APPENDIX

A. *Additional Discussion of Data Sources and Summary Statistics*

A.1. Crime Data

The Chicago Police Department makes detailed geospatial crime data available on the City of Chicago Open Data Portal. This data is compiled by the Chicago Police Department via their Citizen Law Enforcement Analysis and Reporting System and contains the universe of reported crime from 2001 to the present day. These data include variables describing the type of crime committed, the date the crime was reported to have occurred, and the location where the crime was reported to have happened. For a detailed description of the data, see Herrnstadt & Muehlegger (2015).

I will note here that crime which is not reported does not appear in this nor any other data. Thus all the parameters I estimate in this paper are properly interpreted as reflecting the impact of housing demolition on *reported* crime. There are a number of reasons why we might believe that the demolition of housing and subsequent relocation of households throughout the city would lead to systematic reporting biases. I will be able to do little to rule out such effects in general. However, the main conclusions of this paper continue to hold when I restrict my attention to homicides which, it has been frequently argued in the literature, should be less subject to reporting bias concerns. Since all results are robust in this manner, I have dropped the *reported* qualifier when referring to the target parameters in the body of the paper.

I aggregate the incident level data by crime type to the census-block level at a monthly frequency from 2001 to 2014. Thus the final unit of observation in this data set is the block, crime-type, month. Figure A.1 shows the time-series of common crimes from 2001 to 2014. Note that over this time period the total number of reported crimes declined by 44%. Figure

A.2 shows the geospatial distribution of homicides per thousand people.

[Figure 1 about here.]

[Figure 2 about here.]

Because the geo-spatial crime data begins in 2001, while the first public housing demolitions occur in 1995, all cross-sectional comparisons in this paper are restricted to demolitions that occur from 2001 onward. However, the FBI makes available incident level homicide data as part of its supplemental homicide report back to 1976 which I aggregate monthly to the Chicago Police Department level to supplement the portions of the paper that rely on time-series variation (ICPSR 2017). Unfortunately, prior to 1991, the FBI data disagrees dramatically with other publicly available sources on the number of murders per year in Chicago. For this reason, I drop murders in the FBI data occurring prior to January 1st, 1991. Figure A.3 shows the FBI time series as compared to the Chicago Police Department time-series.

[Figure 3 about here.]

A.2. Gang Maps

For interested readers, tables A.1 and A.2 provide summary statistics for city blocks controlled by select gangs.

[Table 1 about here.]

[Table 2 about here.]

TABLE A.1
Gang Territory Demographics

	N	Population	Black	White	Hispanic	Male	Male U-18
No Gang	12095	91.31	0.16	0.68	0.18	0.49	0.11
		(139.8)	(0.31)	(0.32)	(0.22)	(0.1)	(0.07)
Black Disciples	834	113.69	0.97	0.01	0.02	0.45	0.16
		(109.92)	(0.11)	(0.05)	(0.07)	(0.09)	(0.07)
Black P. Stones	1603	133.09	0.88	0.06	0.05	0.46	0.14
		(152.82)	(0.24)	(0.15)	(0.14)	(0.09)	(0.07)
Gangster Disciples	4662	118.15	0.89	0.06	0.05	0.46	0.15
		(130.2)	(0.24)	(0.17)	(0.15)	(0.09)	(0.07)
Latin Kings	1276	198.21	0.1	0.49	0.56	0.5	0.15
		(301.01)	(0.19)	(0.23)	(0.31)	(0.08)	(0.06)
Two-Six	685	156.44	0.04	0.52	0.65	0.51	0.16
		(109.15)	(0.1)	(0.21)	(0.28)	(0.06)	(0.05)
Other Gang	5383	160.99	0.46	0.3	0.34	0.49	0.15
		(144.52)	(0.45)	(0.3)	(0.35)	(0.09)	(0.07)

Note: Summary statistics are averages across census-blocks using demographic data from the year 2000 Census. Black, white, hispanic, male, and male under 18 are block level population shares. Rows correspond to census blocks that intersected with the indicated territory in the year 2004. “No Gang” refers to census blocks that did not intersect with any gang’s territory. “Other Gang” refers to all gangs not explicitly named. The remaining rows correspond to the 5 largest gangs by area. Standard deviations in parentheses.

TABLE A.2
Crime in Gang Controlled Areas

	Population	Violence	Theft	Sex Crime	Murder	Narcotics	Other
No Gang	91.31	1.96	4.95	0.22	0	0.51	3.14
	(139.8)	(4.36)	(11.96)	(1.74)	(0.07)	(2.7)	(5.25)
Black Disciples	113.69	10.77	8.58	0.97	0.04	5.33	8.83
	(109.92)	(12.6)	(8.98)	(3)	(0.22)	(12.13)	(15.14)
Black P. Stones	133.09	8.64	8.99	0.6	0.04	3.92	7.87
	(152.82)	(10.72)	(15.3)	(2.4)	(0.2)	(7.68)	(10.74)
Gangster Disciples	118.15	8.63	8.11	0.63	0.04	4.57	7.77
	(130.2)	(11.17)	(12.99)	(2.39)	(0.19)	(14.4)	(12.9)
Latin Kings	198.21	5.28	7.57	0.67	0.02	1.94	6.52
	(301.01)	(7.66)	(9.21)	(3.04)	(0.16)	(3.62)	(7.45)
Two-Six	156.44	3.53	5.62	0.39	0.02	1.01	4.68
	(109.15)	(4.74)	(9.6)	(3.47)	(0.14)	(2.02)	(4.61)
Other Gang	160.99	7.57	8.38	0.74	0.03	4.92	7.19
	(144.52)	(9.96)	(10.51)	(3.04)	(0.19)	(12.7)	(10.11)

Note: Summary statistics are averages across census-blocks using Chicago Police Department crime data for the year 2004. All crimes are defined according to the Illinois Uniform Crime Reporting Codes. “Violence” includes assault and battery; “Theft” includes burglary, motor vehicle theft, robbery, and theft; “Sex Crime” includes criminal sexual assault, human trafficking, prostitution and sex offenses; “Narcotics” includes narcotics violations; and “Other” includes all other offenses in the data. Rows correspond to census blocks that intersect with the indicated territory in the year 2004. “No Gang” refers to census blocks that did not intersect with any gang territory. “Other Gang” refers to all gangs not explicitly named. The remaining rows correspond to the 5 largest gangs by area. Standard deviations in parentheses.

