The Impact of Living Wage Ordinances on Urban Crime

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ABSTRACT: We examine the impact of living wages on crime. Past research has found that living wages appear to increase unemployment while providing greater returns to market work. The impact on crime, therefore, is unclear. Using data on annual crime rates for large cities in the United States, we find that living wage ordinances are associated with notable reductions in property related crime and no discernable impact on non-property crimes.

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I. Introduction

Over the past 15 years, a number of city governments have adopted living wage ordinances mandating wage floors exceeding the federal minimum wage for certain classes of workers. These floors have been found to impact the labor market for low skilled workers, leading to fairly substantial increases in expected wages and a small but statistically significant reduction in employment (Neumark and Adams, 2003b; Campolieti, Fang, and Gunderson, 2005). To the extent that these wage floors impact the labor market of the low-skilled, they might also affect non-labor market behaviors such as crime. In this paper, we examine the unintended impact of living wage ordinances on crime.

In the standard neo-classical model, the opportunity cost of working in the legal sector may influence the propensity to commit crime (Becker, 1968; Levitt, 1997). These ideas, in fact, are supported in the existing empirical literature which reveals a modest effect of unemployment and a somewhat more pronounced and lasting effect of wages on pecuniary crimes (see, for examples, Grogger, 1998; Freeman, 1999; Gould et al., 2002; Lin, 2008). This model, however, does not lead to a qualitative prediction about the impact of wage floors on crime. Rather, by simultaneously increasing the returns to employment and the likelihood of unemployment, theoretical predictions about the impact of living wage ordinances on crime are ambiguous. An increase in wages among the working low skilled might be expected to decrease crime, yet the associated decrease in employment might lead to an increase in crime. Given that living wage ordinances are found to have only a small negative impact on employment but a much more pronounced positive effect on wages, one might reasonably speculate these ordinances lead to a reduction in crime. Ultimately, however, this is an empirical question which has not yet been addressed in the literature.

To resolve this ambiguity, we use panel data on annual city level crime rates and living wage ordinances from 1990-2010. For each city-year, we observe the rates of different types of property and violent crimes, the minimum and the living wage, and a detailed set of covariates. Given these data, the basic empirical approach compares crime rates in cities before and after the adoption of living wage laws, as well as crime rates between cities that did and did not adopt living wage ordinances.

As with all such studies, a primary concern is that living wage ordinances may not be exogenous; living wages may be adopted or changed in response to factors that are unobserved to the econometrician but are arguably associated with crime. For example, local labor market conditions, the fiscal stability of local governments, and social services provided by local governments may all be associated with living wage provisions and crime.

To account for the nonrandom adoption of living wage laws, we use several nested approaches. First, at the most basic level, we estimate models with a rich set of covariates accounting for city/county and state level socio-economic and criminal justice variables that might confound inferences. Likewise, we exploit the panel nature of the data by incorporating both city and time fixed effects, city specific linear and quadratic time trends, and state-by-year fixed effects.[1] Second, in addition to presenting results for the full sample of cities, we also restrict the analysis to cities that had a formal living wage campaign, some of which passed and others of which did not. Arguably, this sub-sample provides a more credible although smaller comparison group for the analysis

(Adams and Neumark, 2005a). Third, we employ falsification tests by examining the impact of living wage laws on violent crime rates – most notably, the murder, assault, and rape rates -- that seem unlikely to be notably impacted by these wage ordinances. Finally to rule out the possibility that our results are spuriously driven by serial correlation, we use a placebo test that regresses the crime rate on a "fake" living wage ordinance variable that precedes the true adoption date by two years.

After describing the data in Section II, we evaluate the effects of living wage laws on crime rates in Section III. In Section IV, we draw conclusions. Using data on annual crime rates for large cities in the United States, we find that living wage ordinances are associated with notable reductions in property related crime and little impact on non-property crimes such as murder, assault and rape.

II. Data Description

The data are a panel of annual crime rates and living wage ordinances for the 239 largest U. S. cities (approximately all cities with greater than 100,000 persons) over the period 1990 to 2010.[2] Of the 239 cities included in the sample, 49 had successful living wage campaigns and 20 had unsuccessful campaigns. Table 1A lists the 49 cities with living wage ordinances, along with the 2010 living and minimum wages, and Table 1B lists the cities with unsuccessful campaigns.

Several important features of living wage ordinances are revealed. First, the living wage can be substantially higher than the minimum wage. Seventeen of the 49 cities have living wages that exceed $13 per hour, and four cities – Berkeley, Hartford, St. Louis, and San Jose– have living wages of $14 per hour or more. Second, many cities – 53 percent – have state minimum wages in excess of the federal floor. Nearly 47 percent of cities with living wage ordinances are located in states that have minimum wages in excess of the federal floor. Thus, it is important for us to control for the state minimum wage. Finally, in contrast to the minimum wage, living wage ordinances only cover limited groups of workers; those that are municipal employees, contract workers, or workers in businesses receiving assistance from the state.[3]

For each city-year, we observe the living wage, if it exists, and the rates of six different types of crimes as measured by the Federal Bureau of Investigations Uniform Crime Reports (UCR).[4] In particular, we observe rates of burglary, larceny, and motor vehicle theft (MVT) as well as the four violent crime rates for murder, assault, rape, and robbery. In addition, we observe a rich set of covariates measuring both socio-economic, demographic and criminal justice variables that are typically used in crime regression models. [5]

Table 2 displays basic descriptive statistics for the variables used in the analysis. The first column of sample statistics provides means and standard deviations for all cities across all years, while the next two columns display the sample means for cities that adopted living wage ordinances and those that did not, respectively. Cities that adopted living wage ordinances have larger populations and a higher fraction of minorities than non-living wage cities (see Table 2B). In addition, living wage cities have higher crime rates: the average homicide rate in cities adopting a living wage ordinance is 14.33 (per 100,000) whereas the analogous rate for other cities is 9.53.

Additional insight on the association between living wage ordinances and crime is found by tracing out the temporal path of crime rates around the years when ordinances are adopted. Figure 1 displays the time series variation in the difference between the percent change in crime rates in living wage and control cities relative to the year in which the living wage ordinance is adopted. For example, year 0 is 1998 for Boston and 2000 for Denver (see Table 1A).[6] We display the cumulative percent change in the relative crime rates for cities that did and did not adopt living wage ordinances, using five years prior to the adoption of the living wage ordinance as the baseline. While crime rates are consistently falling in living wage cities faster than non-living wage cities throughout, there is a significant decrease in both violent and property crime occurring at the time of the enactment. For example, from year -5 to year -1, crime rates fell faster in living wage cities than control cities by a rate of 1.6% each year for property crime and 0.7% for violent crime. The most striking differences, however, occur just after living wage ordinances are adopted (i.e., year 0), when property crime rates fell 5.7% faster in living wage cities and violent crime fell by 3.1% . After the adoption, the relative change in the property and violent crime rates remained nearly unchanged for three years then continued to fall at the same rate as prior to the adoption of the living wage ordinance.

