THE UNINTENDED CONSEQUENCES OF CONVENTIONS AND POLICIES

by

ALEXANDER S. CAULEY

B.A., University of Colorado, 2012

M.A., University of Colorado, 2014

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This thesis entitled:
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written by Alexander S. Cauley
has been approved for the Department of Economics

Jeffrey S. Zax (Chair)

Terra G. McKinnish

Stephen B. Billings

Richard K. Mansfield

Tania C.J. Barham

Date________________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

Cauley, Alexander S. (Ph.D., Economics)

The Unintended Consequences of Conventions and Policies

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Abstract

In the first chapter, I analyze the dynamic labor effort response to an incentive structure under which productivity is uncertain and underperformance is punished. Using data on SQF practices from New York City, I find that more arrests, summonses, and non-criminal stops occur at the beginning of the month, which could be explained by police officers adopting a strategy of effort front-loading as a precautionary measure against failing to meet monthly performance expectations, thereby avoiding punishment. This is complemented by police officers reducing their labor in the later days of a month so as to avoid the exertion of a higher level of costly efforts than necessary given little incentives for "above-and-beyond" performance. Furthermore, as a month progresses, officers become more averse to difficult tasks and exert less effort in interactions that allow for an officer to use more discretion. This intra-month productivity cycle holds even when accounting for confounding factors that affect contemporaneous crime conditions, such as the timing of welfare payments.

In the second chapter, which uses data from the FBI's UCR and NIBR, I establish the causal relationship between the adoption of Missouri's House Bill 1150 and the subsequent increase in incidents of motor vehicle thefts across Missouri. Accounting for broader contemporaneous national trends in motor vehicle thefts and trends in other types of larceny, this paper finds that an 8% to 14% increase in vehicle thefts arose within a year of the law going into effect, and a 30% to 43% increase within five years.

In the final chapter, my coauthor and I examine the consequences of the alphabetical ordering of surnames. Using the data from the WLS, we find that those with surname initials ranked further from the beginning of the alphabet on average experience substantively worse outcomes in life. These adversities materialize as early as late adolescence through poorer experience in high school, lower human capital accumulation during tertiary education, and reduce early labor market success before dissipating by mid-adulthood. These effects are found to concentrate among those who are of ordinary intelligence and appearance and remain inconsequential for those distinctive in these regards.

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Chapter 1

The Early Bird Gets the Worm: Analysis of Dynamic Effort Allocations from the New York City Police Department.

I. Introduction

The notion so central to introductory economics textbooks—that people respond to incentives—could be mocked for its redundancy, as the word "incentive" already suggests an incitement to action. Such redundancy might be warranted, however, as it stresses the importance of this fundamental principle of economics that all students must understand. Before a rational agent decides to complete any costly task, the expected benefit must offer a return that justifies the effort. These returns lay the foundation for the structure of incentives, without which motivation would be impossible to conceptualize.

Life consists of a series of costly tasks, and employment presents a particularly salient example. The quality of workers' performance directly affects the value of firms, making such performance an issue of importance for management. Work performance depends on many factors, with compensation serving as the most direct incentive for workers to exert high levels of effort. And since firms have a large degree of control over their compensatory regimes, it is critical to implement a compensation schedule that balances workers' performance against the monetary expenditure on wages. Which pay structure leads to the highest returns for firms has been a topic of research interest. Lazear (2018) analyzes a sample of scholarly works, showing that various forms of performance-based pay can lead to significant improvements in workers' productivity compared to compensation based on a fixed wage rate.

One form of performance-based pay is based on a lump-sum return for completion of assignments; for instance, a salesperson attaining a sales quota. Such a compensation scheme is nonlinear in its returns in that a premium is paid upon reaching a specific target. This incentivizes workers to exert more efforts in hopes of reaching the target. Because of this motivational effect, the use of bonuses is widespread among firms (Joseph and Kalwani, 1998).

