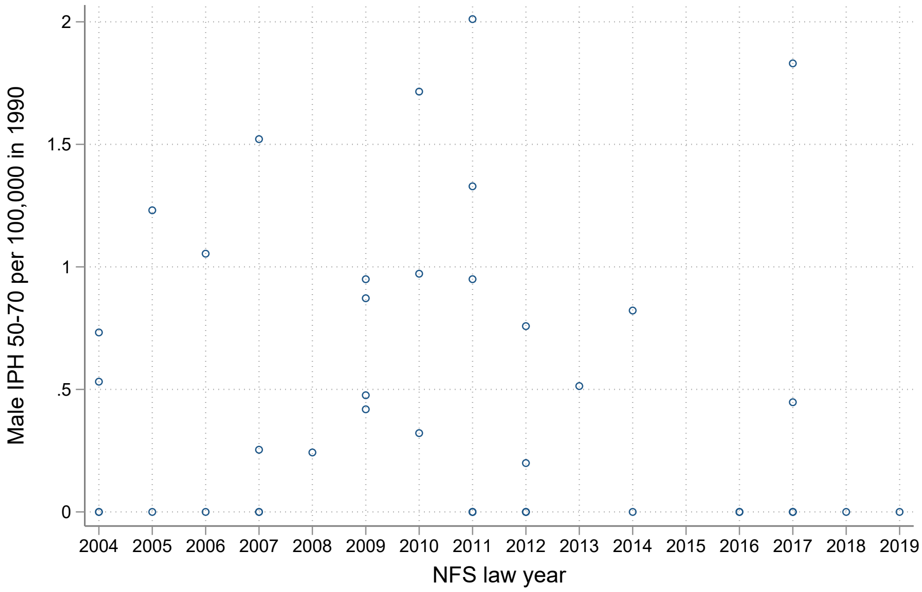

Figure A5: Male IPH 50-70 per 100,000 in 1990

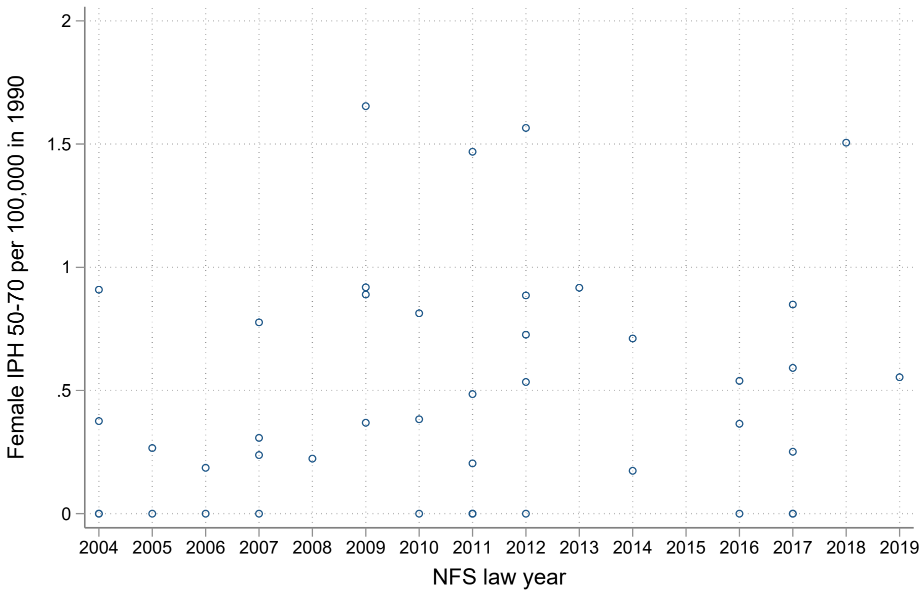

Figure A6: Female IPH 50-70 per 100,000 in 1990

Figure A7: Male IPH 18-34 per 100,000 in 2002

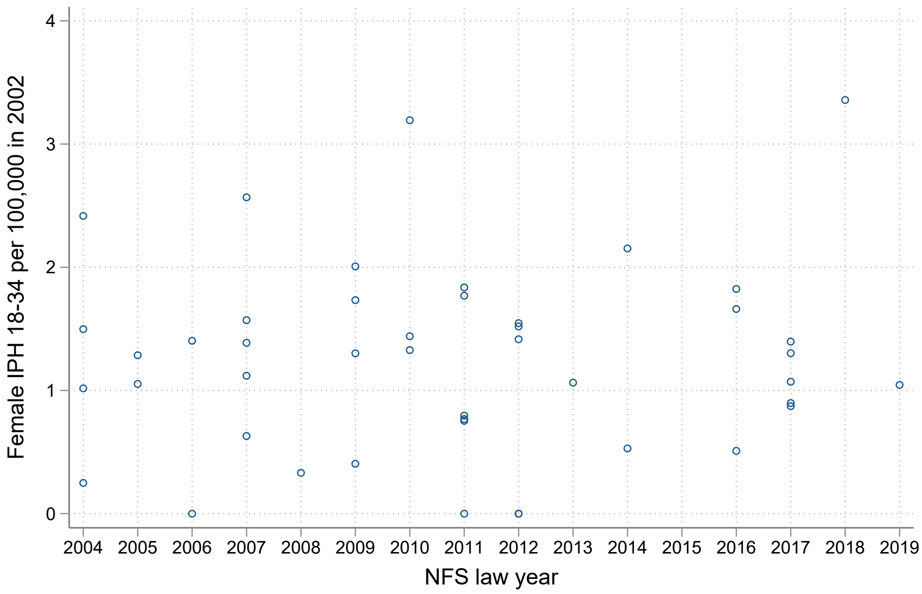

Figure A8: Female IPH 18-34 per 100,000 in 2002