Whether these differences are due, in part, to the living wage ordinances or simply unobserved factors that confound the observed associations remain unclear. To account for factors that are thought to be associated with both crime and living wage rates, we include a number of covariates in the regressions. Most notably, since many cities with living wage ordinances are located in states with minimum wage rates in excess of the federal floor (see Table 1), we include city-year specific minimum wages in our analysis. Likewise, we include a rich set of fixed effect and covariates measuring the demographic characteristics of the city/county, the number of police per capita, and the state incarceration rate (see Table 2).

III. The Effect of Living Wage Ordinances on Crime

To evaluate whether the observed relationships between living wages and crime reflect the effects of living wage laws, we estimate a series of linear mean regression models that account for observed and unobserved city specific characteristics. In Section III.A, we outline the basic fixed effect model that explicitly accounts for unobserved city specific factors that may be related to both crime rates and living wage policies. In Section III.B, we present and discuss the estimates from a series of models that evaluate the effects of living wages on crime rates, and in Section III.C we evaluate the robustness of the results to different specifications. Finally, in Section III.D we provide a brief discussion of the results.

A. Model

To assess the impact of living wage ordinances on crime, we evaluate two basic models. In the first, we evaluated the impact of a living wage (LW) ordinance and in the second we consider the specific wage floor.

Formally, we consider the linear model

$$Y_{it} = \alpha_t + \beta \cdot \ln(w_{it}^{\min}) + \gamma * LW_{it} + X_{it}\theta + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the log-crime rate for city *i* in year *t*, $w_{it}^{\min}$ is the higher of the applicable state or federal minimum wage rates, and X_{it} is the observed vector of other city *i* characteristics in year *t* that are thought to influence the number of crimes. Finally, LW is a measure of the living wage ordinance. For some specifications, this is simply an indicator of whether the city adopted an ordinance. For others, the random variable associated with the living wage is the percentage increase of the living wage relative to the effective minimum wage in cities with non-trivial living wage ordinances and equals zero for all non-living wage cities: =max[ln(w_{it}^{liv})- ln($w_{it}^{\min}$),0]. The parameters α_t, β, γ, and θ are unobserved, with α_t being a year fixed effect. The primary parameter of interest is γ.

Finally, the random variable ε_{it} measures unobserved factors influencing crime rates. The conventional assumption is that this unobserved random variable is mean zero independent of all the covariates, $E[\varepsilon_{it} \mid w^{\min}, LW, X] = 0$, in which case living wage laws are exogenous. Arguably, however, the unobserved factors, ε_{it}, influencing crime are related to unobserved factors associated with the city specific living and minimum wages. For example, unobserved local labor market conditions and social programs may influence the passage of living wage ordinances and crime, in which case the observed correlations between living wage laws and crimes rates will be spurious.

To account for this identification problem, we allow for the expectation of the unobserved factors to vary across city and time as follows:

$$E[\varepsilon_{it} \mid w^{\min}, LW, X] = C_i + T_{1i}t + T_{2i}t^2 + e_{it} \tag{2}$$

Equations (1) and (2) imply a mean regression that includes an identically and independently distributed shock e_{it}, a city fixed effect, C_i, and city specific linear and quadratic time trends, $T_{1i}t + T_{2i}t^2$. Thus, the model explicitly accounts for unobserved time and city specific factors that might jointly influence living wage laws and crime rates. The effect of the living wage is identified using within-city variation in living wage after netting out city-specific time trends. Coupled with the rich set of covariates, this flexible panel data specification should minimize the influence of many unobserved confounders. Incorporating flexible city specific time trends is especially important given the heterogeneous decrease in crime over time between living wage and control cities as noted in Figure 1 as well as the well documented and dramatic fall in crime during the 1990's (Levitt, 2004). Finally, to assess the importance of state-level unobserved heterogeneity, we also estimate a model with state-by-year fixed effects (see Section III.C).

We assess the sensitivity of the parameter estimates to different assumptions on city specific parameters, C_i, T_1, and T_2. In each case, we use a least-squares estimator, weighted to account for differences in city populations, to consistently estimate the parameters, and report robust standard errors clustered by city to allow for arbitrary heteroskedasticity.

B. Results

Table 3 presents the estimated effect of living wage ordinances on crime, where the living wage ordinances are represented by an indicator variable. Table 3A present results for the three property crimes and Table 3B presents results for the four violent crimes. Using data from the entire sample of 239 cities, the table presents estimates from five different panel data specifications: the first uses year fixed effects alone, the second with year and city fixed effects, the third adds other time varying covariates, the fourth adds a city specific linear time trend, and the fifth includes both city specific linear and quadratic trends.[7]

The estimated effect of living wages is sensitive to whether we account for unobserved city specific fixed effects and time trends. Model 1 estimates include year but not city fixed effects or other covariates. Except for rape, violent crime rates are found to be substantially higher after living wage ordinances are passed and are statistically significant at the 5% level. For the three property crimes, the estimates are not statistically significant, yet suggest large negative associations for burglary and larceny and a positive association for MVT.

Once we account for the covariates, city fixed effects and time trends in Models 3-5, however, many of these observed associations appear spurious. Most notably, the estimates from these fixed effects models imply that living wage ordinances decrease the three property crimes analyzed in this study. In particular, the living wage ordinances are estimated to reduce the burglary rate by 6% to 8%, the MVT rate by 6% to 12% and the larceny rate by 2% to 3%. Although the larceny estimates from Models 3-5 are statistically insignificant, the fact that the estimates are consistently negative across all five specifications and that the Model 2 estimate of -7.2% is statistically significant suggests that living wages do have a small negative impact on larceny.

Table 3B presents analogous results for violent crimes. As might be expected, living wage ordinances appear to have little discernable impact on murder, rape, and assault, but do appear to reduce the robbery rate by between 4 and 8%.[8]

Table 4 presents estimates from models using the living wage variable directly. In this case, the living wage coefficient estimates measure the elasticity of the living wage on crime. In particular, holding the minimum wage constant, γ measures the elasticity of crime rates with respect to an increase in the living wage over the effective minimum wage. Again, we find that the living wage reduces the rates of property related crime but not violent crime. For example, the elasticity of burglary and MVT rates with respect to living wage are estimated to be around -0.15. In contrasts, we cannot reject the null hypothesis that living wages have no impact on murder, rape and assault.

C. Robustness Analysis

To further assess the robustness of our findings, we consider three alternative specifications. First, we restrict the analysis to cities that had a formal living wage campaign brought before the city government, some of which passed and others of which did not. Arguably, cities with failed living wage campaigns provide a more natural comparison group for the analysis. Second, with multiple cities in each state, we employ state-year fixed effects to further control for time-varying state specific confounders. Finally, we use a placebo test in which we regress the crime rate on a "fake" living wage ordinance variable that precedes the true adoption date by two years.

i. Failed Campaigns

Living wage campaigns have been unsuccessful in numerous cities. In our sample, for example, 22 of the 239 cities had unsuccessful campaigns (see Table 1B). Arguably, cities that have undergone unsuccessful campaigns provide a better control group for estimating the effects of living wage laws than the broader set of all cities. After all, living wage movements may be accompanied by increased attention, organization and public debate on workers at the bottom of the wage distribution. Narrowing the control group to those cities with living wage campaigns, may avoid confounding the effects of living wage laws and living wage campaigns.

