

Legal protection of dating partners  
and intimate partner homicide:  
Evidence from the U.S. states, 1976–2010

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# Intimate Partner Homicide among Dating Partners

Domestic violence is a huge problem (>1300 homicides in 2010;  
44% of all women shot were killed by an intimate partner)

Although IPH cases have been nearly halved over the last 35 years,  
still represent 12% of all US homicides

Violent Crime Control Act (1994) bans individuals with a DVRO from obtaining firearms

But DVROs only accesible to “intimate partners”:  
federal law and many states omit dating partners who neither cohabit nor have a child

# Intimate Partner Homicide among Dating Partners

Vigdor and Mercy (2006) found significant reductions in IPH from state-level DVRO protections

We follow-up with a state-level analysis of how the scope of intimate partner definitions affects IPH among current dating partners

*Could a simple change in the legal definition of “intimate partners” have a substantial effect on homicide rates?*

Data and Data Problems

First Cut: Exploratory Data Analysis

Second Cut: Negative Binomial Model

Simulating Counterfactual Rates of IPH Nationwide

Policy Implications and Further Directions

# Data & Data Problems

<b>Intimate Partner Homicide (IPH) Victims by Status, 2010</b>	<b>Married, Separated, or Divorced</b>	<b>Current Dating</b>
Total Victims	669	608
Black Victims	20.8 %	39.1 %
Young Victims	25.9 %	56.6 %
Female Victims	83.9 %	76.3 %
Gun-Related Victims	63.8 %	42.9 %

## **Intimate Partner Homicide Rates, by Relationship Status**

Drawn from 1976–2010  
FBI Supplementary  
Homicide Reports

Available: IPH by current  
spouse, former spouse,  
current dating partner

# Data & Data Problems

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## **Intimate Partner Homicide Rates, by Relationship Status**

Likely undercounts;  
former partners and  
same-sex partners not  
identified in SHRs

Incomplete reporting; we  
exclude states that report  
less than 20% of the time  
(FL, MT, ND, VT)

## Timing of Extension of DVRO Protections to Dating Partners

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<b>1978</b>	Massachusetts
<b>1989</b>	North Dakota
<b>1990</b>	Pennsylvania
<b>1992</b>	Washington
<b>1993</b>	Montana
<b>1994</b>	California, New Jersey, Rhode Island
<b>1995</b>	Nevada
<b>1996</b>	Alaska, Illinois, Michigan
<b>1997</b>	North Carolina
<b>1999</b>	Connecticut
<b>2000</b>	Hawaii
<b>2001</b>	West Virginia, Texas, Wisconsin
<b>2002</b>	Iowa, Indiana
<b>2007</b>	Delaware
<b>2009</b>	Arizona

## Timing of Extension of DVROs to Current Dating Partners, by State

Law Center to Prevent Gun Violence identifies state statutes relating to domestic violence and defines “intimate partner”

## Timing of Extension of DVRO Protections to Dating Partners

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<b>1978</b>	Massachusetts
<b>1989</b>	North Dakota
<b>1990</b>	Pennsylvania
<b>1992</b>	Washington
<b>1993</b>	Montana
<b>1994</b>	California, New Jersey, Rhode Island
<b>1995</b>	Nevada
<b>1996</b>	Alaska, Illinois, Michigan
<b>1997</b>	North Carolina
<b>1999</b>	Connecticut
<b>2000</b>	Hawaii
<b>2001</b>	West Virginia, Texas, Wisconsin
<b>2002</b>	Iowa, Indiana
<b>2007</b>	Delaware
<b>2009</b>	Arizona

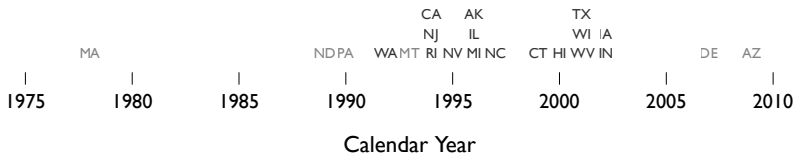
## Timing of Extension of DVROs to Current Dating Partners, by State

Use Lexis-Nexus & state law libraries to find when these statutes first include “dating partners” in IP definition (either initial passage or amendment)

22 states took this step in the study period



## Spread of Laws Protecting Dating Partners



Most of these 22 states acted in 1994 or later

In exploratory work so far, haven't found strong predictors of timing  
(at least among our covariates)

Suggested explanations welcome!

# First Cut: Exploratory Data Analysis

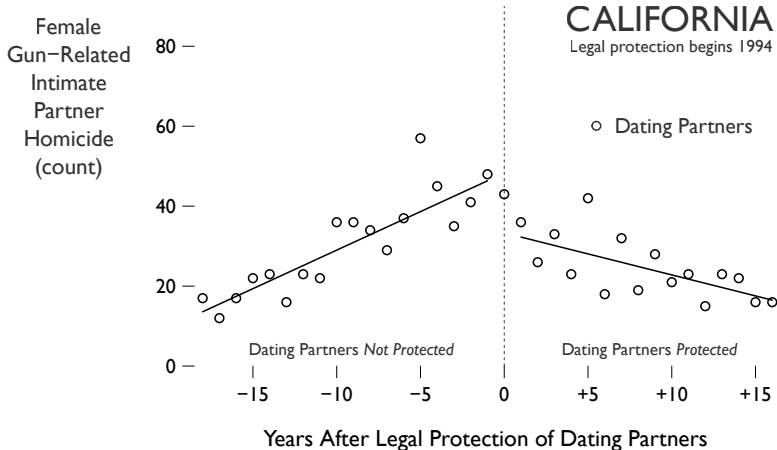
Our basic strategy:

exploit the timing of extension of DVRO protections to dating partners  
*as if that timing were random*

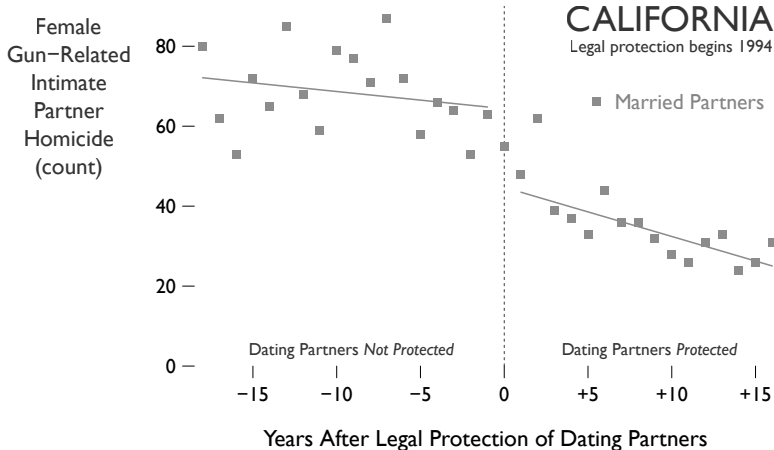
See if the pattern of dating partner IPH changes around that year,  
either in level or trend

