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The political economy of enforcer liability for wrongful police stops

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Abstract

This article questions whether excessive policing practices can persist in an environment where law enforcement policies are subject to political pressures. Specifically, it considers a setting where the police decide whether to conduct stops based on the suspiciousness of a person's behavior and the potential liability for conducting a wrongful stop. We establish that the liability level that results in a voting equilibrium is smaller than optimal, and consequently, that excessive policing practices emerge in equilibrium.

1 | INTRODUCTION

Crime detection and prevention are two important duties performed by police officers every day. To better fulfill these duties, the law often permits police officers to stop a person based upon *reasonable* suspicion that he may be involved in criminal activity, where reasonable suspicion is a weaker requirement than probable cause (which is required for an arrest, to conduct a search, and for a search warrant). A commonly voiced concern is that police officers often cross the fine line to be observed when trading off fighting crime against the protection of individual rights. For example, a common complaint against New York City's stop-and-frisk program was that stops were used with little focus on stopping those most likely to be engaged in crime (e.g., Goel, Rao, & Shroff, 2016; Rudovsky & Rosenthal, 2013). The New York Civil Liberties Union, for example, provides data indicating that the number of New York City Police Department stops was in

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excess of half a million in the period 2006–2012 with innocent individuals making up as much as 90% of stopped individuals.¹

In this article, we demonstrate that political-economy dynamics explain excessive police stops. In brief, we consider a moral-hazard setup in which the electorate as the principal uses a liability payment that the law enforcement enforcer (i.e., the agent) must pay after a *wrongful* stop (i.e., a stop that does not result in a conviction) to guide the enforcer's decision-making in terms of stopping suspects.² With voters exhibiting heterogeneous privately optimal liability policies, the voting procedure selects which liability level will be implemented. After demonstrating the increasing-differences property of voter preferences regarding the unidimensional policy, we find that the political equilibrium is the median voter's ideal liability policy.³ Voting is thus a key component of our analysis and allows us to predict that the liability policy will be laxer than the socially optimal one under circumstances explained below.

More specifically, in our framework, voters may decide to commit offenses after the election, are characterized by heterogeneous criminal tendencies, and suffer the expected harm from crimes committed by others. A higher liability payment induces enforcers to require a higher degree of suspicion for stopping a suspect, which influences potential offenders' criminal behavior. Then, a higher level of liability affects each voter's payoff in three ways: (a) it reduces the expected costs from being subjected to a police investigation (rightfully or wrongfully), (b) it changes tax payments required to finance investigations and sanctioning, and (c) it modifies the expected harm from crimes committed by others. While all voters are symmetrically affected by the last two effects, the first effect's magnitude is influenced by an individual's criminal tendency, and thus creates heterogeneity in policy preferences.

We find that the liability payment in the political equilibrium is higher than the level that would maximize deterrence. Both the costs from being subjected to a police investigation (rightfully or wrongfully) and tax payments are decreasing in the liability payment, such that only a decrease in deterrence introduces marginal liability costs. After liability reaches the deterrence-maximizing level, the heterogeneity among voters becomes important because it makes relevant their willingness to sacrifice deterrence to reduce their likelihood of being stopped by an enforcer. Since people with higher criminal tendencies are more likely to commit offenses, they—in expected terms—gain more from a greater enforcer liability (i.e., a lower number of police stops) than people with low criminal tendencies. When voters who are pivotal for the political equilibrium have a lower criminal tendency than the average citizen—which is an assumption often invoked in similar contexts, for example, Meltzer and Richard (1981)—we observe that elections regarding enforcer liability lead to excessive police stops.

The rest of the paper is structured as follows. We explain how our results relate to the existing literature, and subsequently present a formal model to derive and explain our key results by using the following structure. In Section 2, we briefly refer to other contributions in the related literature.

¹See www.nyclu.org/en/stop-and-frisk-data (last accessed July 17, 2019).

²The liability payment is a shortcut for the consequences from police misconduct internalized by the individual law enforcement agent. These repercussions are themselves the result of political processes. For example, in the United States, police can and frequently are sued for police misconduct. The exact amount that the enforcer internalizes depends on aspects such as indemnification agreements with local governments, insurance mechanisms, and legal immunities available to the officers. Changes in the liability regime in our model thus correspond to changes in the aggregate protections in place in police misconduct cases.

³The increasing-differences property is accessibly explained and used in several economic applications in the survey by Amir (2005).



We describe the model in Section 3. In Section 4, we present the analysis applying backward induction. We conclude in Section 5.

2 | RELATED LITERATURE

Our framework builds on contributions to the literature dealing with police applying potentially asymmetric investigation policies towards members of different racial groups (e.g., Bjerk, 2007; Knowles, Persico, & Todd, 2001; Persico, 2002). There exist circumstances in which focusing law enforcement efforts on subgroups can be welfare-increasing (e.g., Lando & Shavell, 2004). The paper closest to ours from this strand of the literature is Mungan (2020). Using a framework similar to ours, he considers the deterrence implications of statistical and taste-based discrimination for deterrence and the possible role of enforcer incentives in this context.

We contribute to the literature on public law enforcement (e.g., Polinsky & Shavell, 2007). Whereas that literature usually focuses on the policies implemented by a benevolent social planner, we analyze the impact of policies on the voting equilibrium. Thus, our paper is closely related to Mungan (2017) and Langlais and Obidzinski (2017). These papers consider the political economy of imprisonment sentences, and both the detection probability and the fine, respectively. They use a framework in which all citizens are both potential offenders and potential victims, and in which no wrongful convictions can occur (i.e., law enforcement imposes direct costs only on individuals who engage in crime). Mungan (2017) is particularly interested in the consequences of criminal disenfranchisement on the outcome of the political process, following up on the idea that past crime involvement is correlated with future crime engagement. While Mungan (2017) restricts his analysis to a given kind of crime (i.e., a given level of harm), like we do, Langlais and Obidzinski (2017) explore whether political forces have effects that depend on the specific crime considered, that is, the level of harm induced by the criminal act. They indeed find that there are such asymmetric effects, such that the voting equilibrium induces too little (excessive) deterrence for acts with relatively small (higher) social harm.