Thus, in this section, we re-estimate Models 4 and5 on a subset of cities that have had living wage campaigns.[9] The estimates are found in the top panel of Table 5, which displays coefficients and standard errors using the restricted sample of 71 cities with living wage campaigns. As we found with the full sample, the evidence suggests that living wage ordinances and living wages reduce the three property crimes and robbery. In particular, these ordinances are estimated to reduce the robbery rate by 6 to 7 percent, the burglary rate by 7 to 9 percent, the larceny rate by 3 to 4 percent (statistically insignificant), and the MVT rate by 6 to 10 percent. At the same time, there is no statistically significant impact of the living wage on homicide, rape or assault.

Next, following Adams and Neumark (2005a), we consider these failed campaigns within the full sample of cities by constructing an indicator variable marking the initial year and subsequent years after a failed campaign (FLW). Campaigns are de-railed or failed after a significant action by local or state government against the proposal (e.g. mayoral veto or city council rejection).10 Using this indicator for failed campaigns, the regression specification is modified to include these failed campaigns as a second control group as follows:

$$Y_{it} = \alpha_t + \beta \cdot \ln(w_{it}^{\min}) + \gamma * LW_{it} + \lambda * FLW_{it} + X_{it}\theta + \varepsilon_{it} \tag{3}$$

We estimate Models 4 and 5 using the modified specification and report the coefficients in the second panel of Table 5. The estimated effects associated with the living wage ordinance are consistent with the previous findings. Living wage ordinances are estimated to decrease the robbery rate by 3.3 to 4.8 percent and the burglary rate by 5.5 to 7.8 percent, the larceny rate by 1.5 to 2.3 percent (statistically insignificant), and the MVT rate by 6.1 and 11.3 percent. The estimate effects for murder, rape and assault are all statistically insignificant.

In addition to using failed campaigns as an alternative control group, the specification in Equation 3 provides insight on whether the estimates associated with the living wage laws reflect the effects of the laws themselves or just the effects of living wage campaigns. In particular, the coefficient associated with failed or derailed living wage campaigns, λ, reveals the impact of the campaign, albeit ones that have failed. While many of the estimates are large in magnitude -- exceeding 0.05 in absolute value – they are also imprecise. Twelve of the fourteen estimates associated with failed campaigns are statistically insignificant, suggesting that there is no discernible impact of the campaign on crime.

Still, if these estimates associated with FLW reveal the impact of living wage campaigns, a more refined estimate of the impact of living wage laws can be found by differencing the estimate associated with the campaigns, λ, from the estimated effect of the ordinance, γ (see Adams and Neumark, 2005a). Focusing on Model 5 (the Model 4 results are similar), we find the difference and difference type estimates imply that living wage ordinances decrease the robbery rate by about 12%, the burglary rate by 13%, the larceny rate by 7%, and the MVT rate by 2% (statistically insignificant). In contrast, we accept the zero null hypotheses for murder, rape, and assault (the estimate for rape is significant in Model 4).

ii. Type of Living Wage Ordinance and State-Year Fixed Effects

Neumark and Adams (2003a) distinguish between ordinances on businesses receiving government assistance (GA) and ordinances for municipal employees or contract workers (MC). They find that the former have larger impacts on the labor market than the latter. See footnote 3 for further details.

We incorporate these different ordinance types into our regression specification

$$Y_{ijt} = \beta \cdot \ln(w_{ij}^{\min}) + \gamma_1 {*}GA_{ijt} + \gamma_2 {*}MC_{ijt} + X_{ijt}\theta + \alpha_{jt} + u_i + e_{ijt} \qquad (4)$$

where j indexes state, α_{jt} is a state-year fixed effect, u_i is a city fixed effect, and e_{ijt} is the idiosyncratic error. The state-year fixed effect specification captures unobserved non-linear state effects that may be associated with crime rates such as changes in state law or state funding of local police departments. The top panel of Table 6 reports the coefficients of the general living wage indicator for the different crime rates and the lower panel reports the coefficients for the GA and MA living wage indicators for the different crime rates.

The general living wage ordinance is found to have a statistically significant effect on robbery, burglary, and motor vehicle theft, but no discernible effect on murder, rape, or assault. The living wage ordinance decreases robbery by 10 percent, burglary by 3 percent and motor vehicle theft by 5 percent. However, when we disaggregate the living wage indicator we find a heterogeneous effect on the crime rates dependent on the type of ordinance. We find a statistically significant negative effect for the business assistance ordinance (GA) for both larceny and robbery, but not burglary or MVT. The GA ordinance decreases larceny by 8.6 percent and robbery by 9 percent. The MC ordinance is found to decrease burglary by 3.6 percent and robbery by 9 percent, but we accept the zero null hypothesis for larceny and MVT. None of the violent crimes are statistically significant in either specification.[11]

iii. Policy Placebo/Falsification Test

Finally, we conduct a falsification test using fake policy variables to assess whether there is evidence of spurious correlations (see Bertrand, Duflo and Mullainanthan, 2004). In particular, we create a placebo living wage indicator which equals one two years prior to the actual date the living wage ordinance is adopted. So, if a living wage ordinance passed in 1998, the placebo policy indicator will equal 1 in 1996 (and beyond), two years prior to the actual passage date. Since this date is arbitrary, the coefficient associated with this placebo should be zero. A statistically significant estimate would suggest that the model may be mispecified and the resulting coefficient estimates may be biased. In particular, some of the observed decrease in property crime may be due to unobservable factors that are correlated across time and not due to the policy intervention.

The results of the placebo test are divided into three panels in Table 7, with each panel displaying results which include more city specific control: the top panel includes only city fixed effect, the middle panel includes a city specific linear time trend, and the bottom panel includes a city specific quadratic time trend. Without time trends (panel 1), the coefficient estimates associated with the placebo variable on living wage ordinances are relatively small but statistically significant for assault and MVT. Once linear and quadratic time trends are incorporated in the model, however, all of the coefficient estimates associated with the ordinances are small and insignificant. Thus, this test does not reveal evidence that the estimates from models with city specific time trends are biased.

D. Discussion of Results

To summarize our primary findings, we observe that living wages have a modest negative effect on property related crimes. The Model 5 estimated elasticities on property crimes suggest that a 1 percentage point increase in living wage relative to the effective minimum wage results in 0.05 to 0.15 percent drop in property related crime. Likewise, the results found when using a simple living wage indicator variable in our most restrictive Model 5 suggests that a policy that caused a roughly 50% increase in the wages for some fraction of low wage workers is associated with a 8% reduction in burglaries, a 6% reduction in car thefts, a 4% reduction in robberies, and a 3% reduction in larceny. At the same time, we find that the living wage has no discernable effect on crimes with weak pecuniary motives including murder, rape, and assault.