However, such a nonlinear remuneration schedule also creates incentives for the strategic manipulation of how efforts are timed. For workers who discount future costs and benefits, procrastination—where efforts are increasingly allocated towards the end of a work period so as to capture any rewards from meeting the quota—might be the rational approach (Asch, 1990; Oyer, 1998; Misra and Nair, 2011). A further situation in which an uneven allocation of efforts over time might arise may come from unpredictable shock that leads workers to fulfill a quota early, thereby reducing the need for subsequent efforts in settings where incentives for "above-and-beyond" performance do not exist (Jain, 2012; Kishore et al., 2013).

This paper focuses on temporal variations in efforts as a behavioral response to the performance-based incentive structure that New York City police officers face. Namely, the objective of this paper is to empirically identify the pattern of intra-month efforts chosen by police officers when they face uncertainty over their productivity, potential punishment for underperformance imposed by the management, and discontinuous returns to their performance. Although the specific details of this study relate to the operations of the NYPD, the effect of similar evaluation structure on the intertemporal allocation of work effort may be more general.

The manner in which police officers allocate their efforts over time will determine the overall policing climate in a city. Leaving aside the specific context of New York City, this will be the case in any jurisdiction. The allocation of police efforts comprises a fundamental aspect of governance, as police efforts help maintain order through the deterrence of crime and the apprehension of criminals

(Di Tella and Schargrodsky, 2004). In contrast, the overexertion of efforts may intensify any abuses engendered by policing, such as the violation of individuals' constitutional rights. Given the critical role of police activities, the way in which officers formulate their monthly routines merits broad academic interest. This paper examines an aspect of policing practices that has heretofore remained unexplored.

The challenges of policing engender a classical principal-agent problem. The NYPD management is primarily concerned with low crime statistics, and perhaps revenue generation through the issuance of tickets, and in turn demand that their subordinates exert efforts to fulfill these objectives. Rank-and-file officers, who themselves derive less value from meeting objectives relating to citywide crime rates, have incentives to exert less effort so as to minimize the subjective costs of work.[1]

To resolve this dilemma, given that only the agents perfectly observe their true effort levels, the NYPD management maintains what it sees as an appropriate compensation schedule for its subordinates. In addition to standard wages, this schedule includes a return corresponding to an officer's level of output relative to monthly performance goals or requirements imposed by a quota. This performance-based compensation scheme is not monetary. A police officer's failure to meet a monthly objective translates to a disutility for the officer resulting from punitive actions imposed by the commanding management.[2] Conversely, successfully meeting the objective is not immediately met with a discrete material premium, as might be expected in other occupations. Still, over time, officers

[1] Deputy Chief Michael Marino admitted to setting a quota while commanding the 75th precinct because police officers were not doing their job otherwise (Robert Gearty, "High-ranking cop testifies he set monthly quotas at Brooklyn precinct," *New York Daily News*, March 22, 2013, http://www.nydailynews.com/new-york/nypd-deouty-chief-admits-quotas-stand-article-1.1296395.

[2] "They're retaliating against me because of my numbers. Commanding officers do it to bring your numbers up, but I would have to massively write summonses and arrest people to come up with the number close to the number that they want [me] to come up with. You know… the goal." This transcript is taken from a recorded conversation between Officer Sandy Gonzales, an officer in the New York Police Department (NYPD), and Stephen Maing, a documentarian chronicling the struggles of a group of police officers against a policing quota maintained by the NYPD (*Crime + Punishment*).

that consistently meet their monthly goals could potentially be rewarded with career advancements and other benefits. To that end, the performance expectations that NYPD officers face are part of their job requirements, and their compensation is designed to ensure that these expectations are met.