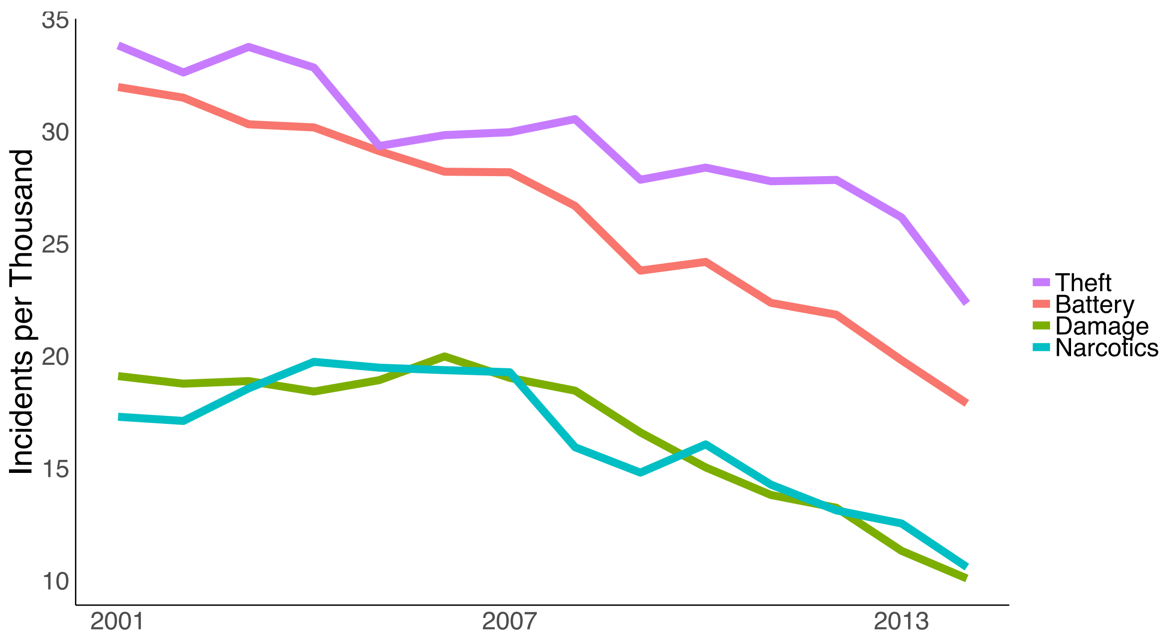

FIGURE A.1
Common Crimes by Year

Note: All crimes are defined according to the Illinois Uniform Crime Reporting Codes. Theft, battery, criminal damage, and narcotics violations are the four most commonly reported crimes in the CPD data between the years 2001 and 2014. Yearly population estimates used to convert total crime to per-capita crime come from FBI data. Results are reported in crimes per thousand Chicago residents.

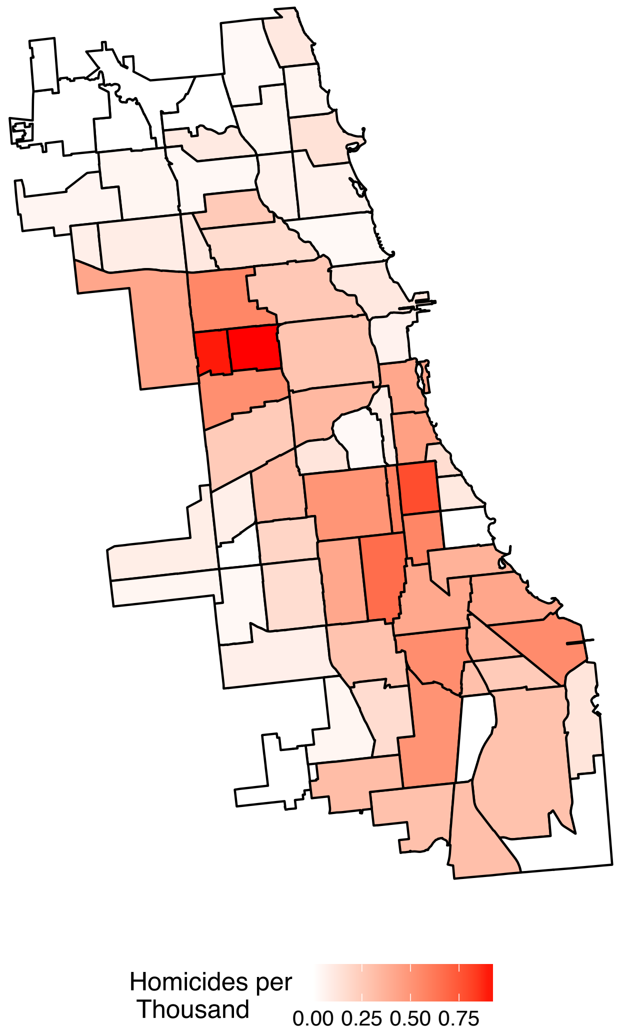

FIGURE A.2
Geo-spatial Distribution of Homicides

Note: Polygons represent boundaries of Chicago community areas. Homicides per thousand Chicago residents in each community area is determined by dividing total homicides from CPD data in 2001 by community area population in the year 2000 as measured by the Census. I use year 2000 population for the denominator since population measurements are unavailable at the necessary geographic resolution in the Census for the year 2001.

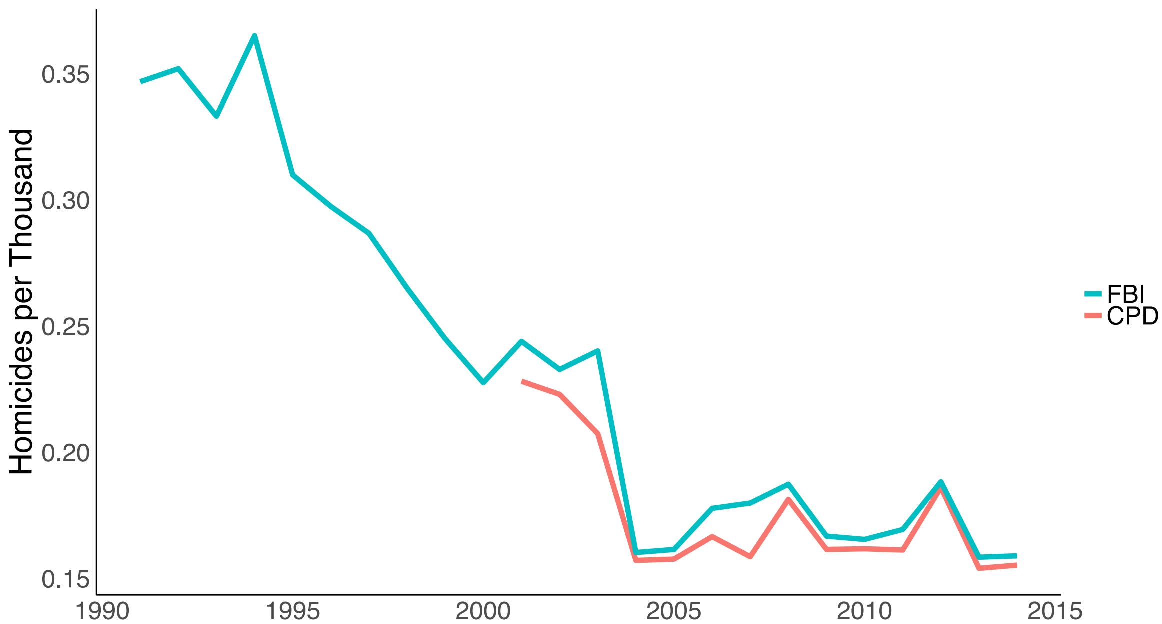

FIGURE A.3
Per Capita Homicides by Year

Note: FBI homicides come from the FBI Supplemental Homicide Report and are defined to include only homicides classified as "Murder and Non-negligent Manslaughter." CPD homicides are defined via the Illinois Uniform Crime Reporting Code. Yearly population estimates used to convert total homicides to per-capita homicides come from the FBI data. Results are reported in crimes per thousand Chicago residents.