These findings are generally consistent with both the literature evaluating the impact of the living wage on the low skilled labor market and the literature evaluating the impact of the labor market on crime. The former literature finds that the living wage has a large positive effect on average wages and a small negative effect on employment. Thus, to the extent the living wage serves to increase the expected benefits of participating the labor market, we would predict an associated drop in crime, especially crimes with pecuniary motives. The latter literature finds, in fact, that the labor market for low skilled persons has a notable impact on crimes with pecuniary motives but little effect on non-pecuniary crimes such as rape and murder (Gould et al., 2002). Since we expect the living wage to impact crime via the low skilled labor market, the lack of relationship between the living wage and homicide, assault, and rape suggests that our conclusions are not due to a spurious correlation between these ordinances and general levels of crime.

Finally, note that while these estimated elasticities are substantial they are notably smaller than estimates found for more direct policy measures aimed at reducing crime. The literature evaluating the impact of incarceration on property crime, for example, reports estimated elasticities that in many cases exceed -0.50 (Levitt, 1996; Johnson and Raphael, 2010). Likewise, the literature examining the impact of policing on property related crimes tends to find point estimates of at least -0.50 (Levitt, 1997, 2002 and 2004; and Evans and Owens, 2007).

V. Conclusion

In this paper, we evaluate the unintended consequences of living wage policies on crime. Using a panel of annual city level crime rates from 1990 to 2010, two contributions are made to the existing literature. First, while previous studies have focused on the impact of living wages on the labor market, we are the first to study the impact of living wages on related deviant behaviors. Second, using the panel data set of cities, we are able to explicitly mitigate the potential endogeneity bias of living wage ordinances using a variety of empirical approaches.

We find robust evidence that living wage ordinances lead to modest reductions in expected robbery, burglary, larceny, and MVT rates, but have no impact on non-pecuniary violent crimes such as homicide, assault, and rape. These findings are supported in a variety of different regression models. Depending on the specification and the crime being examined, our elasticity estimates for the three property related crimes lie between -0.03 and -0.2.

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[1] Adams and Neumark in their work examining the impact of living wages on employment and earnings also consider city specific linear time trends.

[2] The data contain 243 cities, but some cities are dropped either due to a lack of information regarding living wage ordinances, or missing crime or covariate data leaving a total of 239 cities.

[3] There is limited information about the fraction of low-skilled workers potentially impacted by living wage laws. Neumark and Adams (2003a) estimate the fraction of workers in the bottom quartile of the wage distribution potentially covered by living wage ordinances varies from 3-6% for ordinances covering municipal employees, to 15-20% for laws that cover city contractors, and to slightly over 80% for laws that cover businesses receiving government assistance. The fraction of workers actually impacted by the different ordinances, however, will be much smaller (see, for example, Farris

(2005) and Tolley, Bernstein, and Lesage (1999)). For example, based on survey of city contractors in Chicago, Tolley et. al. (1999) estimate that slightly more than one-third of employees in covered businesses would be impacted by the living wage ordinance applied to contract workers. Finally, Brenner, Wicks-Lim, and Pollin (2002) find the enforcement of business assistance ordinances vary greatly between cities and question whether the actual coverage is as large as the estimates in Neumark and Adams (2003a).

[4] Data on the living wage ordinances come from the Employment Policies Institute (www.epionline.org/lw_proposal_map.cfm) and National Law Employment Project (http://www.nelp.org/page/-/Justice/2011/LocalLWLawsCoverageFINAL.pdf?nocdn=1). When possible we verify wage rates with the local municipality.

In years where living wages were adopted or changed, the annual living wage is computed as a weighted average of the corresponding minimum wage rates or living wage rates that applied in a given city in a given year, where the weights were based on the amount of time that year that each wage rate applied. This was done because while the living wage rate information was available by month, the crime rate information by city was only available on an annual basis. Likewise, we lag living wage indicators by one year if the ordinance is enacted after July of the enactment year. The month of July is chosen as it marks a common start month of the fiscal year for many municipalities.

[5] Minimum wage rate data come from the U.S. Department of Labor, the city level number of police per 100,000 from the UCR Law Enforcement Officers Killed or Assaulted data files, the state level year end incarceration rates from the Bureau of Justice Statistics. City population and county demographic data come from the Census Bureau.

[6] Following the basic approach used by Ayres and Levitt (1998, we first calculate the average annual percent change in the crime rate for each city, which differences out city specific fixed effects, and then, to remove year fixed effects, subtract the average percent change in the crime rate for each calendar year in the control cities from the percent change in the crime rate of the living wage cities for the corresponding year. This new variable captures the relative difference in the crime rate between living wage and control cities. Lastly, we calculate the mean of this variable corresponding to the reference year when the ordinance is enacted.

[7] We do not report the coefficient estimates associated with the various covariates. These are available from the authors.

[8] The estimates associated with the minimum wage are somewhat sensitive to the model specification, and are generally often statistically insignificant. While in general, the minimum wage appears to have a negative impact on property related crimes (including robbery), the results are imprecise. Presumably, the lack of variation in the minimum wage leads to imprecise estimates of these coefficients. Evidence on the impact of minimum wages on crime is somewhat mixed and limited. Corman and Mocan (2005) find that minimum wages are associated with large (and statistically significant) reductions in murders, robberies and grand larcenies in New York City, whereas Hashimoto (1997) and Beauchamp and Chan (2012) find that minimum wages increase crime. .

[9] The use of failed living campaign cities used as a control group is first suggested by Adams and Neumark (2005a).

[10] Some failed/de-railed cities do eventually run successful campaigns (e.g. Albuquerque, NM).

[11] We also consider the GA and MC ordinance types using Models 1-5. The estimates are similar in magnitude and significance as those reported in Table 6. For example, the effect of MC living wage ordinances decreases burglary by 6.4 to 7.7 percent and MVT by 5.4 to 11 percent. These estimates are available from the authors.