In our paper, the crime-fighting policy responds to popular demand. This idea has been addressed in other contexts using theoretical and/or empirical analysis. For example, the linkage between crime and the political domain is studied in Bandyopadhyay and McCannon (2014). They consider the role of elections for the split of criminal cases brought to trial and criminal cases that are settled by a plea bargain. Relatedly, judges seem to increase sanction severity at the end of a political cycle (Berdejo & Yuchtman, 2013) and district attorneys seem less likely to dismiss cases in election years (Dyke, 2007). Famously, Levitt (1997) establishes that the number of police officers increases in election years (To use it to explore the deterrent effect therefrom).

3 | THE MODEL

A population of risk-neutral individuals is normalized to 1. Each person may commit a criminal act and thereby impose social loss L on others in the population. Each individual is, in expectation, symmetrically harmed by the crimes committed by others. People differ in their criminal tendencies denoted t . Criminal tendencies are distributed according to the cumulative density function $H(t)$ on $[\underline{t}, \bar{t}] \subset [0, 1]$ and influence the cumulative distribution function F of criminal benefits b on the set $[0, \bar{b}]$ as follows: A person with criminal tendency t expects to draw a criminal benefit smaller than \hat{b} with probability $F(\hat{b}, t) = (1 - t) + t \int_0^{\hat{b}} v(b) db = 1 - t \int_{\hat{b}}^{\bar{b}} v(b) db$. This functional form

may be interpreted as specifying that the individual does not even consider the criminal act with probability $(1 - t)$ (in that case the probability of having an insufficient benefit is one) and will consider the criminal act taking into account the benefit drawn according to the density $v(b)$ with probability t . Thus, people with higher criminal tendencies are characterized by higher t .

This type of stochastic criminal benefits was proposed in Mungan (2012) and departs from the common approach (see e.g., Polinsky & Shavell, 2007) according to which people have fixed criminal benefits known to them ahead of time. Thus, we briefly digress to explain the importance of this approach. In addition to being more realistic, stochastic criminal benefits are particularly useful in analyzing voting behavior in the criminal context, because they generate smooth preferences over policies. Otherwise, that is, when people have fixed criminal benefits known to them ahead of time, given any policy, people know with certainty whether or not they will be criminals in equilibrium (as in Langlais & Obidzinski, 2017). Thus, people with high enough benefits have a common, most preferred policy, and people with low benefits have another most preferred policy. Therefore, once the policy is adjusted from one where a person knows he will commit crime in equilibrium to one where he will not commit crime, he discretely switches his preference. As noted in Mungan (2017), this is not possible with the criminal tendencies specified here, and this is what will allow us to use the representative voter theorem. Having explained why we depart from the standard assumption of fixed benefits, we continue with the description of our model.

To fight crime, risk-neutral law enforcers monitor the behavior of the population, and stop individuals whose behavior appears suspicious. To simplify the analysis, we assume that the entire population is monitored, and that stops reveal whether the person was involved in criminal activity without error. If the person is involved in criminal activity, he is imprisoned for a fixed term of s ,⁴ which generates social punishment costs of ϕs . On the other hand, an innocent individual suffers a cost of ℓ upon being stopped, because it is at least inconvenient to be the subject of an investigation. Naturally, the cost to a guilty individual exceed the cost to an innocent subject, that is, $s > \ell$. If the enforcer stops an individual, society incurs an additional enforcement cost $k \geq 0$.

When monitoring an individual, a law enforcement agent cannot directly observe whether an individual committed a crime. Law enforcers may stop individuals when their behavior appears suspicious. The enforcer's evaluation of whether the individual's behavior is suspicious depends on the realization of a signal σ , where $\sigma \in [0, 1]$. We envision this signal to be an index of the agent's perception of the (possibly multidimensional) circumstances. The signal is informative because higher realizations are more likely when the suspect is guilty. More specifically, we assume that σ is drawn according to the density function ω_g and the cumulative distribution function Ω_g when the individual engaged in crime (index "g" for *guilty*) and according to the density function ω_i and the cumulative distribution function Ω_i when the individual did not engage in crime (index "i" for *innocent*) such that the Monotone-Likelihood Ratio Property is satisfied, that is $\partial(\omega_g/\omega_i)/\partial\sigma > 0$. To make our argumentation below more straightforward, we assume that a signal $\sigma = 0$ can possibly only come from an innocent individual, while a signal $\sigma = 1$ identifies the individual as a guilty one (i.e., $\omega_i(0) > 0 = \omega_g(0)$ and $\omega_g(1) > 0 = \omega_i(1)$). The enforcer's strategy will be a threshold level for σ such that weakly higher signals trigger police stops. Unless the law enforcement agent stops only when $\sigma = 1$, a positive probability for failing to investigate a criminal and mistakenly stopping an innocent individual exists. As emphasized in the introduction, the right balancing of the two errors is of central interest in the context of police stops.

⁴Langlais and Obidzinski (2017) and Mungan (2017) consider elections about sanction levels.