B. *Difference in Difference Robustness Checks and Falsification Tests*

B.1. *Robustness to Lagged Treatment Structure*

Table B.1 shows that the difference in difference estimates are robust to lagging the treatment structure to account for the fact that I do not observe the exact date of building closure. All columns in this table include block and time-period by risk-set fixed effects. Each column assumes that the treatment date is x months earlier than the date I have used in the main text, with x ranging from 3-24 months as listed in a row at the bottom of the table.

[Table 3 about here.]

B.2. *Evidence of Parallel Trends*

Figures B.1, B.2, B.3, and B.4 show the dif-in-dif visually, which is a useful eyeball check on the plausibility of parallel trends. In each case, I take one treatment ring (for example, blocks within 50 meters of demolition) and average total crime in blocks that were treated in that ring early (i.e. prior to median treatment date) and compare it to the average total crime in blocks that were treated late (i.e. after the median treatment date). Since I observe treatment as early as the second month of the sample, in all cases I restrict attention to blocks treated after the date at the first quartile of the treatment vector, to ensure there is a reasonably long pre-period to examine visually. The first vertical line denotes the first quartile of the treatment vector for that treatment ring. Thus, all observations to the left of this line occur prior to any unit included in the averages being treated. The second line denotes the median treatment date. Thus, all blocks in the "Early" group receive treatment between this line and the first line. The third vertical line represents the last treatment date, and thus all blocks in the "Late" treatment group receive treatment in between the second line and the third line.

Table B.2 is the standard test of parallel trends. Because I do not observe a true "pre-period," I implement the test as follows. First I lag the treatment structure by a number of years (3, 4, and 5, respectively). I then restrict the sample to the largest time period feasible such that none of the units in the sample actually become treated. Let's use the 5 year lagged structure as an example. For this test, if a block was treated in December of 2011, I now assume it was treated in December of 2006. I then drop all observations from 2007 onward. Similarly, if a block was treated in January of 2006, I now assume it was treated in January of 2001. I then drop all observations that occur prior to January, 2001. This is necessary because otherwise, the block that was treated in 2006 would actually become treated at some point during the sample period. The end result is a treatment structure that preserves the timing of treatment late in the sample frame but which I assume occurs early in the sample frame when none of the indicated demolitions actually occur. I then repeat the dif-in-dif analysis on this sample and present the results.

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

[Table 4 about here.]

B.3. Heterogenous Dif-in-Dif Effects

Table B.3 repeats the dif-in-dif specification restricting the sample to various sub-categories of crime. All specifications include block fixed effects and time-period by risk-set fixed effects. Importantly, the main results hold for homicide, which suggests they are not driven entirely by reporting biases.

[Table 5 about here.]

TABLE B.1
Dif-in-Dif Estimates: Robustness to Lagged Treatment Structure

	Total Crime				
	(1)	(2)	(3)	(4)	(5)
0 to 50 Meters	−6.16	−5.76	−4.50	−3.25	−2.04
	(1.30)	(1.22)	(1.09)	(1.19)	(0.97)
50 to 100 Meters	−2.45	−2.29	−1.81	−1.36	−0.53
	(0.68)	(0.65)	(0.60)	(0.60)	(0.68)
100 to 200 Meters	−0.18	−0.21	−0.21	−0.25	−0.31
	(0.20)	(0.20)	(0.20)	(0.22)	(0.22)
200 to 300 Meters	−0.07	−0.08	−0.07	−0.09	−0.13
	(0.21)	(0.21)	(0.20)	(0.19)	(0.17)
300 to 400 Meters	−0.10	−0.10	−0.08	−0.07	−0.08
	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)
400 to 500 Meters	0.07	0.09	0.12	0.14	0.13
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
500 to 1000 Meters	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
1000 to 1500 Meters	0.01	0.00	0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1500 to 2500 Meters	0.01	0.01	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2500 to 3500 Meters	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3500 to 4500 Meters	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean of Dependent Variable	1.38	1.38	1.4	1.42	1.43
Months Prior to Demolition	3	6	12	18	24
Observations	4,042,335	3,968,838	3,821,844	3,674,850	3,527,856
Adjusted R^2	0.55	0.56	0.56	0.56	0.56

Note: The specification in this table is identical to the specification used in column (2) of table I in the main body of the paper, with one exception: the treatment vector used in this table is lagged between 3 and 24 months as indicated in the row labeled "Months Prior to Demolition," at the bottom of the table.

TABLE B.2
Parallel Trend Test in Pre-Period

	Total Crime		
	(1)	(2)	(3)
0 to 50 Meters	1.44	1.19	2.35
	(0.64)	(1.26)	(1.48)
50 to 100 Meters	1.88	−0.32	−0.12
	(0.59)	(0.89)	(0.40)
100 to 200 Meters	0.10	−0.23	−0.51
	(0.17)	(0.20)	(0.42)
200 to 300 Meters	0.19	−0.23	−0.51
	(0.14)	(0.13)	(0.26)
300 to 400 Meters	−0.04	0.08	0.02
	(0.14)	(0.11)	(0.07)
400 to 500 Meters	0.10	0.02	−0.02
	(0.10)	(0.12)	(0.06)
500 to 1000 Meters	−0.01	0.03	0.02
	(0.03)	(0.02)	(0.03)
1000 to 1500 Meters	−0.02	0.00	0.03
	(0.02)	(0.01)	(0.02)
1500 to 2500 Meters	−0.02	0.01	0.04
	(0.02)	(0.01)	(0.02)
2500 to 3500 Meters	−0.00	0.02	0.02
	(0.01)	(0.01)	(0.01)
3500 to 4500 Meters	−0.00	−0.01	0.01
	(0.02)	(0.01)	(0.02)
Mean of Dependent Variable	1.38	1.52	1.47
Treatment Lag (Years)	3	4	5
Observations	1,469,940	1,175,952	881,964
Adjusted R^2	0.61	0.63	0.64

Note: The specification in this table is identical to the specification used in column (2) of table I in the main body of the paper, with the exception that the treatment structure has been lagged by the number of indicated years, and the sample trimmed at the beginning and end such that no block ever receives the indicated treatment. This mimics a classic test of trends in the "pre-period" in the case where there is no pre-period data available by asking if the treatment structure late in the sample frame is predictive of outcomes early in the sample frame.