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Figure 1

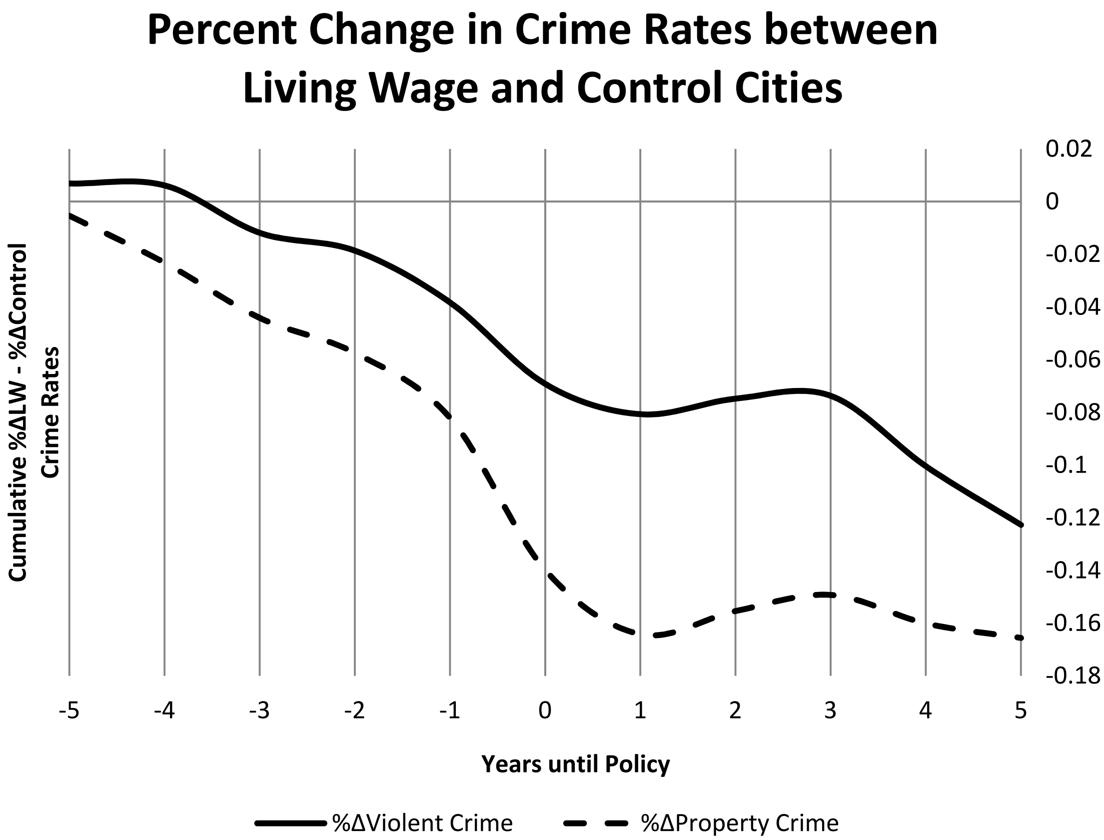
Percent Change in Crime Rates between Living Wage and Control Cities
Cumulative %ΔLW - %ΔControl Crime Rates
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
-0.18
-5
-4
-3
-2
-1
0
1
2
3
4
5
Years until Policy
%ΔViolent Crime
%ΔProperty Crime

Table 1A: Cities with Living Wage Laws

City	Year Enacted	2010 Min. Wage	2010 Living Wage	City	Year Enacted	2010 Min. Wage	2010 Living Wage
Albuquerque, NM	2006	7.50	7.50	Miami, FL	2006	7.25	11.83
Alexandria, VA	2000	7.25	13.13	Milwaukee, WI	1995	7.25	10.56
Ann Arbor, MI	2001	7.40	13.06	Minneapolis, MN	1997	7.25	13.78
Baltimore, MD	1996	7.25	10.59	New Haven, CT	1997	8.25	12.50
Berkeley, CA	2000	8.00	14.47	New York, NY	1996	7.25	11.10
Boston, MA	1998	8.00	13.02	Oakland, CA	1998	8.00	12.82
Buffalo, NY	2000	7.25	11.87	Orlando, FL	2002	7.25	10.20
Chicago, IL	1998	8.00	10.30	Oxnard, CA	2002	8.00	13.25
Cincinnati, OH	2002	7.30	12.10	Pasadena, CA	1996	8.00	11.88
Cleveland, OH	2001	7.30	10.00	Philadelphia, PA	2005	7.25	7.73
Dayton, OH	1998	7.30	12.72	Portland, OR	1996	8.40	11.26
Denver, CO	2000	7.24	10.60	Rochester, NY	2001	7.25	11.83
Des Moines, IA	1988	7.25	9.00	Sacramento, CA	2004	8.00	12.33
Detroit, MI	1998	7.40	13.78	San Antonio, TX	1998	7.25	10.60
Durham, NC	1998	7.25	11.40	San Francisco, CA	2000	8.00	11.69
Gainesville, FL	2003	7.25	11.85	San Jose, CA	1998	8.00	14.19
Hartford, CT	1999	8.25	17.78	Santa Clara, CA	1995	8.00	10.00
Hayward, CA	1999	8.00	12.01	St. Louis, MO	2002	7.25	14.68
Irvine, CA	2007	8.00	13.16	St. Paul, MN	1997	7.25	13.78
Jersey, NJ	1996	7.25	7.50	Syracuse, NY	2005	7.25	13.60
Lansing, MI	2003	7.40	13.79	Toledo, OH	2000	7.30	13.76
Lincoln, NE	2004	7.25	11.66	Tucson, AZ	1999	7.25	10.32
Los Angeles, CA	1997	8.00	11.55	Ventura,, CA	2006	8.00	13.75
Madison, WI	1999	7.25	11.66	Warren, MI	2000	7.40	13.78
Memphis, TN	2006	7.25	12.37				

Notes: Living wage laws are collected from Employment Policies Institute (www.epionline.org/lw_proposal_map.cfm) provided by Scott Adams and National Law Employment Project (http://www.nelp.org/page/-/Justice/2011/LocalLWLawsCoverageFINAL.pdf?nocdn=1). When possible we verify wage rates with the local municipality.

Table 1B: Cities with Failed and De-railed Living Wage Campaigns

City	Estimated Year of Failure or De-railment	Identifiable Reason for End
Albuquerque, NM	December 1999	City Council rejected proposed ordinance
Austin, TX	February 1998	Ballot initiative defeated
Baton Rouge, LA	October 2002	State law blocked living wage ordinance
Charlotte, NC	June 2001	Mayoral veto
Dallas, TX	June 2001	City council rejected proposed ordinance
Eugene, OR	October 2002	City council rejected proposed ordinance
Greensboro, NC	April 2000	City council rejected proposed ordinance
Houston, TX	January 1998	Ballot initiative defeated
Jacksonville, FL	April 2003	State law blocked living wage ordinance
Knoxville, TN	June 1999	City council rejected proposed ordinance
Nashville, TN	June 2001	City council voted down
New Orleans, LA	October 2002	State law blocked living wage ordinance
Omaha, NE	September 2001	City council repealed an existing ordinance
Pittsburgh, PA	April 2002	Law rescinded after passage
Provo, UT	February 2001	State law blocked living wage ordinance
Salt Lake City, UT	February 2001	State law blocked living wage ordinance
Santa Rosa, CA	January 2002	Mayoral veto
Shreveport, LA	October 2002	State law blocked living wage ordinance
South Bend, IN	August 2000	City-appointed committee voted against
Syracuse	June 2002	City council voted down
Tampa	April 2003	State law blocked living wage ordinance
Ventura	April 2002	City council voted down

Notes: This table is replicated from Adams and Neumark (2005a) and we supplement later dates with http://www.epionline.org/livingwage/index.cfm. The dates that the campaigns ended are estimates. For many cities, campaign activity may have resumed. For these cities, we identify these cities as a separate control who initially failed, but upon enactment we declare them a living wage city.