Our key interest in this paper is the liability policy consisting of a penalty for investigations that do not lead to convictions, denoted D with $D \geq 0$. For simplification, we assume that the signal is not verifiable in court so that the imposition of liability cannot be conditioned on the drawn signal.⁵ Apart from enforcer liability, we assume that the agent's stopping and investigation incentives comprise returns c ($-m$) for correct (wrongful) investigations, where $L > c$, $m \geq 0$. These components may include intrinsic motives, peer pressure, and career implications, for example, and are considered as exogenous in this paper.⁶ Empirical results suggest that law enforcement agents in reality "care" about outcomes independent of their monetary consequences. The evidence presented in Friebe, Kosfeld, and Thielmann (2019) indicates that intrinsically motivated and trustworthy individuals self-select into the German Police Force. Dickinson, Masclet, and Villevall (2015) report similar results using police commissioners from France. Such findings regarding the above-average willingness to enforce norms is used by Dharmapala, Garoupa, and McAdams (2016) to motivate a study in which punitive agents may be overzealous when it comes to searching, seizing, and punishing suspects. On a different note, in a cross-jurisdiction comparison, we would expect to see some heterogeneity in terms of m and c . First, there are differences with respect to formal procedures. For example, the extent to which mistakes are publicized depends on the jurisdiction. In addition, there exists evidence that different countries maintain diverging attitudes towards several aspects of the criminal justice system. For example, Doob and Webster (2006) discuss preferences regarding punitiveness in Canada and the United States.

The law enforcement agent expects having to make liability payments when accepting the stopping task. We assume that to ensure the law enforcement agents' participation in the task of investigating sufficiently suspicious people, her total expected payoff consisting of a fixed payment \mathcal{W} and the expected payoffs from rightful and wrongful investigations must be equal to the outside utility \mathcal{O} . This implies that the fixed payment must amount to

$$\mathcal{W} = \mathcal{O} + (1 - \eta)(1 - \Omega_i(\hat{\sigma}))(m + D) - \eta(1 - \Omega_g(\hat{\sigma}))c, \quad (1)$$

where η denotes the crime rate and $1 - \Omega_g(\hat{\sigma})$ ($1 - \Omega_i(\hat{\sigma})$) represents the probability with which a signal greater than the critical level $\hat{\sigma}$ is drawn by an individual who did (not) engage in criminal activity, where the critical level is to be determined by the police officer. Thus, as argued by Dharmapala et al. (2016), for example, expected private benefits from contributing to the punishment of guilty subjects may allow for a decrease of monetary wage payments.

For simplicity, we assume that the enforcement agent will neither be victimized nor offend, and is also exempted from any taxes (or, equivalently, must receive additional remuneration that compensates for the payment of taxes; somewhat analogous to Lazear, 1990). These assumptions jointly with the statement in (1) imply that the enforcement agent is indifferent as to what level of

⁵In many settings, this assumption seems reasonable, for example, because the officer conducting the stop may be on his own. In other circumstances, the officer may be obliged to wear a body camera, or his actions may be recorded. In such circumstances, the signal maybe imperfectly observable and could be used when making liability decisions. We could imagine that the enforcer observes signal σ and also the "perceived" signal σ_p to be used in court, where the latter is a realization from a random distribution with the mean σ . The electorate would then have to decide about $D(\sigma_p)$ in the sense of what liability should be triggered by what verifiable signals. Note that a perfectly verifiable σ would mean that our political-economy exercise is about voting regarding the threshold level of the signal with similar implications in terms of the laxness/strictness of the policy.

⁶Clearly, the level of c may also be considered a policy variable (at least within boundaries since some aspects such as intrinsic motivation may be difficult to overwrite politically). In some sense, our analysis then portrays the analysis of liability for a fixed level of c . In equation (5) below, it will become clear that a given threshold level by the enforcer can be implemented using different combinations of c and enforcer liability. Mungan (2020) endogenizes the level of c .



enforcer liability will be implemented because the participation constraint commands that compensation offsets any liability payments. We thus assume that they abstain from voting.⁷

Taxes are used to finance the compensation of police officers and the expenditures for imprisonment and investigations. We assume that wages paid to and penalties received from law enforcement agents feed into the budget. Financing is achieved by imposing a uniform lump-sum tax τ . Defining the proportion of individuals who will be investigated by \mathcal{I} and using (1), the per-capita tax amounts to

$$\begin{aligned}\tau &= \mathcal{W} + \mathcal{I}k + \phi s\eta(1 - \Omega_g(\sigma)) - D(1 - \eta)(1 - \Omega_i(\sigma)) \\ &= \mathcal{O} + (1 - \eta)(1 - \Omega_i(\sigma))m + \mathcal{I}k + (\phi s - c)\eta(1 - \Omega_g(\sigma))\end{aligned}\quad (2)$$

The level of enforcer liability is thus not directly relevant for the level of taxation because the proceeds must be handed to enforcers in expected terms to incentivize their participation as police officers.⁸

3.1 | Timing

In Stage 1, two political candidates announce their law enforcement agent liability policy (to which they are committed in later stages). In Stage 2, voters with realized criminal tendencies but yet unknown criminal benefits support one of the two candidates. In Stage 3, the elected candidate's announced policy is implemented and potential offenders' criminal benefits b are drawn. In Stage 4, law enforcement agents choose their investigation strategies and potential offenders decide whether or not to engage in crime simultaneously. In Stage 5, payoffs are realized.

4 | THE ANALYSIS

We solve the game using backward induction. We do not explicitly analyze Stages 3 and 5, in which only Nature moves. Thus, we begin our analysis with Stage 4.