Compare these changes to patterns in married partner IPH

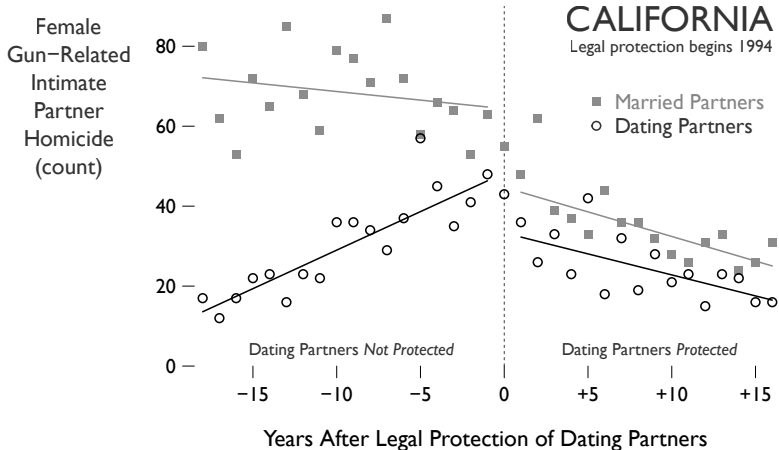
As an example, consider the largest state, California,  
which extended DVRO to dating partners in 1994



IPH among dating partners in CA shifted strongly around the timing of DVRO extension, both in level and slope

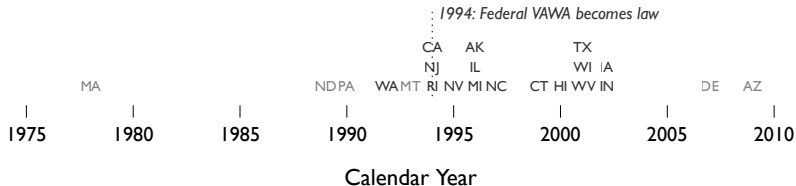


Married partners also saw a level improvement, and a smaller slope reduction



Changes are qualitatively similar for married and dating partners,  
but stronger for dating. Only slope of dating IPH changed direction

## Spread of Laws Protecting Dating Partners

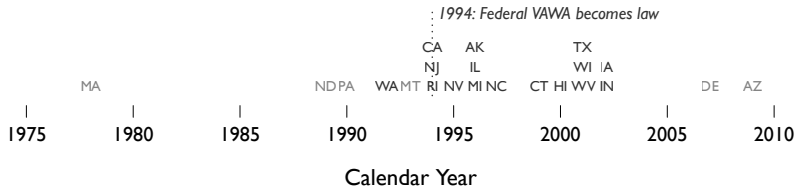


Obvious confounder driving similarity among married and dating partners in the California case:

Federal Violence Against Women Act (VAWA) passed in 1994, protecting married partners at the same time as CA protected dating partners

Likewise the aforementioned Violent Crime Control Act of 1994

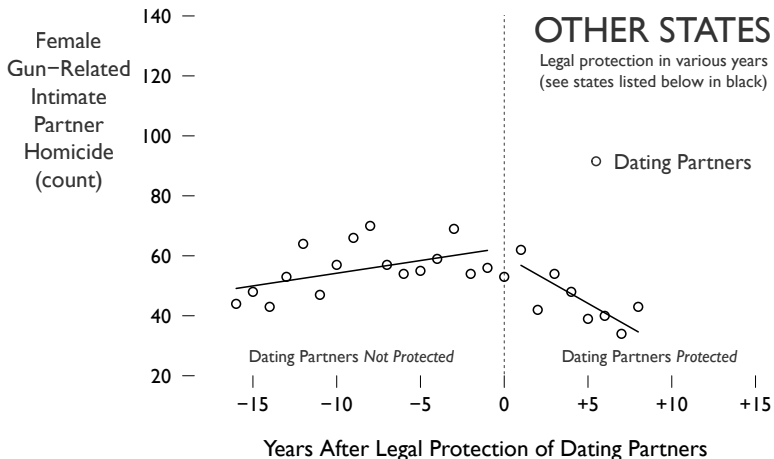
## Spread of Laws Protecting Dating Partners



We can tease apart these effects by looking at other, smaller states

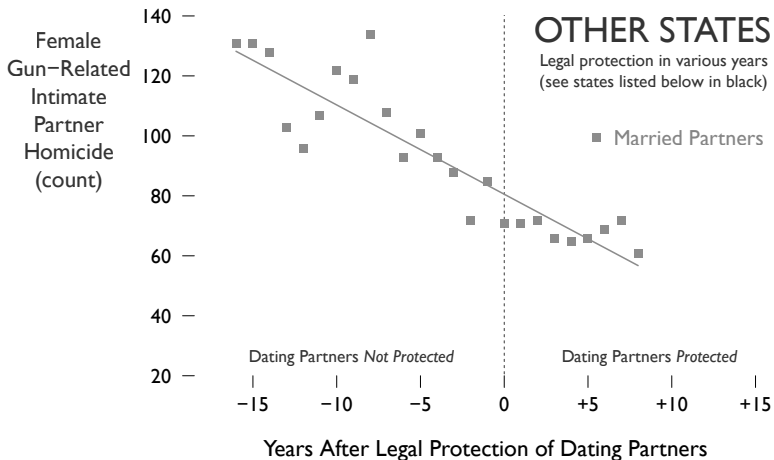
Data too noisy to examine by state, so we *aggregate* based on years before or after state DVRO extension to dating partners

States in **gray** had incomplete time series and are omitted from this exercise to avoid biased slopes

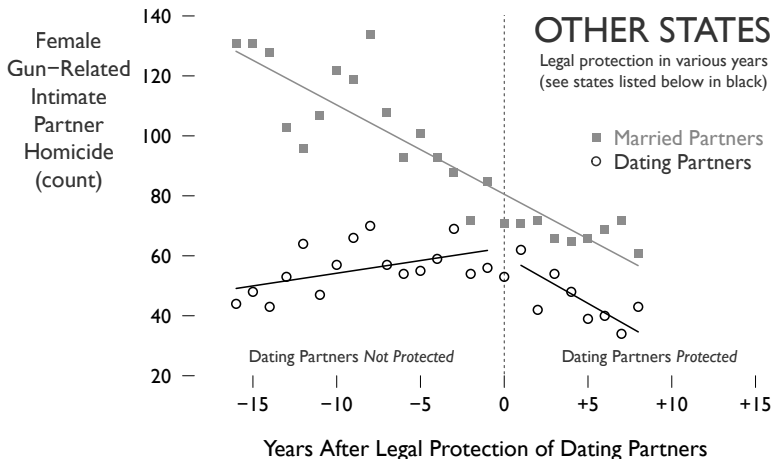


In states other than California,  
there is a strong slope reversal around the extension of DVRO to dating partners





But no change at all in the trend in married IPH, which is consistently downward



We consider this strongly suggestion of a large protective effect of state DVRO protections on dating partner IPH

## Second Cut: Controlling for Confounders

We think the data speak for themselves,  
but it's reasonable to fear uncontrolled confounders

What about state demographics, economic performance, crime,  
and other state laws that might prevent IPH?