Table 2A: Means and Standard Deviations: Outcome and Policy Variables

Outcome Variables (Y)	All	Cities that Adopted Living Wage	Cities without Living Wage	N (number of city-year observations)
Homicide rate per 100,000 population	10.48 (10.91)	14.33 (12.35)	9.53 (10.31)	4973
Forcible Rape per 100,000 population	48.28 (29.00)	57.39 (32.85)	46.02 (27.51)	4799
Assault rate per 100,0000 population	495.87 (360.41)	600.62 (358.05)	470.03 (356.33)	4943
Robbery rate per 100,000 population	310.96 (263.39)	479.99 (331.68)	269.48 (225.14)	4973
Burglary rate per 100,000 population	1226.38 (652.32)	1320.11 (661.38)	1203.38 (648.09)	4973
Larceny rate per 100,000 population	3681.82 (1549.91)	3795.54 (1511.80)	3653.94 (1558.03)	4937
Motor Vehicle Theft rate per 100,000 population	777.74 (545.33)	995.10 (611.72)	724.39 (513.99)	4973
Primary Policy Variables				
Minimum Wage	5.37 (1.16)	5.44 (1.19)	5.36 (1.15)	4984
Living Wage	10.56 (1.82)			541
Living Wage –Minimum Wage	4.41 (1.50)			541
Living Wage Ordinance Indicator	0.11 (0.31)			4984

Notes: Minimum wage rate data come from U.S. Department of Labor, the city level number of police per 100,000 from the UCR Law Enforcement Officers Killed or Assaulted data files, the state level year end incarceration rates from Bureau of Justice Statistics, and population data come from the Census Bureau.
* Multiple living wage ordinances can be adopted by the same city.

Table 2B: Means and Standard Deviations: Covariates

Additional Covariates (X)	All	Cities that Adopted Living Wage	Cities without Living Wage	N (number of city-year observations)
Number of Police per 100,000 population	208.25 (103.5)	258.72 (113.1)	195.44 (96.79)	4865
State Incarceration Rate per 100,000 population	430.38 (145.82)	382.61 (128.97)	442.15 (147.33)	4984
Population (100,000)	3.05 (6.08)	6.44 (12.45)	2.24 (2.27)	4984
City Unemployment Rate	.062 (.028)	.067 (.029)	.061 (.028)	4984
County Unemployment Rate	.058 (.024)	.056 (.022)	.059 (.025)	4984
State Unemployment Rate	.060 (.019)	.061 (.021)	.060 (.019)	4984
State Income Per Capita	$29,937 ($8092)	$31,453 ($8,598)	$29,582 ($7,935)	4984
Percent Female	0.51 (0.01)	0.51 (0.01)	0.51 (0.01)	4984
Percent African-American	0.14 (0.13)	0.17 (0.13)	0.13 (0.12)	4984
Percent White	0.78 (0.13)	0.74 (0.13)	0.79 (0.13)	4984
% Aged 0-19	0.29 (0.03)	0.27 (0.03)	0.29 (0.03)	4984
% Aged 20-29	0.15 (0.03)	0.15 (0.03)	0.15 (0.02)	4984
% Aged 30-39	0.16 (0.02)	0.16 (0.02)	0.16 (0.02)	4984
% Aged 40-49	0.15 (0.02)	0.15 (0.02)	0.15 (0.02)	4984
% Aged 50-64	0.15 (0.03)	0.15 (0.03)	0.14 (0.03)	4984

Notes: City level number of police (per 100,000) come from the UCR Law Enforcement Officers Killed or Assaulted data files, the state level year end incarceration rates from Bureau of Justice Statistics, and population data from the Census Bureau. County demographic information, which come from the Census Bureau, were downloaded from a dataset made available at http://works.bepress.com/john_donohue/89/.

Table 3A: The Estimated Effect of Living Wage Laws on Property Crimes

LN Burglary Rate	Model 1	Model 2	Model 3	Model 4	Model 5
LN Minimum Wage	-1.675***	-0.679***	-0.198*	-0.0142	0.0179
	(0.316)	(0.100)	(0.114)	(0.0782)	(0.0764)
Living Wage Indicator	-0.198	-0.225	-0.0586**	-0.0580***	-0.0826***
	(0.185)	(0.140)	(0.0264)	(0.0221)	(0.0288)
R-squared	0.311	0.877	0.919	0.959	0.968
Observations	4,973	4,973	4,827	4,827	4,827
LN Larceny Rate					
LN Minimum Wage	-1.439***	-0.414***	-0.197**	-0.0249	0.0641
	(0.306)	(0.0999)	(0.0902)	(0.0568)	(0.0531)
Living Wage Indicator	-0.129	-0.0721*	-0.0274	-0.0167	-0.0269
	(0.111)	(0.0429)	(0.0288)	(0.0208)	(0.0243)
R-squared	0.283	0.899	0.910	0.952	0.966
Observations	4,937	4,937	4,791	4,791	4,791
LN MVT Rate					
LN Minimum Wage	-0.0548	-0.458***	-0.135	-0.261*	-0.156
	(0.343)	(0.171)	(0.140)	(0.142)	(0.132)
Living Wage Indicator	0.0270	-0.326*	-0.124***	-0.110***	-0.0585
	(0.215)	(0.197)	(0.0408)	(0.0348)	(0.0492)
R-squared	0.221	0.828	0.876	0.945	0.962
Observations	4,973	4,973	4,827	4,827	4,827
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes	Yes
Year-State FE	No	No	No	No	No
City Time Trend	No	No	No	Yes	Yes
City Quadratic Time Trend	No	No	No	No	Yes
Additional Covariates	No	No	Yes	Yes	Yes

Notes: Standard errors robust to heteroskedasticity and clustering at the city level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The natural log of the minimum wage is used. The living wage variable indicates when the city had a living wage ordinance. The covariates are listed in Table 2B. Observations are dropped due to missing city crime information.

Table 3B: The Estimated Effect of Living Wage Laws on Violent Crimes

LN Murder Rate	Model 1	Model 2	Model 3	Model 4	Model 5
LN Minimum Wage	-2.730***	-0.622**	-0.205	0.186	0.229
	(0.636)	(0.245)	(0.266)	(0.392)	(0.347)
Living Wage Indicator	0.708***	-0.107	0.0372	-0.0407	-0.0319
	(0.176)	(0.111)	(0.0479)	(0.0780)	(0.0860)
R-squared	0.074	0.581	0.591	0.618	0.650
Observations	4,973	4,973	4,827	4,827	4,827
LN Rape Rate					
LN Minimum Wage	-1.512***	-0.258	-0.173	-0.178	-0.229
	(0.303)	(0.174)	(0.151)	(0.162)	(0.181)
Living Wage Indicator	-0.0218	-0.150*	-0.0328	0.0296	0.0372*
	(0.182)	(0.0888)	(0.0492)	(0.0260)	(0.0213)
R-squared	0.182	0.839	0.850	0.911	0.930
Observations	4,799	4,799	4,653	4,653	4,653
LN Assault Rate					
LN Minimum Wage	-1.199***	-0.783***	-0.499***	-0.0958	-0.199
	(0.325)	(0.148)	(0.147)	(0.179)	(0.147)
Living Wage Indicator	0.367***	-0.0408	0.0927*	0.0648	-0.00204
	(0.108)	(0.0855)	(0.0515)	(0.0656)	(0.0448)
R-squared	0.176	0.848	0.861	0.932	0.953
Observations	4,943	4,943	4,797	4,797	4,797
LN Robbery Rate					
LN Minimum Wage	-1.312***	-0.762***	-0.396***	-0.188**	-0.0959
	(0.416)	(0.118)	(0.112)	(0.0832)	(0.0790)
Living Wage Indicator	0.543***	-0.227**	-0.0786**	-0.0537**	-0.0391
	(0.120)	(0.110)	(0.0351)	(0.0233)	(0.0327)
R-squared	0.176	0.928	0.944	0.972	0.979
Observations	4,973	4,973	4,827	4,827	4,827
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes	Yes
Year-State FE	No	No	No	No	No
City Time Trend	No	No	No	Yes	Yes
City Quadratic Time Trend	No	No	No	No	Yes
Additional Covariates	No	No	Yes	Yes	Yes