4.1 | Stage 4: Simultaneous investigation and crime choices

In Stage 4, police officers and potential criminals make their choices simultaneously. The law enforcement agent may either stop a suspect or not. In arriving at a decision, the agent takes into account the realization of the signal σ as an indication of the guilt of the suspect at hand in particular and the expected crime rate denoted η which gives an indication of the guilt of individuals in general. Potential criminals also make a binary choice. They choose whether or not to offend in anticipation of the enforcer's investigation choice which shapes the probability with which innocent individuals will incur stopping costs and the probability with which

⁷If enforcers were also able to offend, their criminal tendencies would have to be specified. Our analysis would not change qualitatively, as long as enforcers are not more prone to committing crime than the rest of the population.

⁸The budget available after lump-sum taxation thus adapts to changes in the policy D . In contrast, Khalil, Kim, and Lawaree (2019), for example, consider the implications of bureaucrats operating against the background of a fixed budget.

criminals will be investigated and sanctioned. The equilibrium of the subgame results where best responses are consistent with each other.

4.1.1 | Enforcer's investigation choice

Even absent liability, the enforcer wants to avoid legal errors and thus is keen to learn the exact conditional probability of the suspect's guilt.⁹ The agent observes the realization of the signal σ and updates the belief (denoted q) about the guilt of the suspect starting from the ex ante probability of guilt—which is the crime rate η —using Bayes' rule to

$$q(\eta, \sigma) = \frac{\eta}{\eta + (1 - \eta) \frac{\omega_i(\sigma)}{\omega_g(\sigma)}}. \quad (3)$$

We have assumed that a higher realization of σ makes it more likely that the individual committed the criminal act (i.e., that ω_g/ω_i increases with σ). Accordingly, the conditional probability in (3) increases with the signal. Our assumption about the extreme signals implies $q(\eta, 0) = 0$ and $q(\eta, 1) = 1$.

Investigating a suspect yields a benefit c when the suspect committed the criminal act. This outcome is obtained with probability $q(\eta, \sigma)$ when the individual triggers a signal realization σ . The investigation is considered wrongful when it does not lead to a conviction in which case the enforcer incurs cost m and liability D . This result is expected with probability $1 - q(\eta, \sigma)$. Consequently, the agent with an outside utility of zero prefers to investigate if

$$q(\eta, \sigma)c - (1 - q(\eta, \sigma))(m + D) \geq 0. \quad (4)$$

The enforcer is indifferent between stopping and not investigating when the condition binds, which defines a threshold value of the signal denoted $\hat{\sigma}$

$$q(\eta, \hat{\sigma}) = \frac{m + D}{c + m + D}, \quad (5)$$

which is a function of both the crime rate (as it influences the level of the term on the left-hand side for a given D and $\hat{\sigma}$) and the level of liability (as it changes the level of the term on the right-hand side for a given η and $\hat{\sigma}$). The law enforcement agent stops and investigates an individual when $\sigma \geq \hat{\sigma}$. Since a higher liability increases the term on the right-hand side, a higher enforcer liability serves the intuitive role of increasing the required conditional belief of guilt, when all else is held equal. The following rearrangement of condition (5) using the specification of $q(\eta, \hat{\sigma})$ in (3) allows one to easily verify these insights:

$$\frac{\omega_g(\hat{\sigma})}{\omega_i(\hat{\sigma})} = \frac{m + D}{c} \frac{1 - \eta}{\eta}. \quad (6)$$

⁹A similar early analysis of legal decision-makers trading off different legal errors when making a binary choice is included in Andreoni (1991).

The left-hand side isolates the likelihood ratio at $\hat{\sigma}$. At the police officer's threshold level of the signal, the likelihood ratio should match the ratio of the no crime and crime probabilities weighted by a ratio following from the enforcer's incentives. From our assumptions, the likelihood ratio on the left-hand side of (6) is increasing in the level of the signal. Intuitively, a decrease in the right-hand side of (6) due to an increase in the crime rate will be met by a decrease in the level of the threshold level and an increase in the liability will induce an increase in the threshold level. Our analysis below will rely on the fact that the threshold decreases in the crime rate and increases in the level of liability, that is, that

$$\partial \hat{\sigma} / \partial \eta < 0 < \partial \hat{\sigma} / \partial D. \quad (7)$$

4.1.2 | Potential offenders' crime choice

In Stage 4, the potential offender knows which specific criminal benefit b from the interval $[0, \bar{b}]$ was drawn. Moreover, the potential offender anticipates the enforcer's choice of the cutoff $\hat{\sigma}$ which implies an investigation probability for innocent individuals, which is $(1 - \Omega_i(\hat{\sigma}))$, and a sanctioning probability for criminals, which is $(1 - \Omega_g(\hat{\sigma}))$. A potential offender with benefit b thus engages in crime when

$$b \geq (1 - \Omega_g(\hat{\sigma}))s - (1 - \Omega_i(\hat{\sigma}))\ell = \hat{b}(\hat{\sigma}). \quad (8)$$

As emphasized in an early contribution by Png (1986), for example, the expected costs from being stopped and incurring costs ℓ despite compliance undermines deterrence. In fact, deterrence is raised only by increasing the difference between the expected costs internalized by a criminal and those of a compliant individual. This is relevant again below when we discuss what investigation policy maximizes deterrence. Incorporating the payoff consequences from taxation, τ , and the expected victimization costs, ηL , we arrive at the respective payoffs from noncompliance (indicated by index N) and compliance (indicated by index C):

$$u_N(b, \hat{\sigma}) = b - (1 - \Omega_g(\hat{\sigma}))s - \tau - \eta L, \quad (9)$$

$$u_C(\hat{\sigma}) = -(1 - \Omega_i(\hat{\sigma}))\ell - \tau - \eta L. \quad (10)$$

These Stage 4 payoff levels are independent of the criminal tendency as the benefit from crime was already drawn in Stage 3 and the tendency influences only the distribution of benefits. The tax as well as the exposure to the crime risk are assumed to be independent of whether or not the individual at hand commits an offense (as in, e.g., Langlais & Obidzinski, 2017).