We turn to a panel data model that controls for these factors, state fixed effects,  
underlying trends and the effect of VAWA/VCCA passage in 1994

Data are from 46 states, available years by state from 1976–2010,  
and limited to reporting areas within states (approximately 50% by population)

Model of dating partner IPH: Negative Binomial of a panel of interrupted time series,  
estimated by maximum likelihood

Variable	Description
Female Gun IPH <sub>it</sub>	Female dating partners killed by guns
Female All IPH <sub>it</sub>	Female dating partners killed, all causes
All Sex All Cause IPH <sub>it</sub>	Dating partners killed, all sexes and causes
Intimate Partner Protection	Do state DVRO laws protect dating partners?
log $n_{it}$	Dating partners at risk (estimated)
Median Income (\$k) <sub>it</sub>	Median household income of state (yearly)
log(Total Crime <sub>it</sub> )	Count of all violent crimes by state and year
% Urban <sub>it</sub>	Urban population, by state and year
% Black <sub>it</sub>	Black population, by state and year
% Age $\leq 35_{it}$	Young population, by state and year
Confiscate <sub>it</sub>	Domestic violence incident $\rightarrow$ police can confiscate guns
Misdemeanor <sub>it</sub>	Domestic violence misdemeanor blocks gun possession
DVRO <sub>it</sub>	Restraining order blocks gun possession
Temp DVRO <sub>it</sub>	Temporary DVRO blocks gun possession

Variable	Source
Female Gun IPH <sub>it</sub>	FBI Supplementary Homicide Reports (SHRs)
Female All IPH <sub>it</sub>	FBI SHRs
All Sex All Cause IPH <sub>it</sub>	FBI SHRs
Intimate Partner Protection	Coded from Lexis-Nexus & state law libraries
$\log n_{it}$	National Historical Geographic Information System (NHGIS)
Median Income (\$k) <sub>it</sub>	NHGIS
$\log(\text{Total Crime}_{it})$	Uniform Crime Reporting Statistics
% Urban <sub>it</sub>	NHGIS
% Black <sub>it</sub>	NHGIS
% Age $\leq 35_{it}$	NHGIS
Confiscate <sub>it</sub>	Mercy & Vigor (2006); limited to 1982–2002
Misdemeanor <sub>it</sub>	Mercy & Vigor (2006); limited to 1982–200
DVRO <sub>it</sub>	Mercy & Vigor (2006); limited to 1982–200
Temp DVRO <sub>it</sub>	Mercy & Vigor (2006); limited to 1982–200

# Model Specification: Interrupted Time Series with Fixed Effects

$$y_{it} \sim \text{Negative Binomial}(\lambda_{it}, \theta)$$

$$\log \lambda_{it} = t\delta_1 + D_{it}\delta_2 + (t - s_i)D_{it}\delta_3 + \mathbf{x}_{it}\beta + \alpha_i + \log n_{it}$$

$y_{it}$	Count of IPH events (various subsets)
$t$	Deterministic time trend
$D_{it}$	Did state $i$ protect dating partners in year $t$ ?
$s_i$	Year state $i$ extended protection to dating partners
$(t - s_i)D_{it}$	Trend since extension to partners
$\mathbf{x}_{it}$	Vector of controls
$\alpha_i$	State fixed effects
$\log n_{it}$	Offset for estimated dating partners at risk

$$y_{it} \sim \text{Negative Binomial}(\lambda_{it}, \theta)$$

$$\begin{aligned} \log \lambda_{it} = & t\delta_1 + D_{it}\delta_2 + (t - s_i)D_{it}\delta_3 \\ & + V_{it}\delta_4 + (t - 1994)V_{it}\delta_5 + \mathbf{x}_{it}\beta + \alpha_i + \log n_{it} \end{aligned}$$

$y_{it}$	Count of IPH events (various subsets)
$t$	Deterministic time trend
$D_{it}$	Did state $i$ protect dating partners in year $t$ ?
$s_i$	Year state $i$ extended protection to dating partners
$(t - s_i)D_{it}$	Trend since extension to partners
$V_{it}$	Was Federal VAWA in place in year $t$ ?
$(t - 1994)V_{it}$	Trend since adoption of VAWA
$\mathbf{x}_{it}$	Vector of controls
$\alpha_i$	State fixed effects
$\log n_{it}$	Offset for estimated dating partners at risk

Sex Cause of Death Specification	Female Gun-Related Baseline	Female Gun-Related Alternate	Female Gun-Related Static	Female All Cause Baseline	All Persons All Cause Baseline
$D_{it}$	-0.181 0.070	-0.164 0.100	-0.208 0.060	-0.181 0.052	-0.208 0.048
$(t - s_i)D_{it}$	-0.007 0.008	-0.007 0.017		-0.006 0.005	-0.003 0.005
$t$	0.015 0.011	0.024 0.018		0.014 0.008	0.009 0.007
$V_{it}$	0.072 0.071	-0.041 0.079	0.144 0.067	0.009 0.055	-0.061 0.050
$(t - 1994)V_{it}$	-0.024 0.009	-0.042 0.021		-0.021 0.007	-0.021 0.006
Median Income (\$k) <sub>it</sub>	-0.002 0.008	-0.009 0.012	0.002 0.003	0.004 0.006	0.002 0.006
log(Total Crime <sub>it</sub> )	0.570 0.109	0.521 0.182	0.776 0.084	0.415 0.081	0.335 0.072
% Urban <sub>it</sub>	-0.726 0.789	2.932 1.461	-1.156 0.741	-0.409 0.620	-0.686 0.549
% Black <sub>it</sub>	-2.177 2.394	-1.762 4.942	-1.862 2.372	-3.297 1.796	-2.599 1.631
% Age ≤ 35 <sub>it</sub>	2.594 2.157	-1.295 4.205	4.145 2.085	2.324 1.625	1.560 1.415
Confiscate <sub>it</sub>		0.172 0.083			
Misdemeanor <sub>it</sub>		0.213 0.096			
DVRO <sub>it</sub>		-0.312 0.084			
Temp DVRO <sub>it</sub>		-0.057 0.091			
(Dispersion)	38.04 12.78	53.67 28.05	33.81 10.25	43.24 11.13	29.64 4.47
State Fixed Effects?	yes	yes	yes	yes	yes
N	1575	924	1575	1610	1610
log likelihood	-2564	-3112	-2568	-3167	-3580
AIC	5240	3230	5243	6449	7273

Don't worry – no need  
to squint!