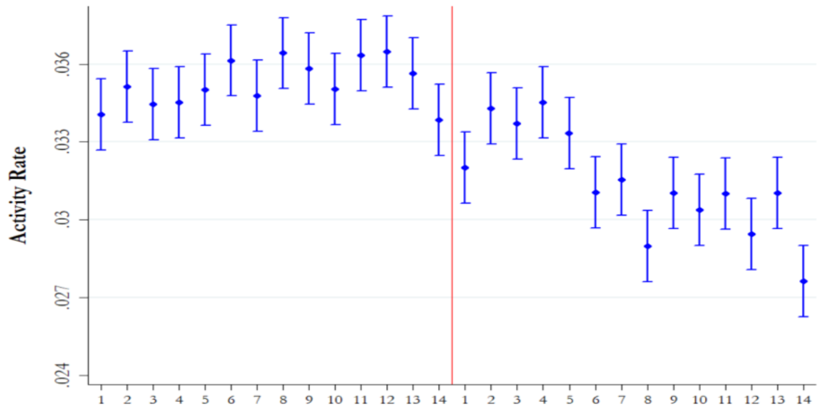
A satisfactory number of summonses issued and arrests made by the end of each month is not a deterministic outcome even for a determined policeman. Ex ante, the level of output an officer will be able to achieve in these metrics is inherently uncertain. The amount will be determined by a combination of factors, including the stochastic crime conditions and the level of effort a police officer undertakes in responding to crime. Ultimately, an officer needs to adopt a strategy of dynamic effort allocation consistent with their own preferences that also minimizes the risk of falling short of performance goals, while adhering to other institutional constraints.

Using data on NYPD Stop, Question, and Frisk (SQF) practices, this paper finds that more interactions between police officers and the community take place in the earlier days of a typical month. Based on data for the years 2003 through 2016, the last two weeks of a month are associated with 10.1% fewer arrests, 6.9% fewer summonses, and 3.3% fewer non-criminal stops compared to the first two weeks of a month, as depicted in Figure 1.1. Figure 1.2 shows that this decreasing pattern of police activity is not driven by the composition of crime and is evident for financially motivated, violent-in-nature, and controlled-substance related crimes.

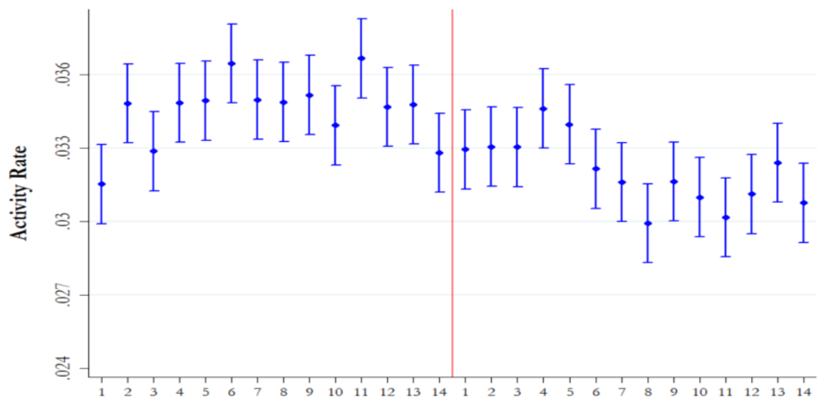
A significant challenge to identifying the pattern that underlies the allocation of efforts as a response to organizational structure is demonstrating that prevailing crime conditions are exogenous to adjustments in effort levels—that is, police officers do not vary their effort levels strictly as a response to the current overall level of crime being committed. The timing of welfare payments and welfare-induced crime can give rise to a situation where the level of criminal activity may systematically fluctuate throughout a month, which could elicit an endogenous police response (Foley, 2011; Riddell