The threshold signal value assessed by the law enforcement agent can be influenced by enforcer liability. In turn, a change in the threshold value bears on the level of deterrence. We find that increasing the threshold signal value signifies a change in the level of deterrence amounting to

$$\frac{d\hat{b}}{d\hat{\sigma}} = \omega_i(\hat{\sigma}) \left[\ell - \frac{\omega_g(\hat{\sigma})}{\omega_i(\hat{\sigma})} s \right]. \quad (11)$$

As explained above, a higher $\hat{\sigma}$ means a higher level of deterrence only if it increases the difference between the expected costs borne by a criminal and those internalized by a compliant

individual. For the potential offender, a higher threshold translates into a lower investigation probability when innocent and when guilty, where the relative decrease is expressed by the likelihood ratio. Our assumptions about the signal density function ω_i for innocent subjects and the signal density function ω_g for guilty subjects summarized in the MLRP property ensure that the derivative in Equation (11) is positive (negative) for $\sigma < (>) \sigma^{\max}$, where σ^{\max} induces an equality between the likelihood ratio and the investigation costs of innocent and guilty subjects, that is, it solves

$$\frac{\omega_g(\sigma^{\max})}{\omega_i(\sigma^{\max})} = \frac{\ell}{s}. \quad (12)$$

Intuitively, when the enforcement agent increases the cutoff at a low level σ (i.e., when $\sigma < \sigma^{\max}$), this decreases the expected investigation costs of innocent subjects (given by $(1 - \Omega_i)\ell$) more than the expected investigation costs of guilty subjects (given by $(1 - \Omega_g)s$). This results because innocent (guilty) subjects have more (less) density on low levels of the signal σ received by the law enforcement agent. This change in the cutoff increases the relative attractiveness of compliance (i.e., the status of an innocent individual) as an alternative to committing crime and thereby promotes deterrence. At high levels of the signal σ , guilty individuals benefit relatively more from an increase in the threshold, and hence crime becomes a relatively more attractive option, meaning that deterrence is undermined. Clearly, in terms of probability levels, the uniquely defined deterrence-maximizing signal threshold level will imply a relatively high (low) probability of being investigated for guilty (innocent) individuals when the density functions are very different on the interval $[0, 1]$, that is, when the signal is very informative. In reality, the informativeness of the signals that law enforcement agents observe will presumably depend on the criminal act considered and external circumstances, meaning that σ^{\max} cannot be assessed at a very general level.

The threshold signal $\hat{\sigma}$ chosen by the enforcer yields a crime rate defined as follows:

$$\eta(\hat{\sigma}) = \int_t^{\hat{t}} [1 - F(\hat{b}(\hat{\sigma}), t)] dH(t) = E[t] \int_{\hat{b}(\hat{\sigma})}^{\hat{b}} v(b) db, \quad (13)$$

where $E[t]$ is the expected criminal tendency.

With the cutoffs regarding the signal σ and the critical level for the criminal gains \hat{b} , we can specify the share of individuals who will be investigated as

$$\mathcal{I} = (1 - \eta(\hat{\sigma}))(1 - \Omega_i(\hat{\sigma})) + \eta(\hat{\sigma})(1 - \Omega_g(\hat{\sigma})). \quad (14)$$

Every investigation creates payoff consequences for the enforcer (either c or $-m - D$), a cost borne by the stopped individual (either s or ℓ), and a cost k that must be financed by society at large. Thus, this expression for \mathcal{I} becomes useful when we later calculate the lump-sum tax.

4.1.3 | Equilibrium characterization

Law enforcement agents choose to investigate a suspect only if he emits a signal strong enough to exceed a cutoff level. The strength of this cutoff signal $\hat{\sigma}(\eta, D)$, characterizes the law enforcer's *best response* to the expected crime rate for a given level of agent liability. The threshold

signal $\hat{\sigma}(\eta, D)$ creates an investigation *probability* and thereby an expected investigation *cost* for people who commit the criminal act and those who abstain from committing the offense. Based on their beliefs about how enforcers set $\hat{\sigma}$ in a context described by a crime rate η and enforcer liability D , potential offenders choose whether or not to violate the law, that is, they select their *best response* to the agent's investigation choices.

In equilibrium, law enforcement agents play the best-response signal threshold value given the equilibrium crime rate and the equilibrium crime rate results from potential offenders' best responding to the equilibrium enforcer investigation policy. Thus, we may state the equilibrium condition as follows:

$$q\left(E[t] \int_{(1-\Omega_g(\sigma^*))s-(1-\Omega_i(\sigma^*))\ell}^{\bar{b}} v(b)db, \sigma^*\right) = \frac{m + D}{c + m + D}, \quad (15)$$

where σ^* is the equilibrium stopping rule adopted by enforcers, and we use $\hat{b}(\sigma^*)$ from (8) in the definition of η in (13) before we substitute it into the conditional probability of guilt $q(\eta, \sigma)$. Accordingly, the Equation (15) gives us an equilibrium cutoff level and the equilibrium level of crime by implication. To see that an equilibrium exists, note that the left-hand side is zero at $\sigma = 0$ and equal to one when $\sigma = 1$, whereas the right-hand side is a fixed value between zero and one. We assume that the equilibrium is unique.¹⁰