Focus in on key  
variables...



<i>Sex</i> <i>Cause of Death</i> <i>Specification</i>	Female Gun-Related Baseline
$D_{it}$	-0.181 0.070
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$V_{it}$	0.072 0.071
$(t - 1994)V_{it}$	-0.024 0.009

First specification  
examines Female  
Gun-related IPH

“Baseline” model omits  
controls for other state  
policies, which have  
limited data coverage

Key for us: marginal  
effect by year  $k$  after  
implementation

This is  $\delta_2 + k\delta_3$ . Always  
significant ( $p < 0.05$ )  
and negative for baseline  
model of Female  
Gun-related IPH.

<i>Sex Cause of Death Specification</i>	Female Gun-Related Baseline	Female Gun-Related Alternate
$D_{it}$	-0.181 0.070	-0.164 0.100
$(t - s_i)D_{it}$	-0.007 0.008	-0.007 0.017
$t$	0.015 0.011	0.024 0.018
$V_{it}$	0.072 0.071	-0.041 0.079
$(t - 1994)V_{it}$	-0.024 0.009	-0.042 0.021

Our “alternative” specification also examines Female Gun-related IPH and includes controls for other state laws protecting victims of domestic violence

Lose about 40% of our data due to missingness

Sex Cause of Death Specification	Female Gun-Related Baseline	Female Gun-Related Alternate
$D_{it}$	-0.181 0.070	-0.164 0.100
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Marginal effect of dating partner protection by year  $k$  after implementation is substantively similar but only significance at  $p < 0.1$

Of the controlled policies, only gun bans with DVROs significantly reduces dating partner IPH

<i>Sex</i> <i>Cause of Death</i> <i>Specification</i>	Female Gun-Related Baseline	Female Gun-Related Alternate	Female Gun-Related Static
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$V_{it}$	0.072 0.071	-0.041 0.079	0.144 0.067
$(t - 1994)V_{it}$	-0.024 0.009	-0.042 0.021	

We also estimate a simpler “static” model that assumes all policies change only levels of IPH, and not trends

The marginal effects (here, simply  $\delta_2$ ) of dating partner protection are similar to the baseline model: negative and significant at  $p < 0.05$

<i>Sex</i> <i>Cause of Death</i> <i>Specification</i>	Female Gun-Related Baseline	Female Gun-Related Alternate	Female Gun-Related Static	Female All Cause Baseline
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$(t - 1994)V_{it}$	-0.024 0.009	-0.042 0.021		-0.021 0.007

We think the biggest action is in Female Gun-Related IPH, but we also consider the baseline specifications for Female All Cause IPH

We obtain similar significant negative marginal effects of dating protection on IPH

<i>Sex Cause of Death Specification</i>	Female Gun-Related Baseline	Female Gun-Related Alternate	Female Gun-Related Static	Female All Cause Baseline	All Persons All Cause Baseline
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$(t - 1994)V_{it}$	-0.024 0.009	-0.042 0.021		-0.021 0.007	-0.021 0.006

Finally, we estimate the baseline specifications for All Sex All Cause IPH

We again obtain similar significant negative marginal effects of dating protection on IPH

# Simulation Strategy

Negative Binomial coefficients are a fairly unsatisfying summary of the model

We're interested in the net effect of dating partner protection over time

We'd like to know what the model predicts in the real world, for our 46 states

Solution: Simulate in-sample counterfactual rates of dating partner IPH under different scenarios for the 46 states' (hypothetical) reforms of DVRO protections

We present results in terms of aggregate annual counts of homicides across all states by year under different scenarios, holding all other covariates at their observed values by state and year

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- 1 Draw a vector of simulated model parameters from the asymptotic multivariate normal distribution implied by the MLE.



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- 4 Sum up the simulated IPH counts across all states within each year.  
This is a vector of simulated nationwide IPH counts.

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- ➎ Repeat steps 1 to 4 many times to assemble a range of simulated nationwide IPH counts reflecting uncertainty in model parameters.

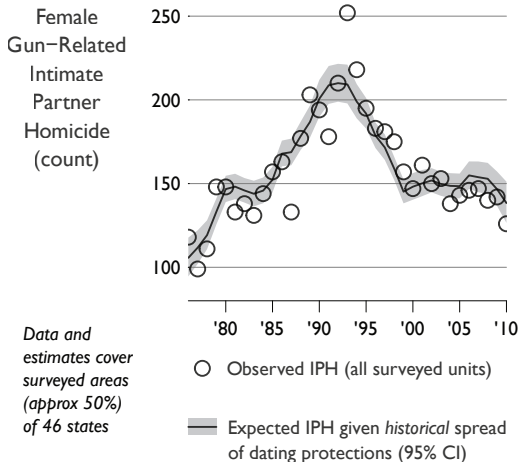
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- 5 Repeat steps 1 to 4 many times to assemble a range of simulated nationwide IPH counts reflecting uncertainty in model parameters.
- 6 Summarize this uncertainty with year-wise 95% CIs.
- 7 Repeat steps 1 to 6 as needed for different counterfactual values of protection for dating partners.

## Negative Binomial Estimates of IPH Under Observed Policies

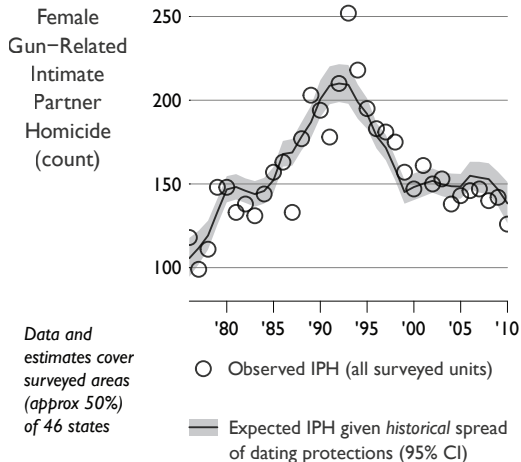


We begin with simulations from the baseline model of Female Gun-Related IPH

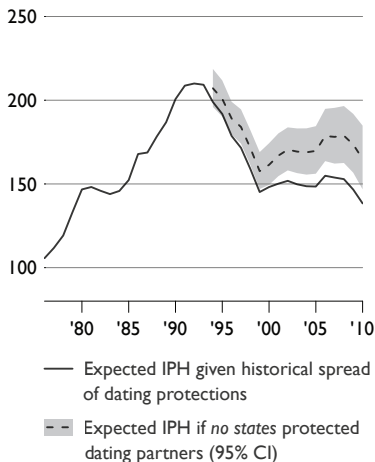
As a check, we simulate under the factual implementation of dating partner DVRO in each state, as it happened by year