Figure A9: Male IPH 35-49 per 100,000 in 2002

Figure A10: Female IPH 35-49 per 100,000 in 2002

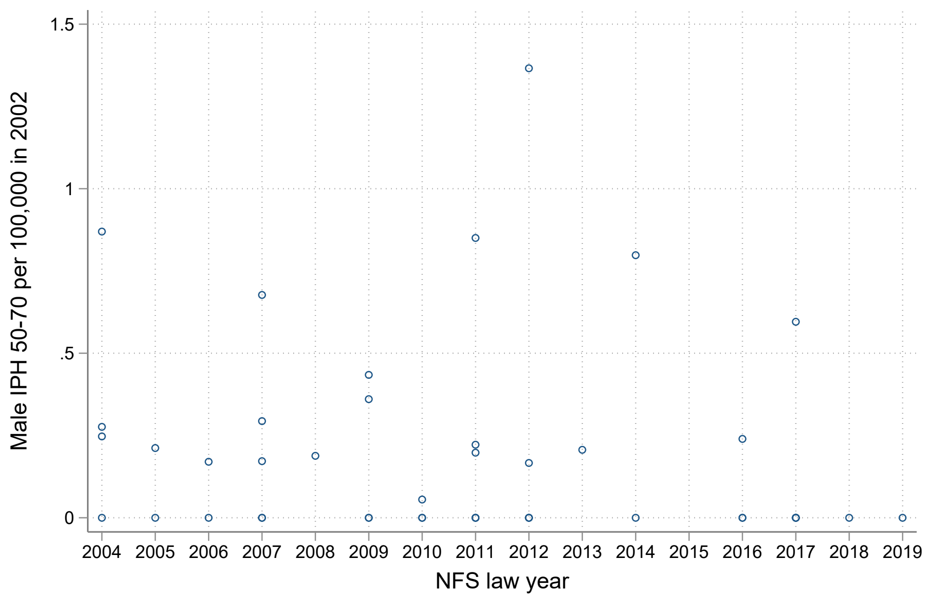

Figure A11: Male IPH 50-70 per 100,000 in 2002

Figure A12: Female IPH 50-70 per 100,000 in 2002

Figure A13: Change 1990-2002 in Male IPH 18-34 per 100,000