Since our analysis concerns the political equilibrium in terms of enforcer liability as a mean to guide the enforcer's stopping behavior, it is central to understand how liability influences the law enforcement agent's stopping behavior *in equilibrium*. Our statement in (7) concerned only the partial effect, that is, the effect from a higher level of enforcer liability holding the level of crime constant. For the total effect, we must incorporate that the level of crime responds to a change in enforcer liability precisely because the latter influences the enforcer's investigation policy. Starting from (15), we can derive

$$\frac{d\sigma^*}{dD} = \frac{\frac{c}{(c+m+D)^2}}{\frac{dq}{d\sigma}} > 0, \quad (16)$$

when $dq/d\sigma > 0$. We thus find that a higher agent liability increases the cutoff used by law enforcement agents when choosing whether or not to investigate. In other words, enforcer liability is a policy instrument that effectively reduces the number of police stops in equilibrium. As explained above, the implication of this variation in the enforcer's investigation policy on the level of crime depends upon whether $\sigma^* > \sigma^{\max}$. If so, a higher enforcer liability increases the crime rate and lowers the number of police stops.

¹⁰There may be more than one equilibrium. This follows because the left-hand side changes with the level of σ according to

$$\frac{dq}{d\sigma} = -\frac{\partial q}{\partial \eta} E[t] v(\hat{b}(\sigma)) s \omega_i(\sigma) \left[\frac{\ell}{s} - \frac{\omega_g(\sigma)}{\omega_i(\sigma)} \right] + \frac{\partial q}{\partial \sigma},$$

which is unambiguously positive if $\sigma > \sigma^{\max}$ as $\frac{\ell}{s} < \frac{\omega_g}{\omega_i}$. In that range, there can be only one equilibrium level that solves (15). However, the derivative may be negative if $\sigma < \sigma^{\max}$. This means that there is a range of levels of σ that produce a counteracting influence and a range of σ that do not. The equilibrium will be unique when the influence from changes in the crime rate cannot dominate, which is what we will assume in the following analysis.

4.1.4 | Crime, enforcement, and taxation

To fully understand how individual payoffs depend on enforcer liability to prepare the vote, we must address the lump-sum tax payment as a key component next. Using the subgame equilibrium crime rate and the enforcer's stopping rule, (η^*, σ^*) , we can state the per-capita tax in the subgame equilibrium as

$$\tau = \mathcal{O} + (1 - \eta^*)(1 - \Omega_i(\sigma^*))(m + k) + (k + \phi s - c)\eta^*(1 - \Omega_g(\sigma^*)).$$

As explained above, variations in the level of enforcer liability induce changes in the critical cutoff describing the law enforcement agent's investigation policy and the crime rate, but they do not directly impact the financing required per (correct or wrongful) stop. Next, we inquire how these indirect effects influence the lump-sum tax in equilibrium.

The tax impact of a marginally higher crime rate for a fixed threshold signal can be expressed as follows:

$$\frac{\partial \tau}{\partial \eta^*} = k(\Omega_i(\sigma^*) - \Omega_g(\sigma^*)) + (1 - \Omega_g(\sigma^*))(\phi s - c) - m(1 - \Omega_i(\sigma^*)). \quad (17)$$

Because the last term (i.e., the marginal cost effect stemming from the fact that the enforcer will make fewer false positives when more people are truly guilty) is negative, in general, the impact of higher crime on taxes is ambiguous. This ambiguity turns out to play no important role in our analysis, because, as we note in our analysis of the voting stage, an increase in the crime rate produces a greater effect on people's preferences through its impact on criminal harms than through its impact on the compensation received by enforcers.

The tax impact of a marginally higher signal threshold for a fixed crime rate is

$$\frac{\partial \tau}{\partial \sigma^*} = -[(1 - \eta^*)\omega_i(\sigma^*)(m + k) + \eta^*\omega_g(\sigma^*)\{k + \phi s - c\}] < 0. \quad (18)$$

This implies that an increase in the signal cutoff level decreases the per-capita tax when crime incentives remain constant.

4.2 | Stage 2: The vote

In the voting stage, individuals consider the different states that may arise in terms of their materialized criminal gain, the probability of these states which depend on the individual's criminal tendency t and the density $v(b)$, and the private payoffs in the various states. For a given level of deterrence \hat{b} , an individual will offend and obtain payoff u_N from (9) when the criminal gain is drawn such that $b \geq \hat{b}$. With criminal tendency t , the probability that this happens is

$$1 - F(\hat{b}, t) = t \int_{\hat{b}}^{\bar{b}} v(b) db.$$



Likewise, an individual will comply and obtain payoff u_C from (10) when the benefit is drawn such that $b < \hat{b}$, which happens with probability

$$F(\hat{b}, t) = 1 - t \int_{\hat{b}}^{\bar{b}} v(b) db.$$

Accordingly, an individual with a very low (high) criminal tendency will be concerned primarily with seeking to maximize u_C (u_N) using the enforcer liability to shape the enforcer's investigation policy. We can state *expected* payoffs for a person with a criminal tendency t as follows:

$$\begin{aligned} \mathcal{U}(D; t, \hat{b}, \sigma^*, \eta^*) &= F(\hat{b}(\sigma^*), t) u_C(\sigma^*, \eta^*) + t \int_{\hat{b}(\sigma^*)}^{\bar{b}} u_N(b, \sigma^*, \eta^*) v(b) db \\ &= t \int_{\hat{b}(\sigma^*)}^{\bar{b}} (b - \hat{b}(\sigma^*)) v(b) db - (1 - \Omega_i(\sigma^*)) \ell - \tau(\sigma^*, \eta^*) - \eta^* L. \end{aligned} \quad (19)$$