The simulated national rates of dating partner IPH closely match the data

Negative Binomial Estimates of  
IPH Under Observed Policies



Counterfactual Estimates of  
IPH without Dating Protections

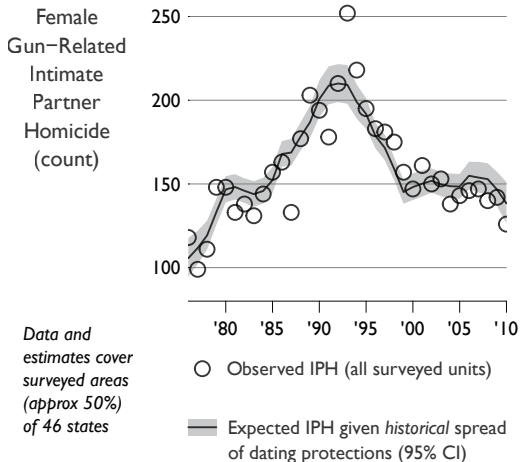


Now consider a counterfactual scenario:

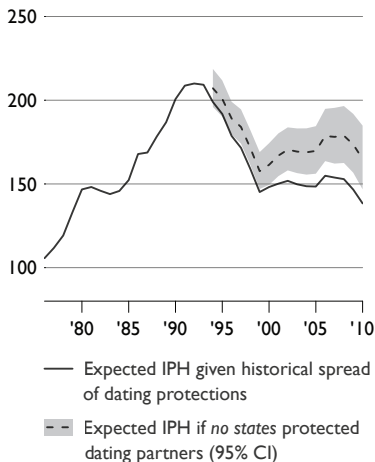
suppose no states added dating protections to DVRO after 1994



Negative Binomial Estimates of  
IPH Under Observed Policies

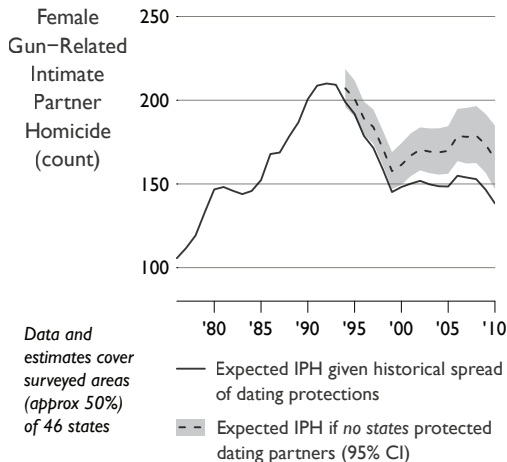


Counterfactual Estimates of  
IPH without Dating Protections

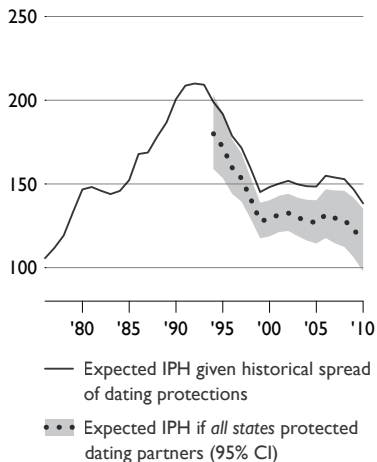


We find homicides would have been higher each year nationwide:  
perhaps dozens of additional cases in each year in the surveyed area

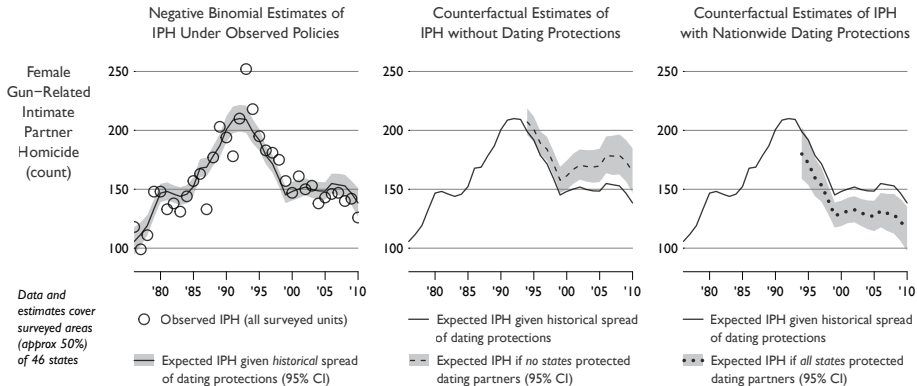
Counterfactual Estimates of  
IPH without Dating Protections



Counterfactual Estimates of IPH  
with Nationwide Dating Protections



On the other hand, if *all* states had protected dating partners starting in 1994, the model predicts dozens of fewer homicides

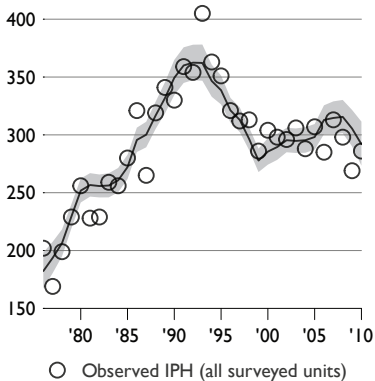


Results are clearly significant at the 0.05 level

Note this pattern of results for Female Gun-Related Homicides – you'll see it again

## Negative Binomial Estimates of IPH Under Observed Policies

Female  
All Cause  
Intimate  
Partner  
Homicide  
(count)

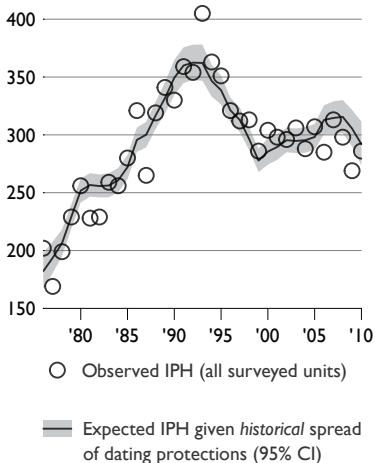


Data and estimates cover surveyed areas (approx 50%) of 46 states

Turning to all causes of Female dating partner IPH, we again check the model against the data...