TABLE B.3
Dif-in-Dif Heterogeneity by Crime Type

	Total (1)	Homicide (2)	Violent (3)	Narcotics (4)	Weapons (5)
0 to 50 Meters	−6.429	−0.006	−1.470	−2.181	−0.052
	(1.312)	(0.002)	(0.365)	(0.531)	(0.011)
50 to 100 Meters	−2.633	−0.003	−0.756	−0.806	−0.030
	(0.713)	(0.001)	(0.281)	(0.207)	(0.007)
100 to 200 Meters	−0.140	−0.001	−0.014	−0.018	−0.002
	(0.199)	(0.001)	(0.046)	(0.088)	(0.002)
200 to 300 Meters	−0.070	0.000	−0.011	−0.012	−0.001
	(0.212)	(0.001)	(0.062)	(0.082)	(0.002)
300 to 400 Meters	−0.101	−0.000	0.006	−0.033	−0.002
	(0.102)	(0.000)	(0.025)	(0.030)	(0.001)
400 to 500 Meters	0.056	0.000	0.012	−0.004	−0.001
	(0.046)	(0.000)	(0.008)	(0.011)	(0.001)
500 to 1000 Meters	0.012	0.000	0.016	0.006	−0.000
	(0.011)	(0.000)	(0.005)	(0.004)	(0.000)
1000 to 1500 Meters	0.007	0.000	0.012	0.002	−0.000
	(0.011)	(0.000)	(0.004)	(0.004)	(0.000)
1500 to 2500 Meters	0.012	−0.000	0.008	0.003	−0.000
	(0.009)	(0.000)	(0.003)	(0.003)	(0.000)
2500 to 3500 Meters	0.011	−0.000	0.008	0.006	−0.000
	(0.007)	(0.000)	(0.002)	(0.002)	(0.000)
3500 to 4500 Meters	−0.001	−0.000	0.003	−0.000	−0.000
	(0.009)	(0.000)	(0.003)	(0.002)	(0.000)
Mean of Dependent Variable	1.369	0.002	0.334	0.156	0.013
Observations	4,115,832	4,115,832	4,115,832	4,115,832	4,115,832
Adjusted R^2	0.553	0.003	0.375	0.233	0.038

Note: The specification in this table is identical to the specification used in column (2) of table I in the main body of the paper, with the exception that the outcome variable reflects different sub-categories of crime.

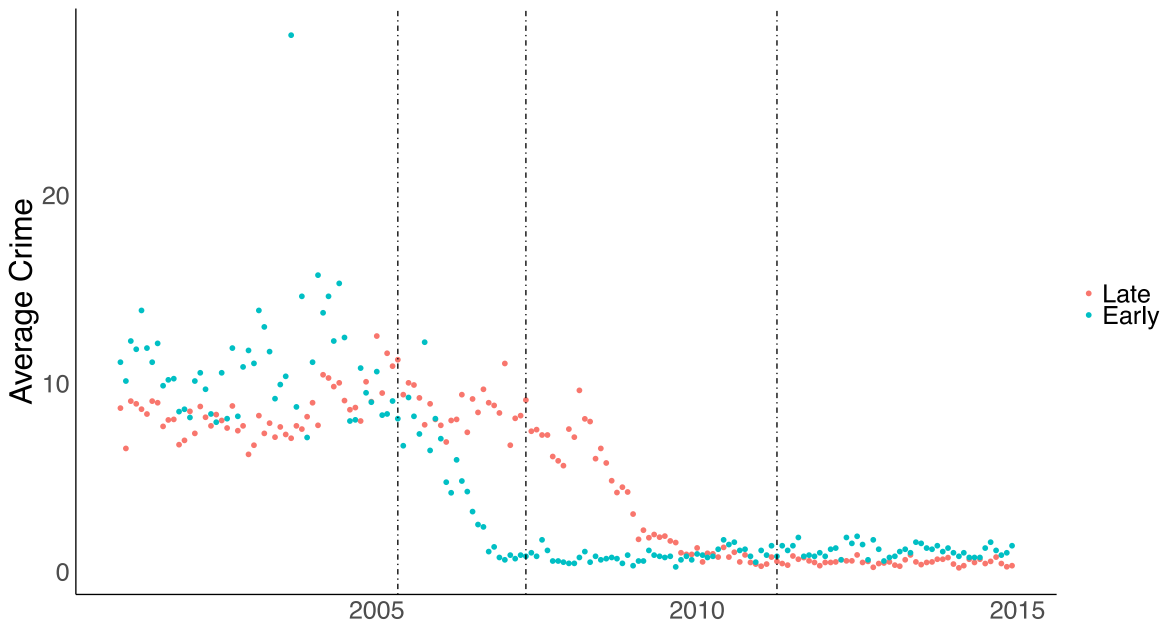

FIGURE B.1
Total Crime in Blocks within 50 Meters of Demolition

Note: The first vertical line corresponds to the first quartile of the vector of treatment dates for the sub-sample of blocks that ever experience a demolition within 50 meters of their centroid. The second vertical line corresponds to the median, and the third vertical line corresponds to the date the last block in this sub-sample becomes treated. The "Early" group corresponds to all blocks that experience at least one demolition at a date between the first and second lines. The "Late" group refers to all blocks that experience at least one demolition at a date between the second and third vertical lines.