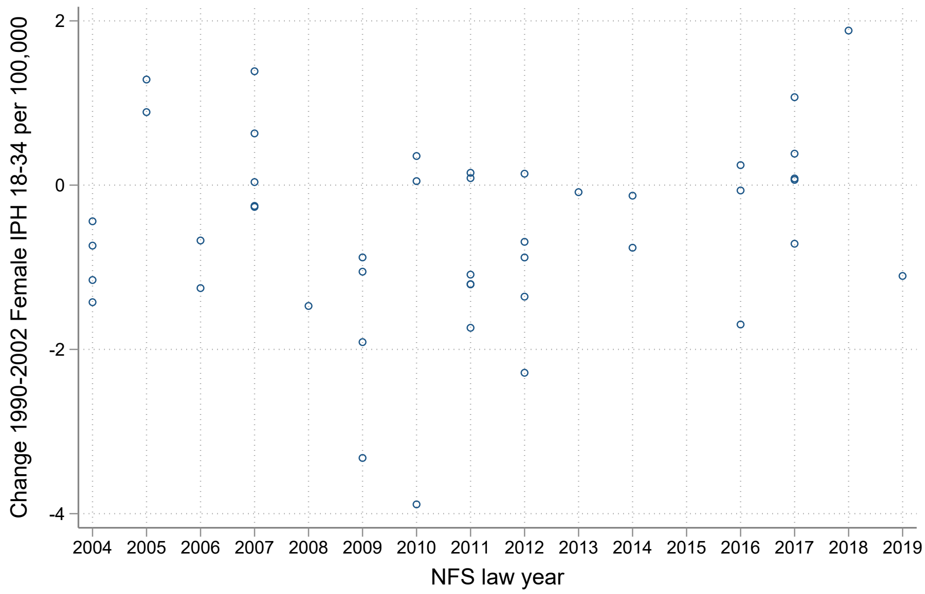

Figure A14: Change 1990-2002 in Female IPH 18-34 per 100,000

Figure A15: Change 1990-2002 in Male IPH 35-49 per 100,000

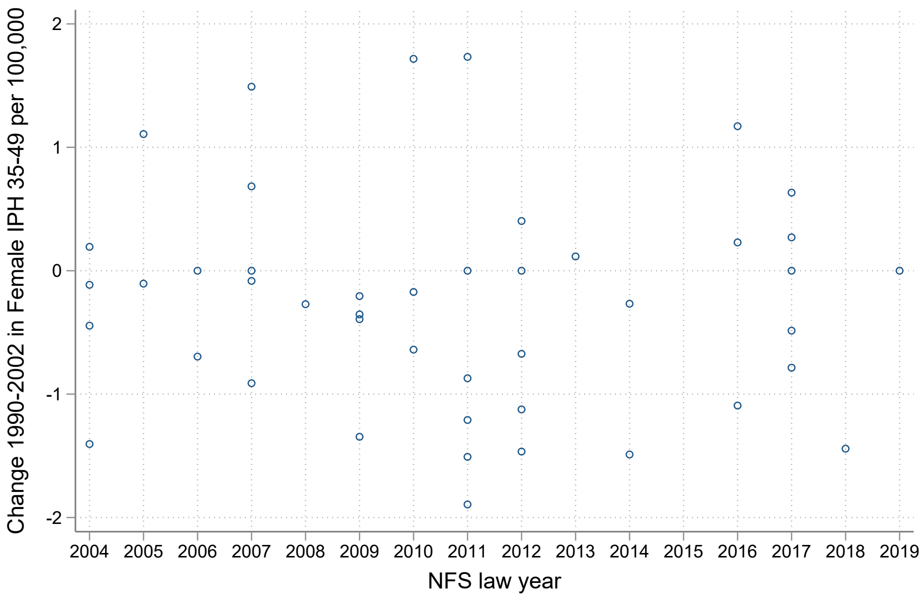

Figure A16: Change 1990-2002 in Female IPH 35-49 per 100,000