We consider voting as a way to resolve heterogeneous preferences regarding the policy variable, that is enforcer liability. The heterogeneity originates from the differences in criminal tendencies. An investigation of (19) reveals that a person's criminal tendency is relevant only to the first term.¹¹

The ideal (interior) enforcer liability level for an individual with criminal tendency t can be described by the first-order condition $\partial \mathcal{U} / \partial D = 0$. A change in enforcer liability influences expected payoffs \mathcal{U} through its impact on the law enforcement agent's investigation cutoff which is in turn relevant for: (a) the expected costs from being investigated which show up in Equation (19) in the term $\hat{b}(\sigma^*)$ in the integrand and the term $1 - \Omega_i(\sigma^*)$, (b) the own crime incentives via the deterrence level which shows as as term $\hat{b}(\sigma^*)$ in the lower limit of integration (the marginal effect of which is zero due to the envelope theorem), (c) tax payments, and (d) the overall crime rate (which is relevant for both tax payments and the expected harm from victimization; see the last term in (20)). We obtain the derivative

$$\frac{\partial \mathcal{U}}{\partial D} = \frac{d\sigma^*}{dD} \left(\underbrace{\omega_i(\sigma^*) s \left[\frac{\ell}{s} - t \left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] \int_{\hat{b}(\sigma^*)}^{\bar{b}} v(b) db \right]}_A - \frac{\partial \tau}{\partial \sigma^*} \right) - \frac{d\eta^*}{dD} \left(\frac{\partial \tau}{\partial \eta^*} + L \right). \quad (20)$$

The term in the first parentheses in (20) is positive independent of the level of σ^* induced by the agent liability (in particular, independent of how the induced level σ^* compares to σ^{\max}), using $\partial \tau / \partial \sigma^* < 0$ from (18), and

$$\frac{\ell}{s} - t \left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] \int_{\hat{b}(\sigma^*)}^{\infty} v(b) db = \frac{\ell}{s} F(\hat{b}(\sigma^*), t) + \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} (1 - F(\hat{b}(\sigma^*), t)) > 0.$$

¹¹The enforcement agent is by assumption indifferent regarding the different levels of enforcer liability because there will be compensation in terms of wages for higher enforcer liability. We thus assume that the enforcement agent will not participate in the voting procedure.

This is intuitive as Term A in (20) comprises marginal effects from a variation in the enforcement agent's investigation policy on the own expected investigation costs, and all individuals are always privately better off when there are fewer stops as investigations are costly to both compliant and noncompliant individuals. The criminal tendency bears on the term representing the impact on expected investigation costs conditional on criminal behavior (i.e., when the criminal benefit draw exceeds $\hat{b}(\sigma^*)$), which is clearly more important for individuals with a higher criminal tendency. In fact, more frequent investigations are desirable only when they reduce the crime rate. This is because a lower crime rate means lower expected victimization costs, which surely outweigh any potentially countervailing tax implications. This can be verified by comparing $\frac{\partial \tau}{\partial \eta^*}$ in (17) to expected victimization costs, which reveals that $\frac{\partial \tau}{\partial \eta^*} + L > 0$ since $m < L$. Thus, the second term in (20) always has the sign of $\frac{d\eta^*}{dD}$ (which is positive when $\sigma > \sigma^{\max}$).

An interior privately optimal level of enforcer liability requires the trading off of positive marginal benefits and positive marginal costs. Our argumentation so far makes clear that positive marginal costs result only if the change in the liability level lowers deterrence, that is, when the increase in D raises the signal cutoff σ^* when it already exceeds the deterrence-maximizing threshold level. Thus, the privately optimal level of liability for every person is greater than the level of liability D^{\max} that induces $\sigma^* = \sigma^{\max}$, meaning that crime is in equilibrium greater than the minimal attainable level of crime. In this sense, our analysis relates to the well-known underdeterrence result when enforcement is costly (e.g., Polinsky & Shavell, 2007). This implies the following result.

Lemma 1. *The equilibrium level of enforcer liability exceeds that which maximizes deterrence (i.e., elections result in $D > D^{\max}$).*

Lemma 1 reveals that all individuals prefer a level of enforcer liability which is above the deterrence-maximizing level. Thus, the chosen liability regime results in a trade-off between deterrence on one hand, and taxes and stopping costs on the other. Since people have different criminal tendencies, they differ in their most preferred way of addressing this trade-off. In particular, a person with high criminal tendencies places a greater weight on stopping costs, because he is more likely to be stopped in the role of a criminal compared to a person with low criminal tendencies. This is verified by noting that

$$\frac{\partial^2 \mathcal{U}}{\partial D \partial t} = -\omega_i(\sigma^*)s \left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] \int_{\hat{b}(\sigma^*)}^{\bar{b}} v(b) db \frac{d\sigma^*}{dD} > 0. \quad (21)$$

since

$$\left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] < 0,$$

due to $\sigma^* > \sigma^{\max}$. For this range of signal thresholds, the marginal effects from a higher level of agent liability are such that if an individual with criminal tendency t_1 benefits from a fixed increase in D , then individuals with criminal tendencies $t > t_1$ will also benefit from that fixed increase. The increasing-differences property exposed in Equation (21) is important because it allows us to apply the representative voter theorem (e.g., Rothstein, 1991) when we turn to the politicians' platform choice in Stage 1. Before moving on to the analysis of Stage 1, we thus note:

Lemma 2. *The increasing-differences property applies. Individuals with a relatively higher criminal tendency prefer a relatively higher level of enforcer liability in the domain $D > D^{\max}$.*