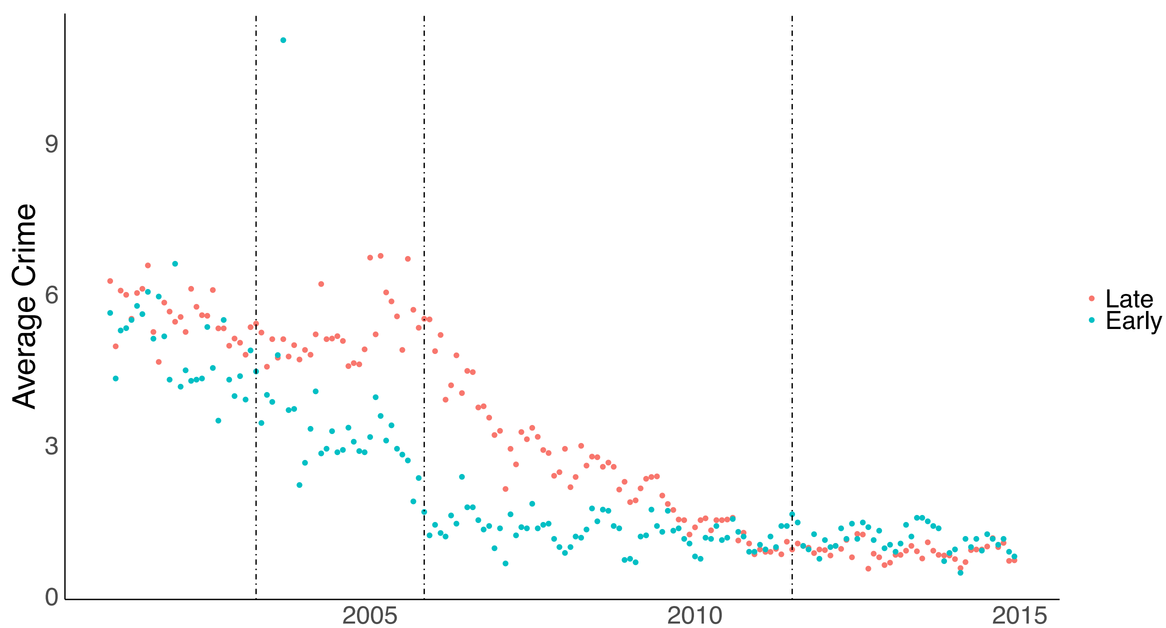

FIGURE B.2
Total Crime in Blocks between 50 and 100 Meters of Demolition

Note: The first vertical line corresponds to the first quartile of the vector of treatment dates for the sub-sample of blocks that ever experience a demolition between 50 and 100 meters of their centroid. The second vertical line corresponds to the median, and the third vertical line corresponds to the date the last block in this sub-sample becomes treated. The “Early” group corresponds to all blocks that experience at least one demolition at a date between the first and second lines. The “Late” group refers to all blocks that experience at least one demolition at a date between the second and third vertical lines.

FIGURE B.3
Total Crime in Blocks between 100 and 200 Meters of Demolition

Note: The first vertical line corresponds to the first quartile of the vector of treatment dates for the sub-sample of blocks that ever experience a demolition within 100 and 200 meters of their centroid. The second vertical line corresponds to the median, and the third vertical line corresponds to the date the last block in this sub-sample becomes treated. The "Early" group corresponds to all blocks that experience at least one demolition at a date between the first and second lines. The "Late" group refers to all blocks that experience at least one demolition at a date between the second and third vertical lines.

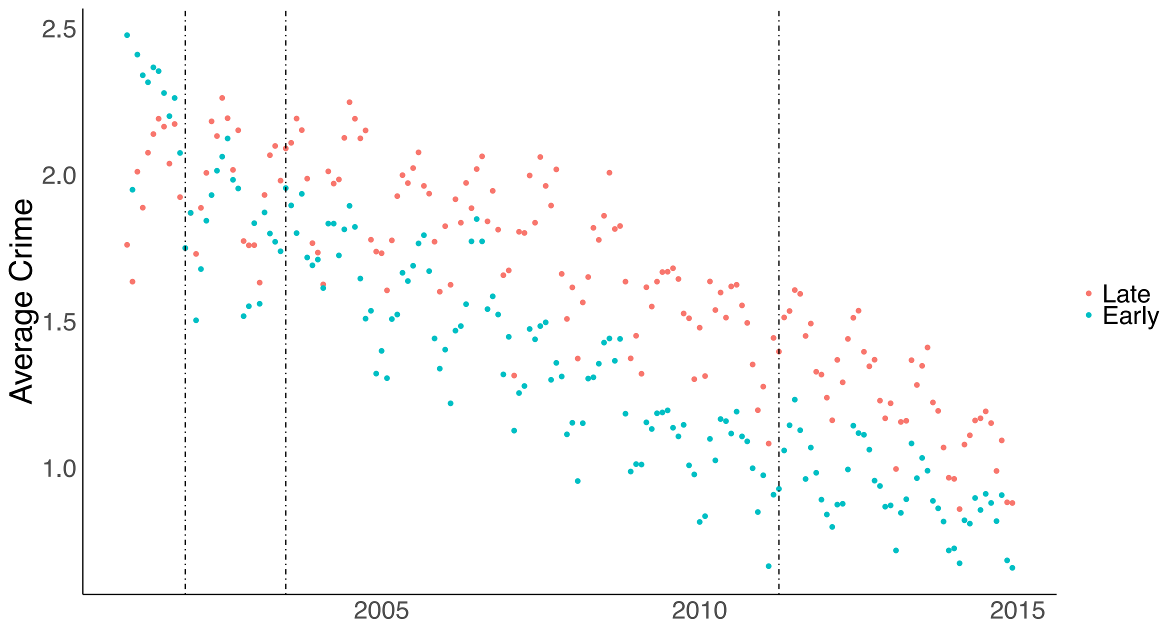

FIGURE B.4
Total Crime in Blocks between 500 and 1000 Meters of Demolition

Note: The first vertical line corresponds to the first quartile of the vector of treatment dates for the sub-sample of blocks that ever experience a demolition within 500 and 1000 meters of their centroid. The second vertical line corresponds to the median, and the third vertical line corresponds to the date the last block in this sub-sample becomes treated. The "Early" group corresponds to all blocks that experience at least one demolition at a date between the first and second lines. The "Late" group refers to all blocks that experience at least one demolition at a date between the second and third vertical lines.

C. *Time Series Robustness Checks and Falsification Tests*

C.1. *Permutation Tests*

Figures C.1, C.2, C.3, C.4, and C.5 check for the possibility that the regression results in table III are driven by spurious trends. I do this via permutation test by choosing a random vector of 63 treatment dates from the years 2001-2011, generating the treatment variable as described in the text, and then estimating the models from table III. After repeating this procedure 10,000 times, I graph placebo distributions of the target parameter for each specification in table III, which vary the order of the trend polynomial from 1-5 respectively.

In all cases, the placebo distribution is centered on zero, suggesting the main results are not the result of spuriously trending variables. However, the densities of the placebo distribution with first and second order polynomials exhibit some evidence of non-normality, which suggests the specifications with lower order trends may not provide correct inference in finite sample. Table III indicates that adding higher order terms beyond a cubic does not appreciably change the point estimates, hence I take the cubic trend as my preferred specification since it is the most parsimonious specification that does not exhibit the non-normality. This permutation test also generates non-parametric p-values of around .065 for the specifications containing a third order and higher polynomial trend.

[Figure 8 about here.]

[Figure 9 about here.]

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

C.2. *Time Series Robustness*

Table C.1 replicates table III but restricting attention to homicides in the Chicago Police Department Data. With the exception of the linear trend (which is imprecisely estimated), the main conclusion holds, suggesting that the result is unlikely to be driven entirely by reporting biases.