Figure A17: Change 1990-2002 in Male IPH 50-70 per 100,000

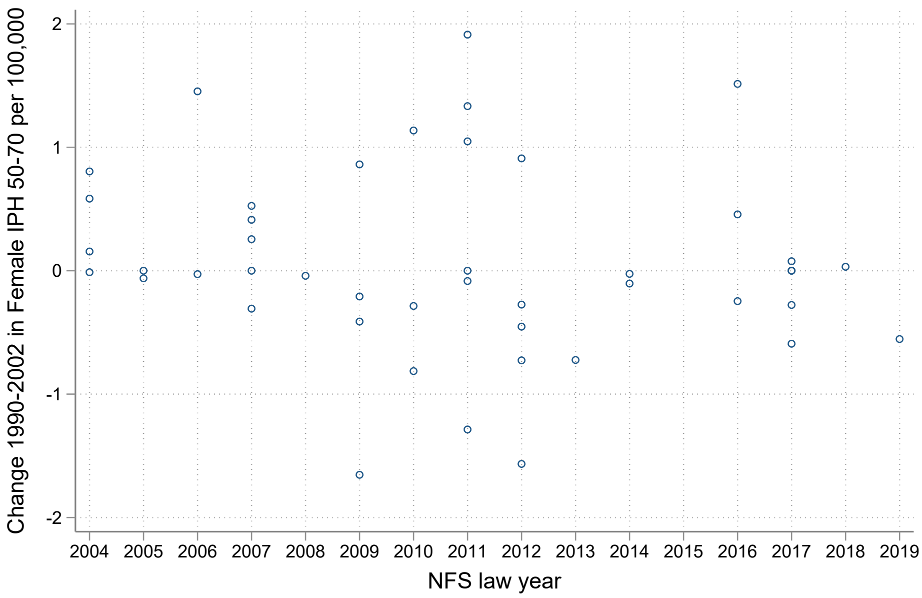

Figure A18: Change 1990-2002 in Female IPH 50-70 per 100,000

B. Dynamic ATT Estimates of NFS Law on IPH (with controls)

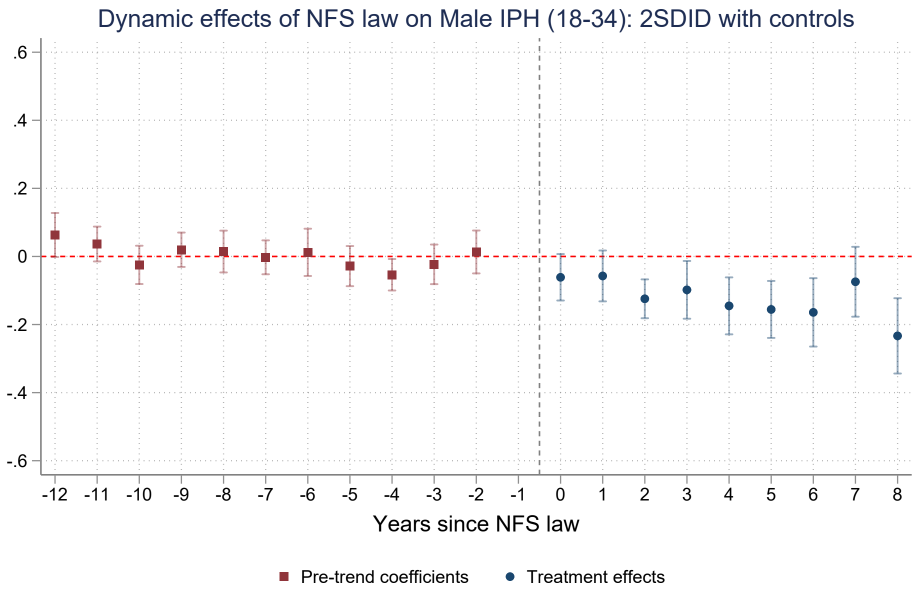

Figure A19: 2SDID Dynamic Effects of NFS Laws on Male IPH 18-34 per 100,000