4.3 | Stage 1: Candidates' policy choice

4.3.1 | Candidates' platform choice

Lemma 1 allows us to focus on political candidates who select a policy from the set $D \geq D^{\max}$ when they choose their platform in terms of enforcer liability. Lemma 2 makes clear that we can apply the representative voter theorem (e.g., Rothstein, 1991). Candidates thus target the policy preferences of the voter whose ideal enforcer liability level is the median of the distribution of all bliss points. Because the privately optimal enforcer liability levels are ranked in correspondence with the ranking of criminal tendencies, the median voter may be identified by

$$t_m = H^{-1}\left(\frac{1}{2}\right), \quad (22)$$

that is, by the individual whose level of criminal tendency exactly halves the population of potential offenders. As a result, the equilibrium level of enforcer liability Δ_m is implicitly defined by¹²

$$\frac{\partial \mathcal{U}}{\partial D} = \frac{d\sigma^*}{dD} \left(\omega_i(\sigma^*) s \left[\frac{\ell}{s} - \mathbf{t}_m \left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] \int_{\hat{b}(\sigma^*)}^{\infty} v(b) db \right] - \frac{\partial \tau}{\partial \sigma^*} \right) - \frac{d\eta^*}{dD} \left(\frac{\partial \tau}{\partial \eta^*} + L \right) = 0,$$

which states the first-order condition discussed extensively above for the voter whose ideal enforcer liability level is the median of the distribution of all bliss points.

4.3.2 | Socially optimal liability

To evaluate the political equilibrium, we require an indication of what liability would be socially optimal. To derive socially optimal enforcer liability, we assume that a benevolent social planner chooses the level of D to influence the simultaneous choices of potential offenders and law enforcement agents in Stage 4. We thus consider a second-best outcome because the social planner cannot influence choices directly, but uses one policy instrument to influence several policy targets. We proxy social welfare using the utilitarian welfare function

$$S(D) = \int_t^i \mathcal{U}(D, t) dH(t),$$

¹²We assume that the second-order conditions are satisfied for all t .

that takes as given the enforcer's investigation policies as a function of law enforcement agent liability (described by $\sigma^*(D)$) and equilibrium crime rates as a function of agent liability (described by $\eta^*(D)$).¹³

The social planner would seek to fulfill the first-order condition

$$\frac{dS}{dD} = \frac{d\sigma^*}{dD} \left(\omega_i(\sigma^*) s \left[\frac{\ell}{s} - \mathbf{E}[\mathbf{t}] \left[\frac{\ell}{s} - \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)} \right] \int_{\hat{b}(\sigma^*)}^{\infty} v(b) db \right] - \frac{\partial \tau}{\partial \sigma^*} \right) - \frac{d\eta^*}{dD} \left(\frac{\partial \tau}{\partial \eta^*} + L \right) = 0.$$

4.3.3 | Comparing the political equilibrium to the social optimum

When we compare the last expression to the median voter's derivative, we note that the difference between marginal incentives concerns only one term and has to do with the fact that being investigated is undesirable for non-offenders and offenders. The difference to the outcome from the voting procedure will thus stem from the fact that the voting equilibrium reflects the preferences of the pivotal individual but does not reflect the preferences of the other types. This observation allows us to note the following result.

Proposition 1. *The enforcer liability in the political equilibrium falls short of [exceeds] the socially optimal enforcer liability—implying an excessive [suboptimal] number of stops—when $E[t] > t_m$ [$E[t] < t_m$].*

Proof. Derivatives are positive for all affected society members as long as $D \leq D^{\max}$. The solution thus lies in the range of D such that

$$\frac{\ell}{s} < \frac{\omega_g(\sigma^*)}{\omega_i(\sigma^*)}.$$

Accordingly, having $E[t] > t_m$ implies that marginal benefits from raising the enforcer liability are perceived as higher by the social planner as compared to the median voter. \square

The intuition behind Proposition 1 is closely related to our previous observations regarding the increasing-differences property of individuals' preferences. Specifically, people who will, in all likelihood, refrain from crime (i.e., individuals with a low criminal tendency) do not care much about the cost the guilty will have to suffer when investigated, and are relatively tolerant towards investigations because they place comparatively greater value in deterrence. Accordingly, these individuals do not want to induce high levels of enforcer liability when these levels of liability imply losses in terms of deterrence. In contrast, individuals with high criminal tendencies anticipate that they may have to bear significant costs due to an investigation and thus prefer to lower the number of police stops.

Quite importantly, $t_m < E[t]$ corresponds to what we intuitively expect to find in most jurisdictions: relatively few individuals with high criminal tendencies shift the average value of the criminal tendency up. The assumption that the median is smaller than the mean is invoked

¹³Note that, in setting up $S(D)$, we focus on potential offenders and potential victims because enforcement agents are indifferent as a result of (1), as explained above.



in other contexts, including income distributions (see, e.g., Meltzer & Richard, 1981). For this circumstance, our model predicts that the level of enforcer liability will fall short of what would be optimal for society. This is important because it directly bears on the discussion about the potential excessiveness of police stops.

5 | CONCLUSION

Stops and investigations play an important role in crime detection and prevention. Balancing these enforcement objective with the preservation of individuals' rights is challenging, and there are frequent claims that many police departments are engaging in excessive stops. We present a political economy analysis that yields the finding that excessive stops result in equilibrium when we take the probable ranking of the median voter criminal tendency and the average criminal tendency into account.

Our analysis is kept very simple but nevertheless generates interesting insights. Future work may consider the possibility that law enforcement agents apply signal thresholds that depend on the group to which an individual belongs. This may be of interest to policy makers, given the interactions between the differential turnout rates of different racial groups in elections and the potentially racially discriminatory nature of police investigations (e.g., MacDonald & Fagan, 2019).

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