FIGURE 1.1: POLICE ACTIVITY RATES OVER THE COURSE OF THE MONTH

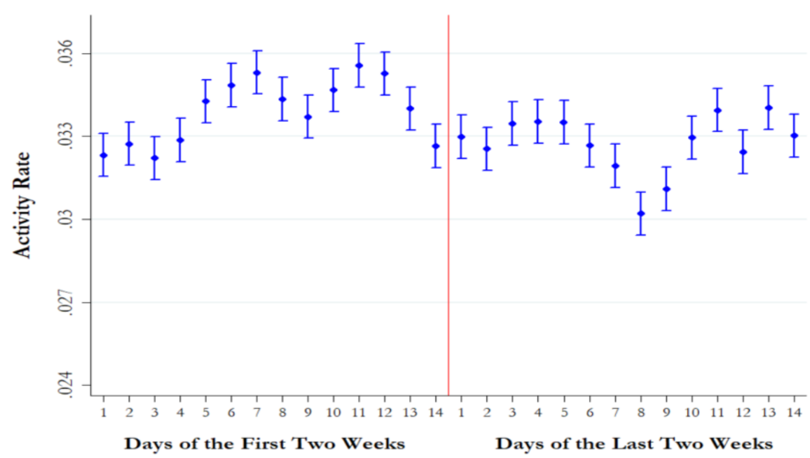
Panel A. Daily Fraction of Monthly Arrests



Panel B. Daily Fraction of Monthly Summonses



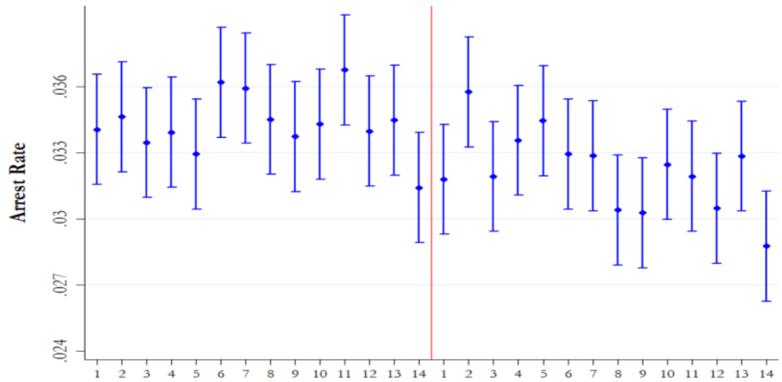
Panel C. Daily Fraction of Monthly Non-Criminal Stops



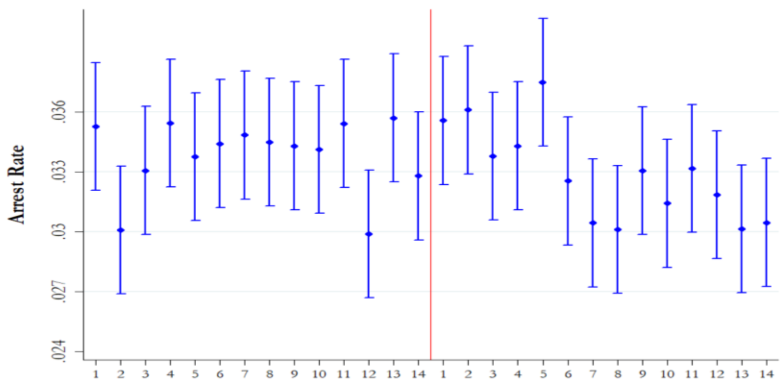
Notes: Daily shares of monthly activity based on SQF data for 2003–2016 (New York City). Panels A, B, and C display the daily shares of monthly arrests, summonses, and stops resulting in neither an arrest nor a summons, respectively. Vertical blue bars indicate 90% confidence intervals. Vertical red bar indicates a division between the first two weeks and the last two weeks of the month. The mean daily share of monthly activity is normalized to equal $0.03\overline{3}$ for each calendar month.