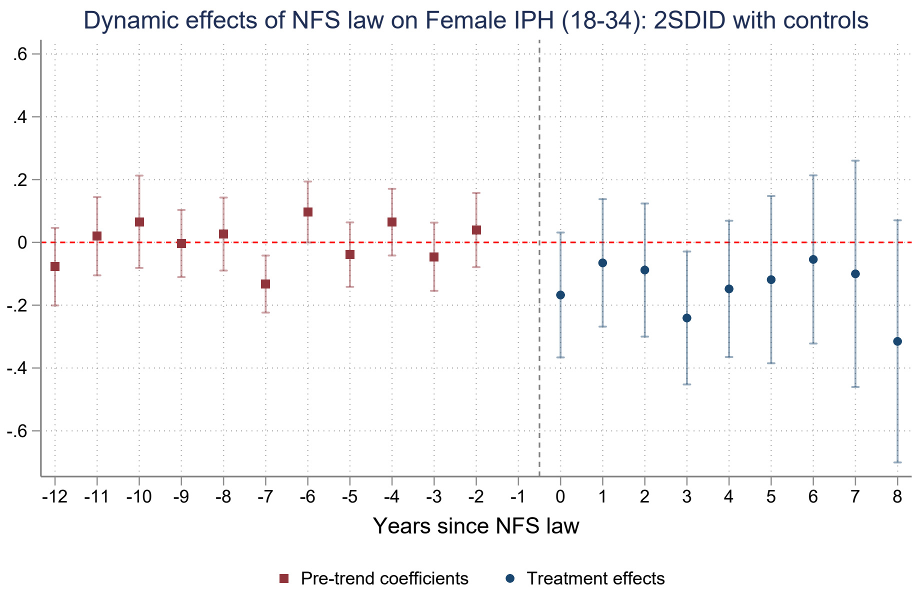

Figure A20: 2SDID Dynamic Effects of NFS Laws on Female IPH 18-34 per 100,000

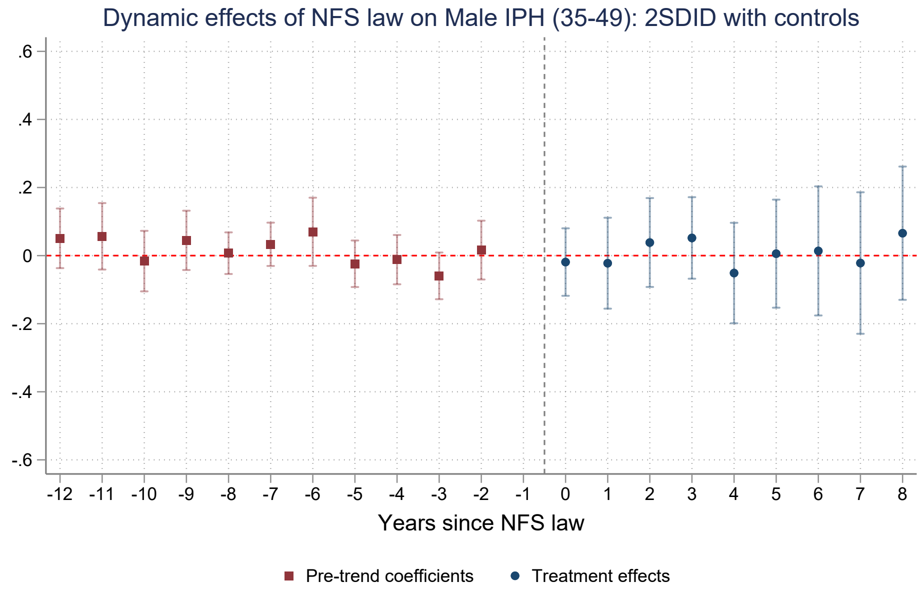

Figure A21: 2SDID Dynamic Effects of NFS Laws on Male IPH 35-49 per 100,000

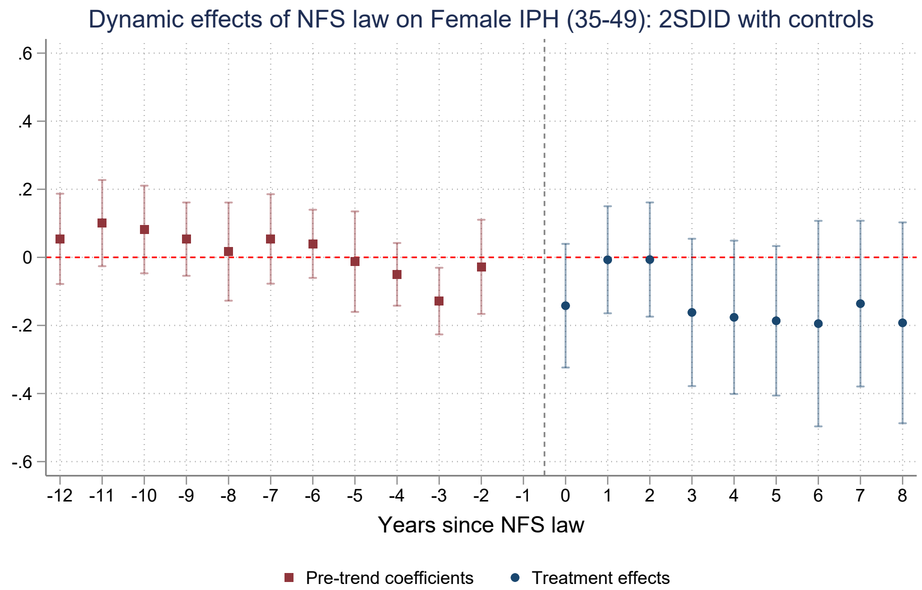

