Empirical Strategy

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Baseline Specification

To estimate the causal effect of Shotspotter technology on police response times, we estimate the following two-way fixed effects model using OLS:

$$ResponseTime_{dt} = \beta ShotSpotter_{dt} + \delta_d + \gamma_t + \lambda \mathbb{X}_{dt} + \varepsilon_{dt} \tag{1}$$

where $ResponseTime_{dt}$ is the average call-to-dispatch or call-to-on-scene in police district d at time t. The treatment variable is $ShotSpotter_{dt}$, which is an indicator variable equal to one when a police district is equipt with Shotspotter. Moreover, δ_d and γ_t are police district and day-by-month-by-year fixed effects respectively. Finally, $\mathbb{X}_{dt}$ is a vector of time varying controls that differ across police districts, and ϵ_{dt} is the error term. Intuitively, Equation 1 is comparing average response times on days with ShotSpotter activated to days without ShotSpotter actived, while accounting for the expected differences in police districts and different times of the year.

Police district fixed effects, δ_d, are included to account for the systematic differences between police districts. For instance, Chicago is a segregated city in which levels of crime vary substantially between each police district. By adding police district fixed effects, we account for time-invariant differences in demographics, levels of crime, and policing practices that may vary across different parts of the city. Additionally, the day-by-month-by-year fixed effects, γ_t, are included to control for time-varying fluctuations that occur over particular days of each year.

Within $\mathbb{X}_{dt}$, we control for two important factors that vary between districts and over time: officer hours and the number of 911 dispatches. Each of these controls are included to ensure that the estimates are not confounded by days in which there are more police resources or a higher amount of reported crimes to respond to. As mentioned in Section BLANK, officer hours is the number of working hours by police officers within a district-day. Officer hours are preferred over number of shifts in order to account for the possibility of overtime.

Identification

The coefficient of interest is β, which measures the average change in average response times between times with and without ShotSpotter technology. To identify β as a causal effect, there are several assumptions that must be addressed.

The first key identification assumption is that police districts that adopt ShotSpotter would have continued to have similar response times in the absence of ShotSpotter (i.e., *common trends*). In particular, ShotSpotter adoption must not be correlated with a systematic rise or fall in response times. To address this concern we estimate an event study framework given by the following model:

$$ResponseTime_{dt} = \sum_{\substack{i=-12, \\ i\neq -1}}^{12} \beta^i \text{Shotspotter}^i_{dt} + \gamma_t + \delta_d + \lambda \mathbb{X}_{dt} + \varepsilon_{dt} \tag{2}$$

Where $\text{Shotspotter}^{i}_{dt}$ is a set of indicators that each equal 1 if Shotspotter is adopted i months from day t in district d. We use month periods, rather than day periods, to maximize the statistical power of each estimate and to reduce the amount of noise that could arise at the daily level. This also allows to explore dynamic treatment effects over a longer period of time, in this case 12 months. The indicator corresponding to the month before Shotspotter adoption is omitted, making estimates relative to this time period. Additionally, periods that are greater than 12 months before or after Shotspotter adoption are pooled together and not shown (following GGG) This event study framework accomplishes two objectives: (1) the pre-period estimates serve as a placebo test to explore if Shotspotter was enacted as a result of a trend in an outcome and (2) to explore the potentially dynamic treatment effects as officers and dispatchers adjust to Shotspotter usage.