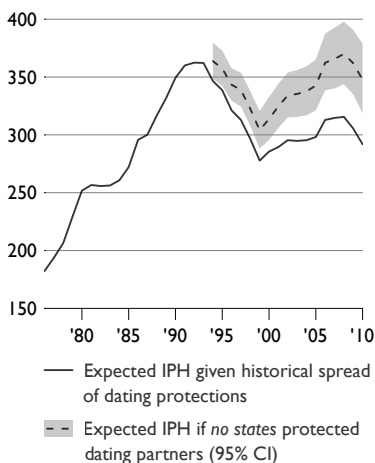
Female  
All Cause  
Intimate  
Partner  
Homicide  
(count)

Negative Binomial Estimates of  
IPH Under Observed Policies



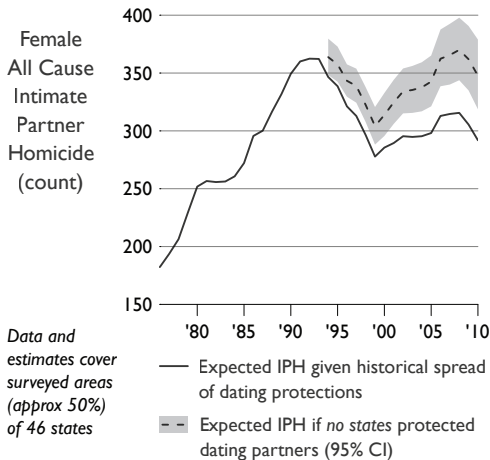
Data and estimates cover surveyed areas (approx 50%) of 46 states

Counterfactual Estimates of  
IPH without Dating Protections

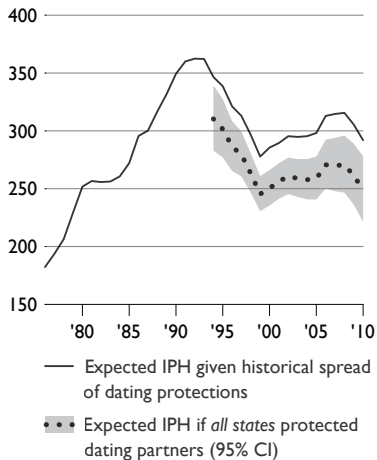


and find the model predicts IPH from all causes would have been significantly higher had no new states extended DVRO protections to dating partners after 1994...

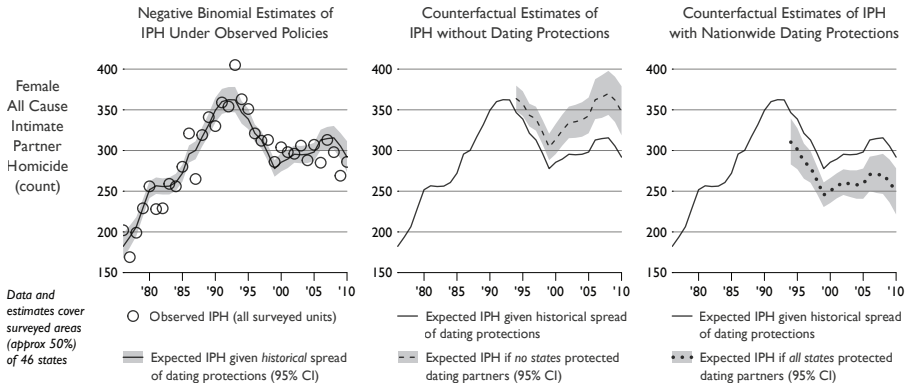
Counterfactual Estimates of  
IPH without Dating Protections



Counterfactual Estimates of IPH  
with Nationwide Dating Protections

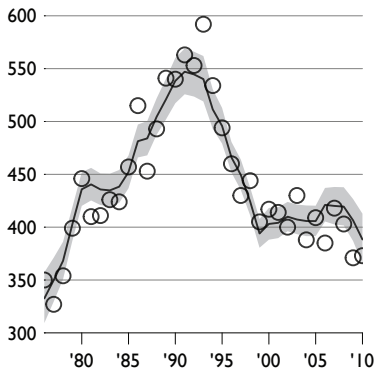


finally, the model still find evidence that nationwide protection would have further reduced homicides



## Negative Binomial Estimates of IPH Under Observed Policies

All Persons  
All Cause  
Intimate  
Partner  
Homicide  
(count)



Data and  
estimates cover  
surveyed areas  
(approx 50%)  
of 46 states

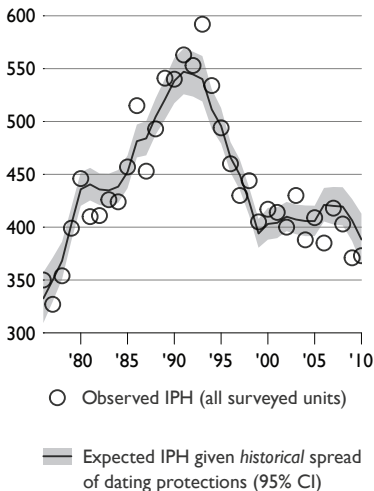
- Observed IPH (all surveyed units)
- Expected IPH given *historical* spread of dating protections (95% CI)

We find these results  
persist for the total IPH  
across sexes



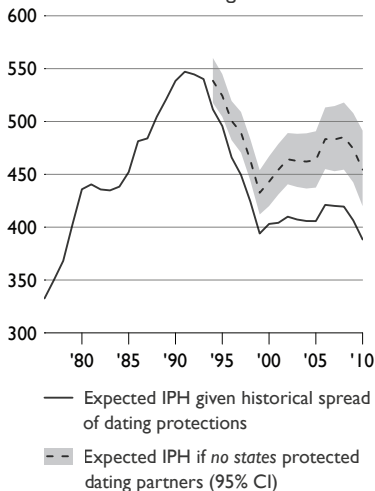
All Persons  
All Cause  
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Homicide  
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Negative Binomial Estimates of  
IPH Under Observed Policies



Data and estimates cover surveyed areas (approx 50%) of 46 states

Counterfactual Estimates of  
IPH without Dating Protections

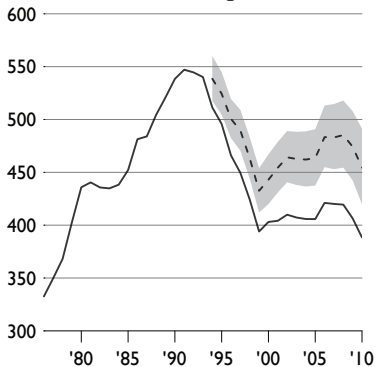


As do the counterfactual results

(Results for males alone are not significant; counts are much lower/noisier)

All Persons  
All Cause  
Intimate  
Partner  
Homicide  
(count)

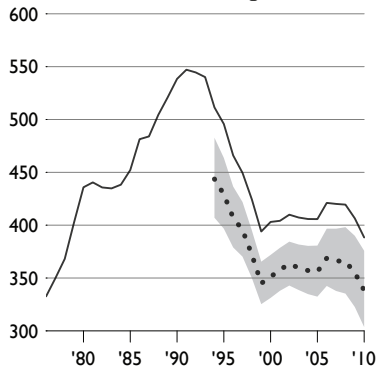
Counterfactual Estimates of  
IPH without Dating Protections



Data and  
estimates cover  
surveyed areas  
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of 46 states

- Expected IPH given historical spread of dating protections
- - Expected IPH if no states protected dating partners (95% CI)

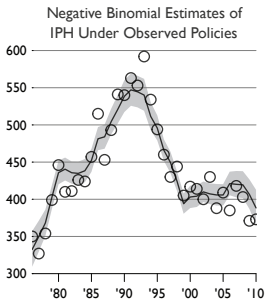
Counterfactual Estimates of IPH  
with Nationwide Dating Protections