Figure 1.2: Police Arrest Rates Over the Course of the Month

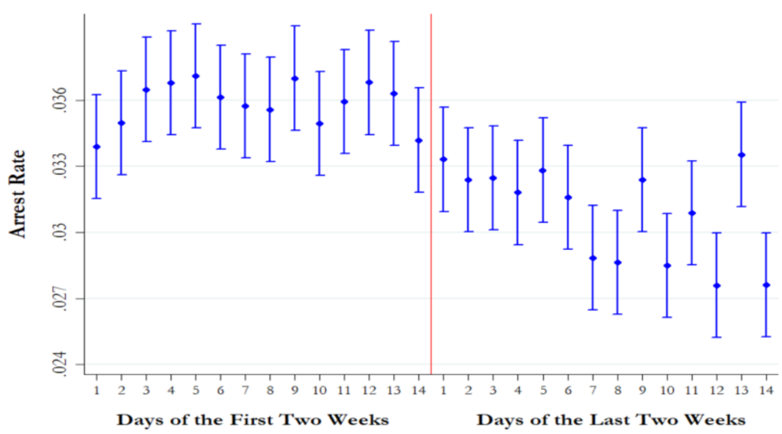
Panel A. Daily Fraction of Monthly Arrests for Financially Motived Crimes



Panel B. Daily Fraction of Monthly Arrests for Violent Crimes



Panel C. Daily Fraction of Monthly Arrests for Substance-Related Crimes



Notes: Daily shares of monthly arrests based on SQF data for 2003–2016 (New York City). Panel A displays the daily share of monthly arrests for financially motivated crimes (robbery, burglary, and all types of larceny). Panel B considers arrests for crimes that are violent in nature (all degrees of assault, sexual assault, menacing, harassment, kidnapping, and homicide). Panel C depicts arrests for substance-related crimes (consumption, possession, and distribution). Vertical bars indicate 90% confidence intervals. Vertical red bar indicates a division between the first two weeks and the last two weeks of the month. The mean daily share of monthly activity is normalized to equal $0.03\overline{3}$ for each calendar month.

and Riddell, 2006; Dobkin and Puller, 2007; Cotti et al., 2016; Hsu, 2017). For detailed discussion of such phenomena, see the Appendix A.

This paper presents several ancillary empirical results demonstrating the independence of crime conditions and intra-month adjustment in police officers' effort levels. These results show that the decrease in officers' efforts manifests itself through a higher aversion to difficult tasks, with difficulty of a task proxied by the physical characteristics of detained individuals. That is, the probability that a police officer stops a larger individual declines with days of the month. Furthermore, more pronounced monthly cycles of police apprehensions are found for interactions that were self-initiated by an officer, suggesting that police officers' discretion is a fundamental determinant of intra-month fluctuations in criminal activities. Lastly, differences in participation rates in social assistance programs across precincts do not produce discernable differences in the cycles of arrests and summonses, suggesting that welfare-induced crime is limited in its explanation of the empirical results of this paper.

The main results of this paper suggest that police officers preproperate—a phenomenon of front-loading efforts—and then reduce their efforts in the second half of the month. The former finding stands in contrast to many scholarly works, both empirical and theoretical, that study the allocation of efforts over time. Existing literature on the allocation of efforts predicts that work in early periods is delayed in favor of leisure; as deadlines approach, leisure is substituted with an increased workload. This phenomenon can be explained assuming time-consistent (Fischer, 2001) or dynamically-inconsistent, present-biased preferences (Akerlof, 1991; O'Donoghue and Rabin, 1999, 2001).[3] The empirical literature corroborates the attraction of immediate gratification and the

[3] Although not formally framing his analysis with time-inconsistent preferences, Akerlof first articulated an akin idea with regard to procrastination in which the opportunity costs of today's work are salient whereas tomorrow's are vague. Agents thus feel more pressure from today's opportunity costs and postpone actions until later. Later works by O'Donoghue and Rabin add to Akerlof's conception of individuals that possess limited knowledge about the future by introducing quasi-hyperbolic discounting. They show that across all types of individuals that vary in their expectations of their time preferences in the future, time-inconsistent preferences

postponement of work in various real-world contexts (Solomon and Rothblum, 1984; Schouwenburg and Groenewoud, 2001; Nguyen, Steel, and Ferrari, 2013), including in work environments characterized by a nonlinear remuneration schedule (Asch, 1990; Oyer, 1998; Misra and Nair, 2011). The reason for this divergence could stem from two possible channels. The first explains why efforts are allocated towards earlier periods and the second explains why efforts are reduced in later periods.