Table C.2 replicates table C.1 using FBI homicide data which extends back to 1991. This allows me to use the full set of demolitions, including the 7,000 units demolished between 1995 and 2000. The result continues to hold here for the 3rd, 4th, and 5th order trend polynomials, which suggests that the main result is not a feature of the particular set of demolitions I am able to use with the CPD data.

Table C.3 replicates table C.2 but normalizing the dependent variable by yearly population figures contained in the FBI data. Since the results continue to hold for the 3rd, 4th, and 5th order polynomials, this suggests that the result is not biased by demolition induced migration outside of the city limits.

[Table 6 about here.]

[Table 7 about here.]

[Table 8 about here.]

C.3. *Estimating the Time Path of Treatment*

While the VAR provides an explicit accounting of the time path of treatment as estimated via the time-series, for completeness I also estimate the time path here using specifications analogous to those in table III. I do this by replacing the independent variable, which counts the cumulative number of demolitions, with a series of variables that count the number of demolitions that have occurred within a given calendar quarter relative to the current date.

Figure C.6 shows the results for the 2nd though 5th order polynomials. The top left panel is 2nd order, top right is 3rd, bottom left is 4th, and bottom right is 5th.

[Figure 13 about here.]

TABLE C.1
Time Series Estimates: Homicides (CPD Data)

	Homicides				
	(1)	(2)	(3)	(4)	(5)
Number of Demolitions	−0.32	1.02	1.21	1.95	1.89
	(0.16)	(0.33)	(0.63)	(0.65)	(0.62)
Mean of Dependent Variable	41.3	41.3	41.3	41.3	41.3
Polynomial Order	First	Second	Third	Fourth	Fifth
Observations	168	168	168	168	168
Adjusted R^2	0.58	0.63	0.63	0.64	0.66

Note: Estimation uses CPD data on homicides aggregated to the city wide level. All specifications include month of year fixed effects to control for seasonality. Columns 1-5 vary the order of the polynomial trend from 1st to 5th respectively. Standard errors account for auto-covariance of the residuals using the method of Lumley & Heagerty (1999) which builds on Andrews (1991).

TABLE C.2
Time Series Estimates: Homicides (FBI Data)

	Homicides				
	(1)	(2)	(3)	(4)	(5)
Number of Demolitions	0.12	−0.09	1.01	1.18	1.23
	(0.13)	(0.10)	(0.45)	(0.61)	(0.65)
Mean of Dependent Variable	54.8	54.8	54.8	54.8	54.8
Polynomial Order	First	Second	Third	Fourth	Fifth
Observations	288	288	288	288	288
Adjusted R^2	0.69	0.72	0.72	0.72	0.72

Note: Estimation uses FBI homicide data at city of Chicago level. All specifications include month of year fixed effects to control for seasonality. Columns 1-5 vary the order of the polynomial trend from 1st to 5th respectively. Standard errors account for auto-covariance of the residuals using the method of Lumley & Heagerty (1999) which builds on Andrews (1991).

TABLE C.3
Time Series Estimates: Homicides Per Million People (FBI data)

	Homicides Per Million				
	(1)	(2)	(3)	(4)	(5)
Number of Demolitions	0.04	−0.05	0.48	0.40	0.43
	(0.06)	(0.04)	(0.16)	(0.22)	(0.23)
Mean of Dependent Variable	19.52	19.52	19.52	19.52	19.52
Polynomial Order	First	Second	Third	Fourth	Fifth
Observations	288	288	288	288	288
Adjusted R^2	0.68	0.72	0.73	0.73	0.73

Note: Estimation uses FBI homicide data normalized by yearly city population. All specifications include month of year fixed effects to control for seasonality. Columns 1-5 vary the order of the polynomial trend from 1st to 5th respectively. Standard errors account for auto-covariance of the residuals using the method of Lumley & Heagerty (1999) which builds on Andrews (1991).

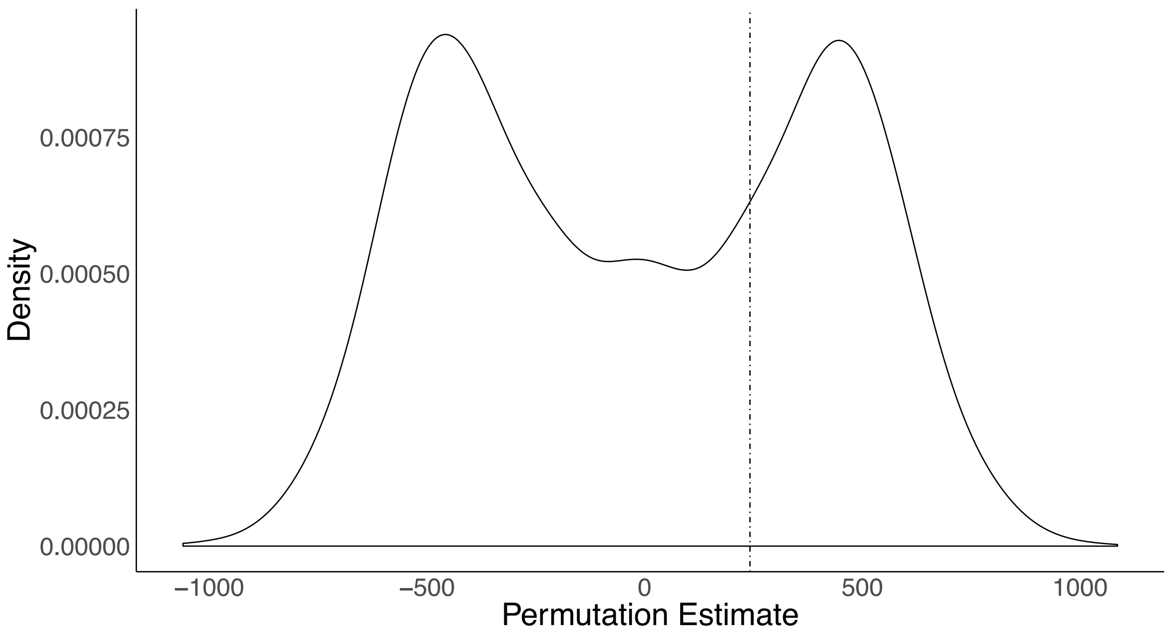

FIGURE C.1
Time Series Permutation Test: First Order Polynomial Trend

Note: This figure plots a non-parametric density estimate from a distribution of 10,000 placebo treatment effects each estimated with randomly chosen treatment dates. In this case, I use a specification with a first order polynomial trend to estimate the placebo effect. The vertical line corresponds to the actual treatment effect estimated with the real vector of treatment dates.