Figure A22: 2SDID Dynamic Effects of NFS Laws on Female IPH 35-49 per 100,000

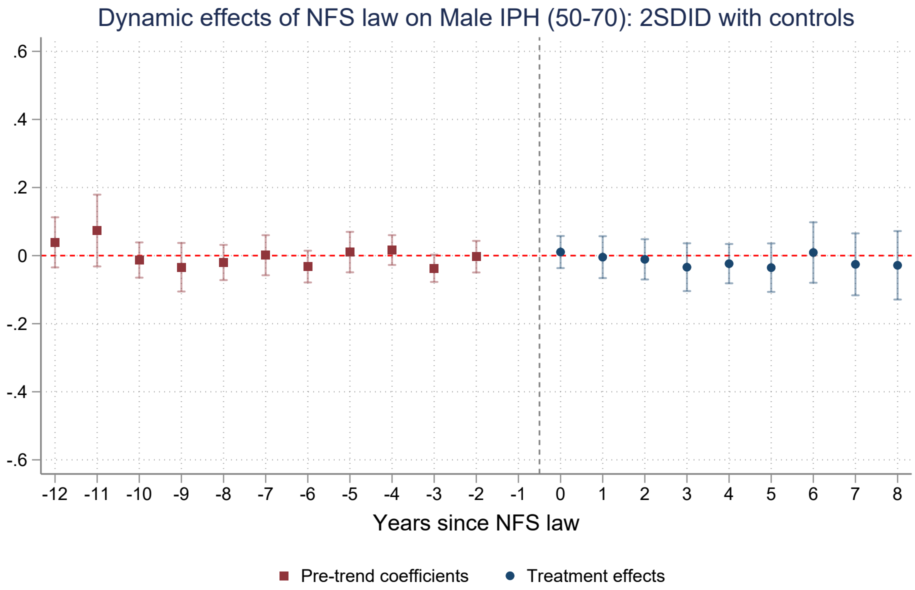

Figure A23: 2SDID Dynamic Effects of NFS Laws on Male IPH 50-70 per 100,000

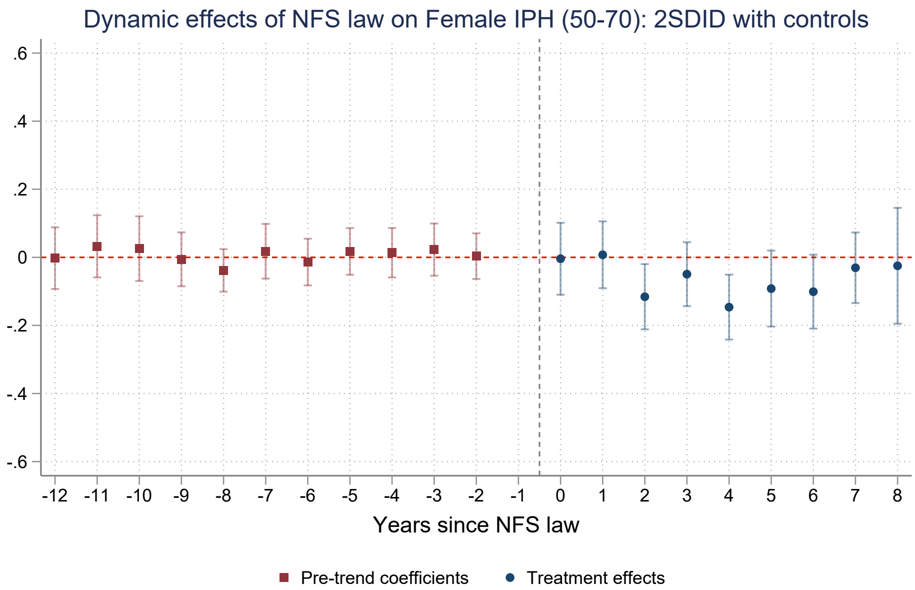

Figure A24: 2SDID Dynamic Effects of NFS Laws on Female IPH 50-70 per 100,000