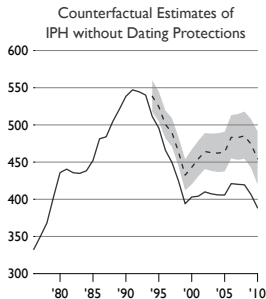
- Expected IPH given historical spread of dating protections
- • • Expected IPH if all states protected dating partners (95% CI)

All Persons  
All Cause  
Intimate  
Partner  
Homicide  
(count)

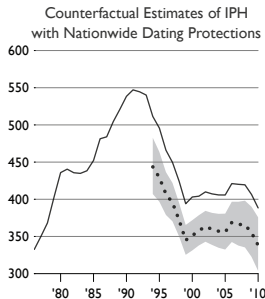
Data and  
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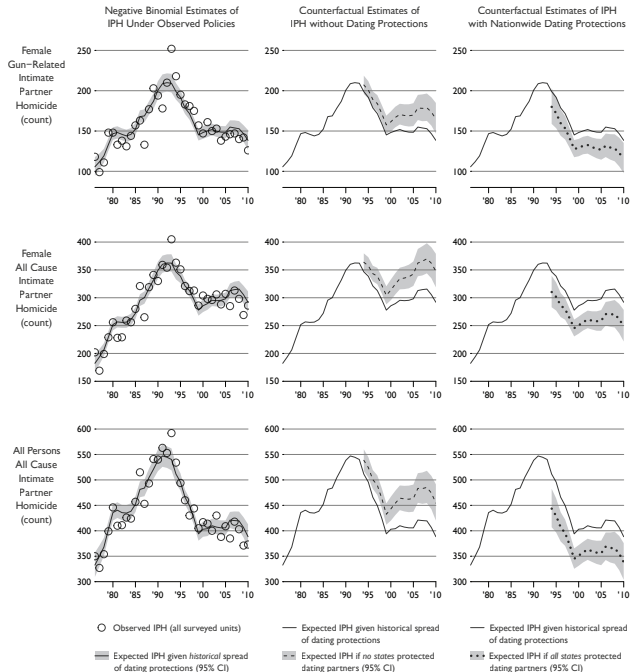
- Observed IPH (all surveyed units)
- Expected IPH given historical spread of dating protections (95% CI)



- Expected IPH given historical spread of dating protections
- - Expected IPH if no states protected dating partners (95% CI)



- Expected IPH given historical spread of dating protections
- Expected IPH if all states protected dating partners (95% CI)



Highly consistent results

What exactly are the policy implications? How many lives has dating partner protection saved? How many could further extension still save?

## Cumulative (1994–2010)

### Female gun-related intimate partner homicide

*Homicides reduced by observed extension to dating partners. . .*

in reported area	292.3	[130.4,	463.7 ]
in total population	641.8	[285.3,	1016.6 ]

*Additional reduction achievable with nationwide dating partner protection. . .*

in reported area	332.4	[157.1,	498.9 ]
in total population	785.7	[371.4,	1180.1 ]

Let's sum up the simulated counterfactual differences across years and states

We'll also extrapolate to the "full" population from the surveyed areas  
(this probably needs to be redone with better imputation)

## Cumulative (1994–2010)

## Recent (2010)

### Female gun-related intimate partner homicide

*Homicides reduced by observed extension to dating partners. . .*

in reported area	292.3	[130.4, 463.7]	21.5	[ 7.6, 36.2]
in total population	641.8	[285.3, 1016.6]	48.7	[16.7, 82.3]

*Additional reduction achievable with nationwide dating partner protection. . .*

in reported area	332.4	[157.1, 498.9]	16.9	[ 3.0, 29.9]
in total population	785.7	[371.4, 1180.1]	42.6	[ 8.4, 74.6]

Not only are differences in homicides substantively large  
(several % of total reported homicides)...

but the gap persists to the most recent data in our study

## Cumulative (1994–2010)

## Recent (2010)

### Female all cause intimate partner homicide

*Homicides reduced by observed extension to dating partners. . .*

in reported area	607.7	[351.2, 874.8]	47.5	[24.5, 71.6]
in total population	1406.7	[811.1, 2026.8]	112.6	[57.2, 170.2]

*Additional reduction achievable with nationwide dating partner protection. . .*

in reported area	611.9	[371.8, 842.6]	34.5	[14.6, 53.8]
in total population	1457.1	[883.8, 2008.7]	86.5	[37.5, 133.8]

Similar implications for all cause female IPH among dating partners

## Cumulative (1994–2010)

## Recent (2010)

### All persons all cause intimate partner homicide

*Homicides reduced by observed extension to dating partners. . .*

in reported area	817.7	[ 508.3, 1139.8]	58.2	[30.9, 86.6]
in total population	1952.0	[1209.0, 2725.0]	141.8	[74.0, 212.1]

*Additional reduction achievable with nationwide dating partner protection. . .*

in reported area	861.7	[ 555.4, 1159.1]	41.4	[16.3, 65.5]
in total population	2071.4	[1331.6, 2789.8]	104.7	[42.5, 164.6]

And across all dating partner IPH

And recall we are surely undercounting former dating partners and same-sex dating partners



## Concluding thoughts

Simple legal changes at the state level extending DVRO protections to dating partners seem to have large preventive effects on intimate partner homicide

Evidence is clear on face and based on a variety of models

This extension is only half complete –  
benefits to finishing the job are potentially huge in lives saved

Broader implication: state-level evidence suggests VAWA-style laws may have very positive effects on IPH outcomes

Renewal of VAWA at the federal level has been highly contentious and divided by party – are the stakes even higher than we thought?

## Further directions

What drives timing of dating partner extension?

Is it reasonable to treat it as exogenous?

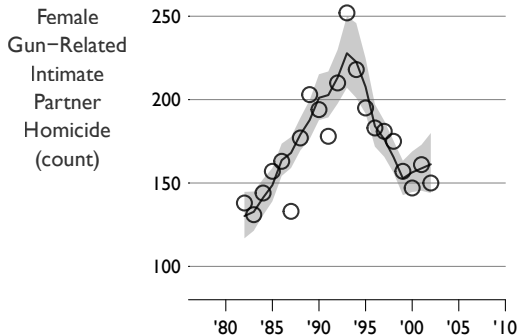
Would laggards be as effective if they extended DVRO to dating partners?

Better imputation models – and issues of undercounting

Subgroup analyses: are the young and non-white at greater risk?

Other ideas?