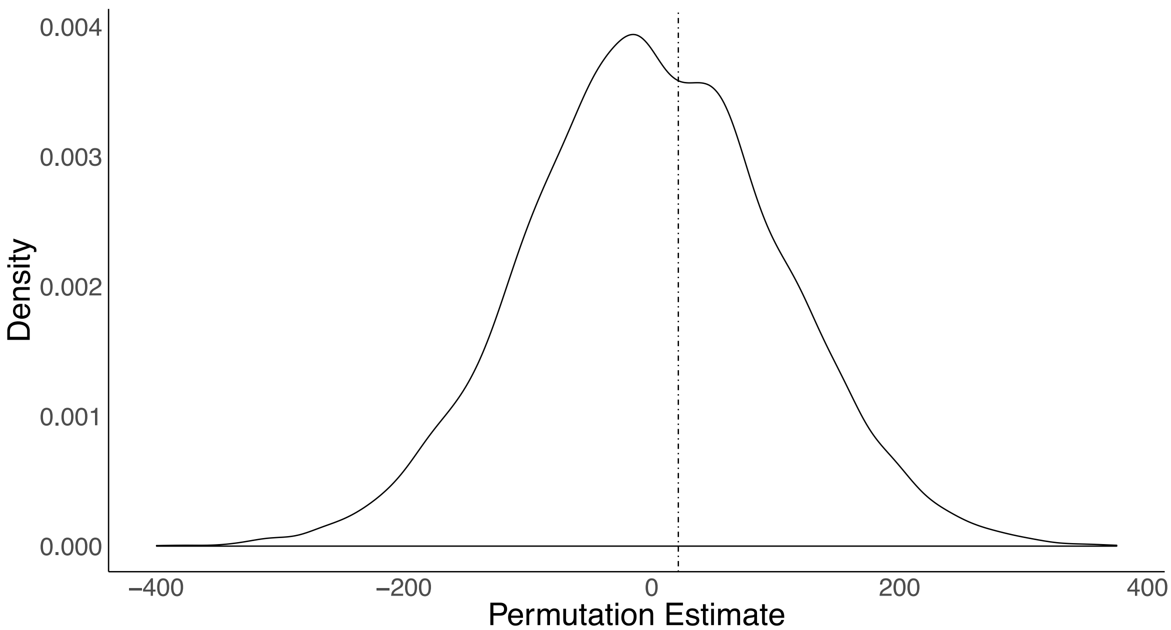

FIGURE C.2
Time Series Permutation Test: Second Order Polynomial Trend

Note: This figure plots a non-parametric density estimate from a distribution of 10,000 placebo treatment effects each estimated with randomly chosen treatment dates. In this case, I use a specification with a second order polynomial trend to estimate the placebo effect. The vertical line corresponds to the actual treatment effect estimated with the real vector of treatment dates.

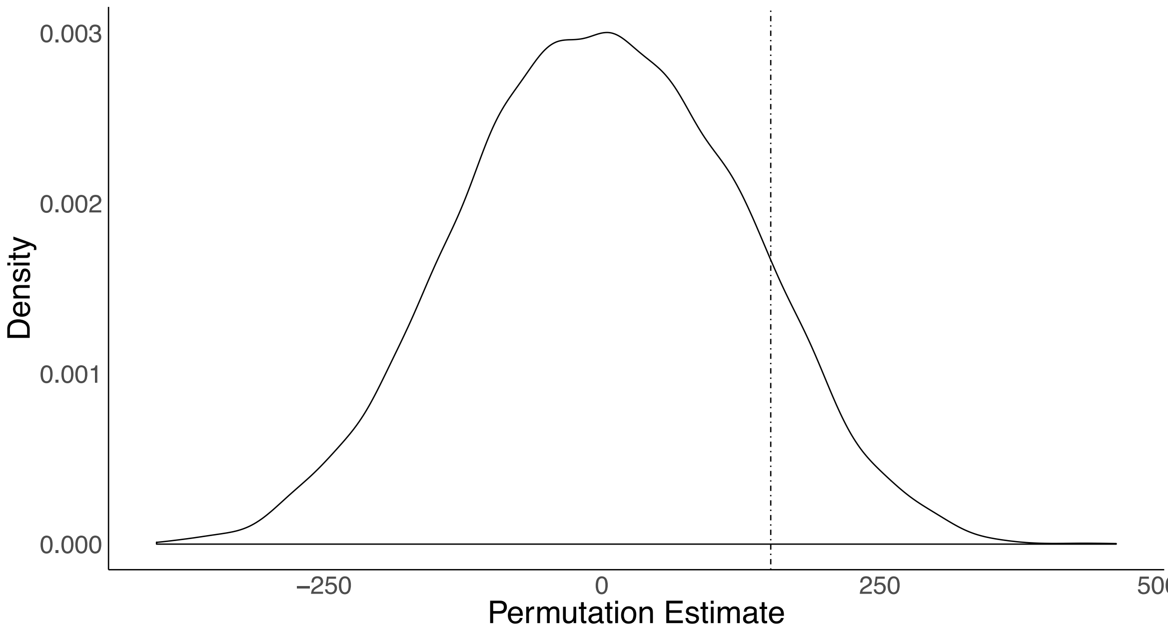

FIGURE C.3
Time Series Permutation Test: Third Order Polynomial Trend

Note: This figure plots a non-parametric density estimate from a distribution of 10,000 placebo treatment effects each estimated with randomly chosen treatment dates. In this case, I use a specification with a third order polynomial trend to estimate the placebo effect. The vertical line corresponds to the actual treatment effect estimated with the real vector of treatment dates.