Notes: Standard errors robust to heteroskedasticity and clustering at the city level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The natural log of the minimum wage is used. The living wage variable indicates when the city had a living wage ordinance. The covariates are listed in Table 2B. Observations missing crime or demographic data are not included.

Table 4A: The Estimated Effect of Living Wages on Property Crimes

LN Burglary Rate	Model 1	Model 2	Model 3	Model 4	Model 5
LN Minimum Wage	-1.768***	-0.814***	-0.235**	-0.0541	-0.0298
	(0.274)	(0.142)	(0.112)	(0.0782)	(0.0765)
LN Living Wage	-0.345	-0.374	-0.125**	-0.114***	-0.145***
	(0.345)	(0.233)	(0.0485)	(0.0346)	(0.0461)
R-squared	0.309	0.876	0.919	0.959	0.968
Observations	4,973	4,973	4,827	4,827	4,827
LN Larceny Rate					
LN Minimum Wage	-1.494***	-0.456***	-0.218**	-0.0363	0.0473
	(0.286)	(0.0951)	(0.0909)	(0.0569)	(0.0520)
LN Living Wage	-0.257	-0.161**	-0.0810*	-0.0335	-0.0525
	(0.200)	(0.0674)	(0.0454)	(0.0344)	(0.0372)
R-squared	0.285	0.900	0.910	0.952	0.966
Observations	4,937	4,937	4,791	4,791	4,791
LN MVT Rate					
LN Minimum Wage	-0.0428	-0.655**	-0.205	-0.328**	-0.196
	(0.338)	(0.261)	(0.135)	(0.149)	(0.139)
LN Living Wage	0.0502	-0.514	-0.208***	-0.189***	-0.123*
	(0.407)	(0.344)	(0.0752)	(0.0559)	(0.0661)
R-squared	0.221	0.826	0.875	0.945	0.962
Observations	4,973	4,973	4,827	4,827	4,827
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes	Yes
Year-State FE	No	No	No	No	No
City Time Trend	No	No	No	Yes	Yes
City Quadratic Time Trend	No	No	No	No	Yes
Additional Covariates	No	No	Yes	Yes	Yes

Notes: Standard errors robust to heteroskedasticity and clustering at the city level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The natural log of the minimum wage and living wage are used. The living wage variable represents the percent change increase above the minimum wage. The covariates are listed in Table 2B. Observations missing crime or demographic data are not included.

Table 4B: The Estimated Effect of Living Wages on Violent Crimes

LN Murder Rate	Model 1	Model 2	Model 3	Model 5	Model 6
LN Minimum Wage	-2.375***	-0.687***	-0.189	0.155	0.209
	(0.688)	(0.252)	(0.262)	(0.403)	(0.354)
LN Living Wage	1.075***	-0.192	0.0249	-0.0891	-0.0622
	(0.327)	(0.193)	(0.0891)	(0.127)	(0.126)
R-squared	0.065	0.581	0.591	0.618	0.650
Observations	4,973	4,973	4,827	4,827	4,827
LN Rape Rate					
LN Minimum Wage	-1.521***	-0.341	-0.194	-0.160	-0.211
	(0.270)	(0.212)	(0.149)	(0.159)	(0.176)
LN Living Wage	-0.0407	-0.268**	-0.0995	0.0569	0.0554
	(0.327)	(0.123)	(0.0653)	(0.0409)	(0.0367)
R-squared	0.182	0.839	0.850	0.911	0.930
Observations	4,799	4,799	4,653	4,653	4,653
LN Assault Rate					
LN Minimum Wage	-1.028***	-0.808***	-0.447***	-0.0645	-0.203
	(0.345)	(0.153)	(0.153)	(0.205)	(0.157)
LN Living Wage	0.629***	-0.0499	0.157*	0.0874	-0.0138
	(0.207)	(0.150)	(0.0808)	(0.0900)	(0.0668)
R-squared	0.170	0.848	0.861	0.932	0.953
Observations	4,943	4,943	4,797	4,797	4,797
LN Robbery Rate					
LN Minimum Wage	-1.046**	-0.899***	-0.439***	-0.213**	-0.116
	(0.451)	(0.141)	(0.110)	(0.0831)	(0.0779)
LN Living Wage	0.861***	-0.350*	-0.119**	-0.0710*	-0.0614
	(0.223)	(0.191)	(0.0553)	(0.0406)	(0.0525)
R-squared	0.160	0.927	0.944	0.972	0.979
Observations	4,973	4,973	4,827	4,827	4,827
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes	Yes
Year-State FE	No	No	No	No	No
City Time Trend	No	No	No	Yes	Yes
City Quadratic Time Trend	No	No	No	No	Yes
Additional Covariates	No	No	Yes	Yes	Yes

Notes: Standard errors robust to heteroskedasticity and clustering at the city level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The natural log of the minimum wage and living wage are used. The living wage variable represents the percent change increase above the minimum wage. The covariates are listed in Table 2B. Observations missing crime or demographic data are not included.