## Negative Binomial Estimates of IPH Under Observed Policies

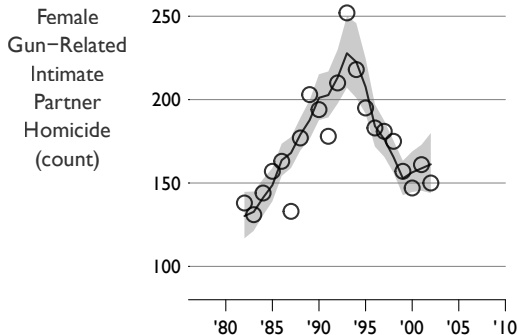


*Data and  
estimates cover  
surveyed areas  
(approx 50%)  
of 46 states*

- Observed IPH (all surveyed units)
- Expected IPH given historical spread of dating protections (95% CI)

**Robustness check:  
controlling for state laws  
(limited years)**

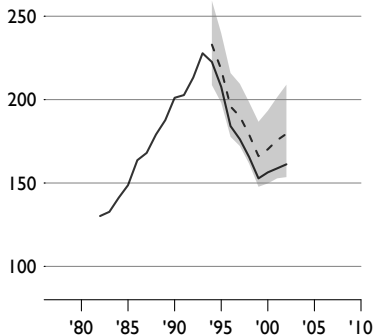
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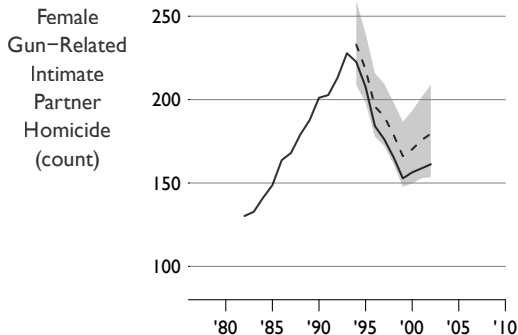
Counterfactual Estimates of  
IPH without Dating Protections



- Expected IPH given historical spread of dating protections
- - Expected IPH if no states protected dating partners (95% CI)

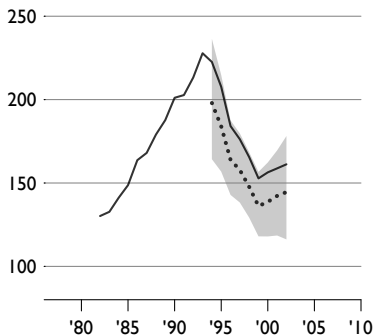
Similar results, but not quite significant at 0.05 level

Counterfactual Estimates of  
IPH without Dating Protections

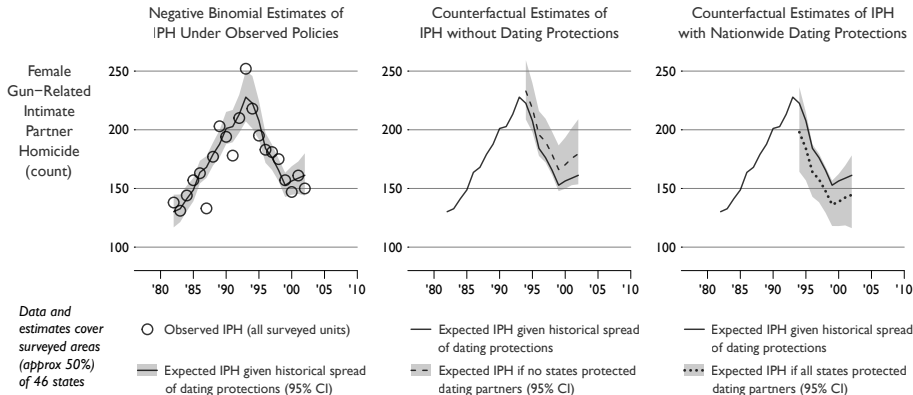


*Data and estimates cover surveyed areas (approx 50%) of 46 states*

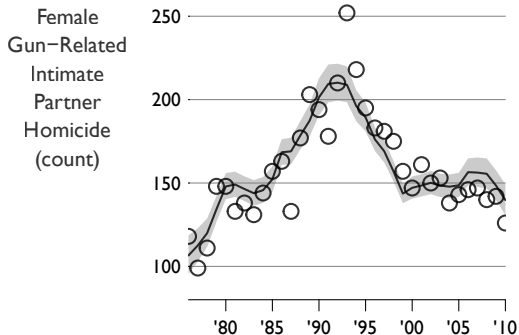
Counterfactual Estimates of IPH  
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## Negative Binomial Estimates of IPH Under Observed Policies

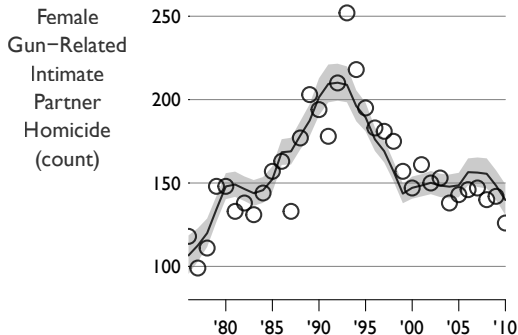


*Data and  
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- Observed IPH (all surveyed units)
- Expected IPH given historical spread of dating protections (95% CI)

Robustness check:  
Static Model

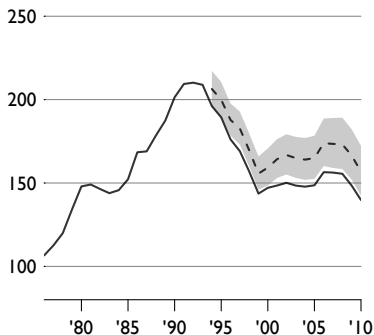
Negative Binomial Estimates of  
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Counterfactual Estimates of  
IPH without Dating Protections

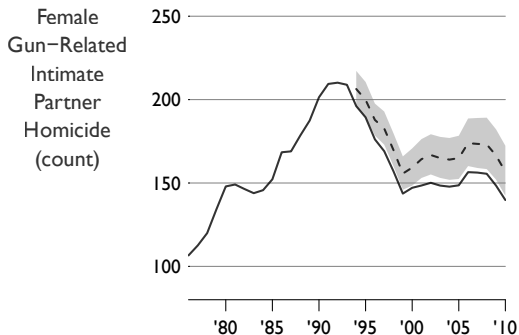


- Expected IPH given historical spread of dating protections
- - Expected IPH if no states protected dating partners (95% CI)

Extremely similar results: the models are driven by level changes after accounting for prior and VAWA trend effects

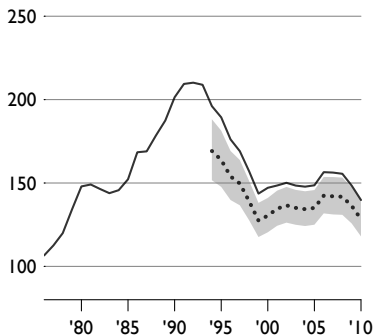


Counterfactual Estimates of  
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Data and estimates cover surveyed areas (approx 50%) of 46 states

Counterfactual Estimates of IPH  
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Extremely similar results: the models are driven by level changes after accounting for prior and VAWA trend effects