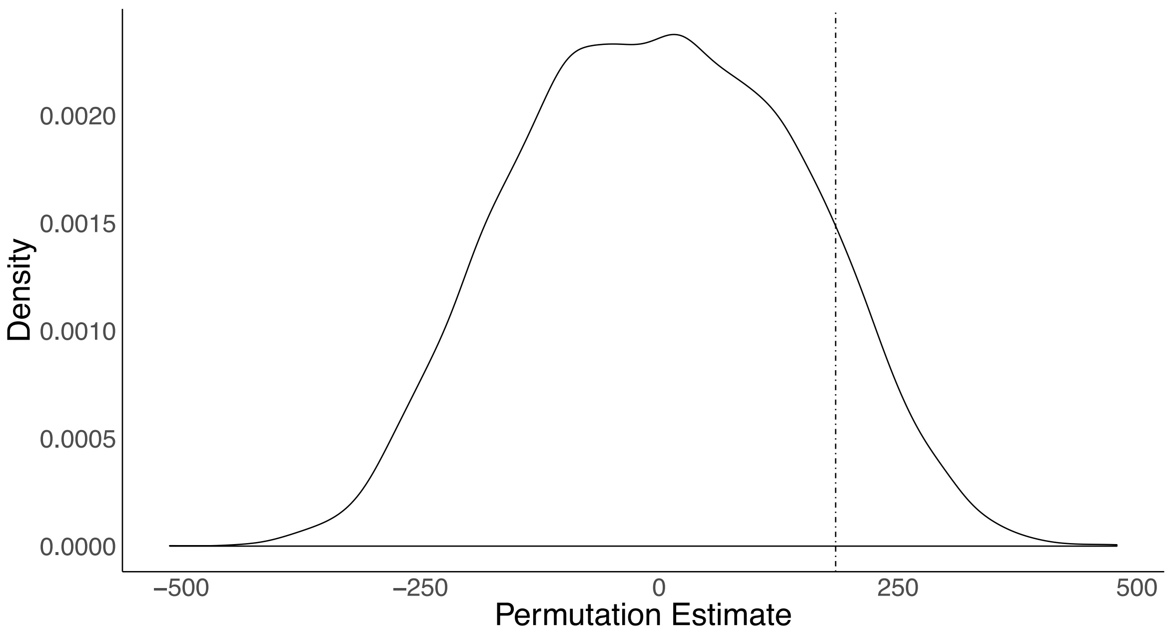

FIGURE C.4
Time Series Permutation Test: Fourth Order Polynomial Trend

Note: This figure plots a non-parametric density estimate from a distribution of 10,000 placebo treatment effects each estimated with randomly chosen treatment dates. In this cases, I use a specification with a fourth order polynomial trend to estimate the placebo effect. The vertical line corresponds to the actual treatment effect estimated with the real vector of treatment dates.

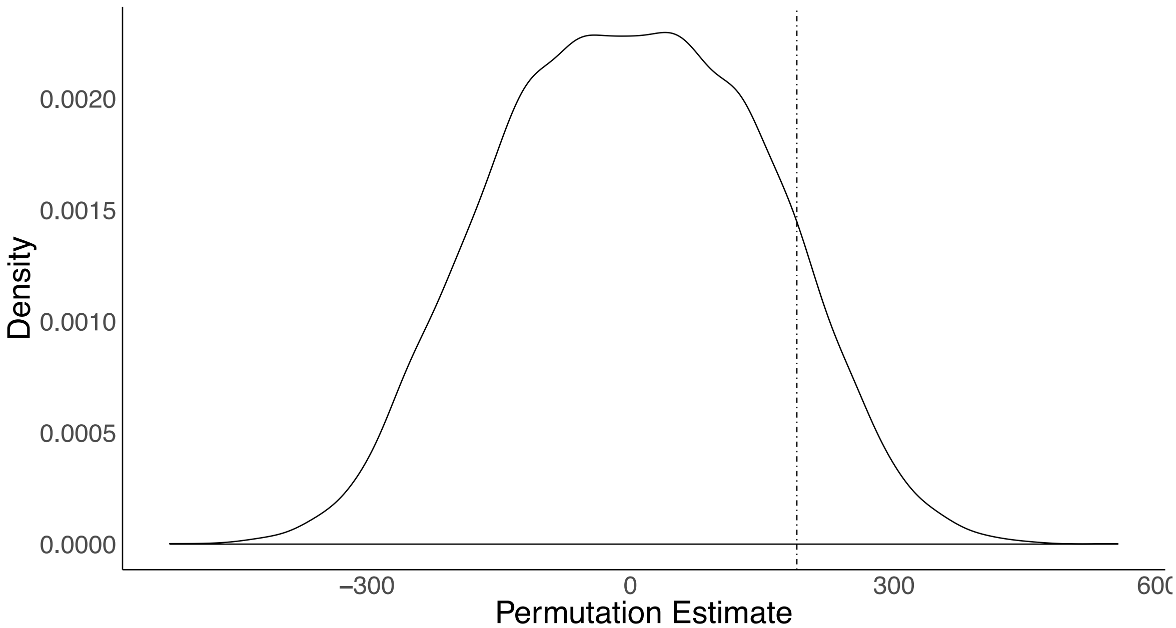

FIGURE C.5
Time Series Permutation Test: Fifth Order Polynomial Trend

Note: This figure plots a non-parametric density estimate from a distribution of 10,000 placebo treatment effects each estimated with randomly chosen treatment dates. In this case, I use a specification with a fifth order polynomial trend to estimate the placebo effect. The vertical line corresponds to the actual treatment effect estimated with the real vector of treatment dates.

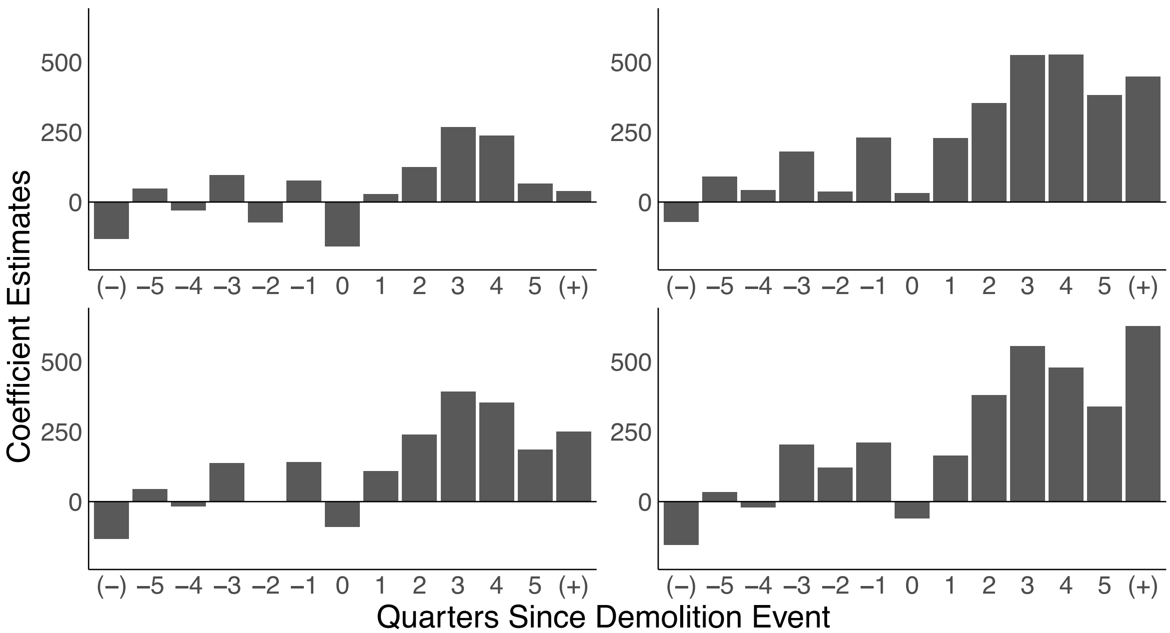

FIGURE C.6
Time Path of Treatment for Main Specification

The specifications used to generate this figure are identical to those of columns 2-5 in table III in the body of the main paper but, instead of estimating the average effect over time, I allow the treatment effect to vary by calendar quarter relative to demolition date. The pattern is broadly similar to that uncovered by the VAR analysis.

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