Table 5: The Effect of Living Wage Laws on Crime Rate: Robustness Analysis on Cities with Failed or Derailed Campaigns

VARIABLES	LN Murder Rate	LN Rape Rate	LN Assault Rate	LN Robbery Rate	LN Burglary Rate	LN Larceny Rate	LN MVT Rate
Restricted Sample							
LN Minimum Wage	-0.184	-0.138	-0.157	-0.220*	0.00496	-0.0874	-0.245
	(0.325)	(0.226)	(0.318)	(0.129)	(0.123)	(0.0798)	(0.215)
Living Wage Indicator	-0.107	0.0358	0.0386	-0.0667***	-0.0667**	-0.0279	-0.101***
	(0.0806)	(0.0281)	(0.0508)	(0.0239)	(0.0277)	(0.0218)	(0.0359)
R^2	0.747	0.947	0.934	0.970	0.969	0.967	0.958
Model 4: Includes Covariate, Year FE, City FE, and City Linear Time Trend							
LN Minimum Wage	-0.299	-0.201	-0.222	-0.173	-0.0419	-0.0361	-0.199
	(0.3410)	(0.2630)	(0.2680)	(0.1260)	(0.1250)	(0.0778)	(0.1950)
Living Wage Indicator	-0.0547	0.0409	-0.016	-0.0648*	-0.0918***	-0.0386	-0.0558
	(0.0848)	(0.0254)	(0.0405)	(0.0364)	(0.0327)	(0.0255)	(0.0519)
R^2	0.783	0.956	0.953	0.977	0.974	0.975	0.972
Model 5: Includes Covariate, Year FE, City FE, City Linear and Quadratic Time Trend							
Observations	1411	1383	1407	1411	1411	1401	1411
Successful and Failed De-Railed Campaigns as a Control							
LN Minimum Wage	0.186	-0.187	-0.0918	-0.179**	-0.00940	-0.0228	-0.266*
	(0.392)	(0.160)	(0.181)	(0.0843)	(0.0783)	(0.0568)	(0.141)
Living Wage Indicator	-0.0403	0.023	0.0676	-0.0478**	-0.0547**	-0.0153	-0.113***
	(0.079)	(0.0258)	(0.0665)	(0.0239)	(0.0225)	(0.0211)	(0.0348)
Failed Living Wage Indicator	0.00563	-0.0954**	0.0427	0.0895*	0.0504	0.0219	-0.0522
	(0.0629)	(0.0373)	(0.0494)	(0.0487)	(0.0333)	(0.0282)	(0.0634)
R^2	0.618	0.911	0.932	0.972	0.959	0.952	0.945
F Test: FLW = LW (p-value)	0.578	0.0123	0.845	0.00653	0.00692	0.245	0.364
Model 4: Includes Covariate, Year FE, City FE, and City Linear Time Trend							
LN Minimum Wage	0.23	-0.234	-0.198	-0.0898	0.0223	0.0678	-0.159
	(0.3470)	(0.1780)	(0.1480)	(0.0810)	(0.0776)	(0.0535)	(0.1310)
Living Wage Indicator	-0.0314	0.0326	-0.000879	-0.033	-0.0782***	-0.0234	-0.0611
	(0.0872)	(0.0209)	(0.0455)	(0.0329)	(0.0290)	(0.0249)	(0.0481)
Failed Living Wage Indicator	0.00769	-0.0661	0.0173	0.0908	0.0646	0.0527	-0.0397
	(0.0956)	(0.0515)	(0.0512)	(0.0591)	(0.0474)	(0.0347)	(0.0959)
R^2	0.65	0.93	0.953	0.979	0.968	0.966	0.962
F Test: FLW = LW (p-value)	0.737	0.104	0.713	0.0631	0.00907	0.0453	0.868
Model 5: Includes Covariate, Year FE, City FE, City Linear and Quadratic Time Trend							
Observations	4,827	4653	4792	4,827	4,827	4,791	4,827

Notes: Standard errors robust to heteroskedasticity and clustering at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The living wage indicator variable indicates when the city had a living wage ordinance. Observations missing crime or demographic data are not included.

Table 6: The Effect of Living Wage Laws on Crime Rates: Robustness Analysis with State-Year Fixed Effects and City Fixed Effects

VARIABLES	LN Murder Rate	LN Rape Rate	LN Assault Rate	LN Robbery Rate	LN Burglary Rate	LN Larceny Rate	LN MVT Rate
Living Wage Indicator	0.041	-0.014	0.040	-0.098***	-0.030*	-0.017	-.0547*
	(0.107)	(0.039)	(0.0542)	(0.0207)	(0.0172)	(0.037)	(0.030)
R^2	0.546	0.750	0.844	0.928	0.875	0.821	0.871
GA Indicator	0.0418	-0.0280	0.0952	-0.0964***	-0.0197	-0.0858***	-0.0188
	(0.0956)	(0.0338)	(0.0791)	(0.0344)	(0.0347)	(0.0278)	(0.0684)
MC Indicator	0.0519	0.00241	0.00594	-0.0964**	-0.0361*	0.0292	-0.0743
	(0.138)	(0.0603)	(0.0714)	(0.0370)	(0.0183)	(0.0260)	(0.0533)
R^2	0.549	0.750	0.845	0.939	0.874	0.823	0.872
Observations	4,571	4391	4539	4,571	4,571	4,533	4,571

Notes: Standard errors robust to heteroskedasticity and clustering at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The living wage indicator variable indicates when the city had a living wage ordinance. The covariates are listed in Table 2. All variables are state-year demeaned to account for the state-year fixed effects. City fixed effects are also included. States with only one observed city are dropped. Observations missing crime or demographic data are not included. GA indicates the government assistance living wage and MC indicates the municipal/contract worker living wage.

Table 7: The Effect of Living Wage Laws on Crime Rates: Falsification Test

VARIABLES	LN Murder Rate	LN Rape Rate	LN Assault Rate	LN Robbery Rate	LN Burglary Rate	LN Larceny Rate	LN MVT Rate
Model 3: No Time Trend							
LN Minimum Wage	-0.312	-0.193	-0.453***	-0.448***	-0.272**	-0.156	-0.176
	(0.276)	(0.150)	(0.158)	(0.117)	(0.118)	(0.100)	(0.153)
Living Wage Indicator (+2 years)	0.0985	-0.0183	0.120**	-0.0576	-0.0356	-0.00248	-0.114**
	(0.064)	(0.053)	(0.048)	(0.038)	(0.030)	(0.031)	(0.046)
R^2	0.599	0.854	0.872	0.948	0.92	0.914	0.871
Model 4: Linear Time Trend							
LN Minimum Wage	0.182	0.0178	0.0488	0.0190	0.0491	0.133**	-0.0654
	(0.396)	(0.142)	(0.191)	(0.0780)	(0.0770)	(0.0616)	(0.109)
Living Wage Indicator (+2 years)	0.101	0.0197	0.0864*	-0.0310	-0.0202	0.0181	-0.0661
	(0.0682)	(0.0364)	(0.0455)	(0.0282)	(0.0325)	(0.0336)	(0.0455)
R^2	0.630	0.915	0.935	0.974	0.958	0.955	0.946
Model 5: Quadratic Time Trend							
LN Minimum Wage	0.119	-0.0261	-0.144	-0.0371	0.125*	0.128**	-0.0732
	(0.4240)	(0.1460)	(0.1770)	(0.0838)	(0.0732)	(0.0572)	(0.1080)
Living Wage Indicator (+2 years)	0.1	-0.00323	0.00997	-0.0292	-0.0459	-0.000575	-0.00864
	(0.0879)	(0.0315)	(0.0377)	(0.0276)	(0.0366)	(0.0276)	(0.0410)
R^2	0.657	0.934	0.956	0.98	0.968	0.969	0.962
Observations	4308	4153	4283	4308	4308	4280	4308
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors robust to heteroskedasticity and clustering at the state level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The living wage indicator variable indicates when the city had a living wage ordinance. Observations missing crime or demographic data are not included.