That officers preproperate can be explained by the adoption of a strategy by NYPD officers in response to uncertainty. More efforts are allocated to the earlier days of a month as a precautionary measure against failing to meet performance expectations, thereby reducing the likelihood of punishment for underperformance. During the first two weeks, this effort front-loading is manifested in performance that exceeds the level of productivity necessary to meet the expectations if such a level were maintained throughout a full month. Faced with little incentive to exceed monthly performance goals, police officers adjust efforts as a month progresses in a way that keeps the probability of failure to an acceptable minimum while avoiding the exertion of higher level of costly efforts than necessary. This translates to a diminished demonstration of efforts in favor of leisure during the final days of a month.

The latter effect of reduced efforts could also be reinforced by the NYPD's formal evaluation procedures, in which police officers' output is compared against the average performance of the unit. A high-effort police officer raises the standards against which his colleagues are compared, thereby imposing a negative externality on them. A joint action by his coworkers through retaliation or other punishments might induce an officer to internalize this externality. Therefore, high-effort police officers with social preferences will have an incentive to reduce the efforts in order to maintain an acceptable relationship with other police officers.[4]

introduce an incentive to procrastinate. Fischer (2001) shows that a model with dynamic consistency and a positive time preference can also lead to procrastination, albeit not as severe as under a model with dynamic inconsistency.

[4] A similar disincentive effect among farm workers in the UK was explored in Bandiera, Barankay, and Rasul (2005).

The remainder of the paper is organized as follows. The next section provides institutional information on NYPD operations, the incentive structures faced by officers, recounts allegations of the existence of an informal quota system, and summarizes the public assistance regime in New York City. Section III discusses police behavior in an economic framework. Section IV describes the data and primary methodology used in the estimation of intra-month cycles. Section V presents the main results. Section VI provides further evidence of effort allocations that are independent of prevailing crime conditions. Section VII concludes.

II. Institutional Background

The NYPD is the largest police force in the U.S., employing a little over 38,000 uniformed members as of 2018. The department is divided into twenty bureaus, with the Patrol Service Bureau being the most visible among them due to its oversight over the majority of uniformed police officers. This bureau is partitioned into eight borough commands which is further separated into 77 police precincts.[5] Each of these precincts will constitute a geographical unit of analysis in later sections.

The purpose of this paper necessitates at least a partial understanding of the NYPD command structure. Similar to the military, the NYPD hierarchy of rank is rigid. The upper echelon of management consists of several higher ranks, with the police commissioner being the highest among them. The duties of the commissioner include the planning of departmental missions and oversight of their execution. At the level of the precinct, captains—who serve a role of commanding officers—tend to exert the highest authority, and are held responsible by the top management for the performance of officers in their charge. Below them are lieutenants who generally supervise their own platoon (a unit of police force), and who are responsible for all operations of command during their

[5] Information from New York City Police Department www.nyc.gov/html/nypd.

patrol tours. The lowest commanding rank is sergeant who is the immediate field supervisor of patrolling officers. Police officers comprise the majority of uniformed employees who carry out orders and perform patrolling duties.

A. *Formal Evaluations of Officers' Performance*

In a January, 2015 press conference, NYPD commissioner William Bratton was quoted saying "[t]here is no specific target number that we go for. There are no quotas, if you will."[6] The commissioner echoed the same sentiment a year later in insisting that "[t]here are no numerical quotas in the NYPD. However, we expect our members to do their jobs. Just like any other organization, there are performance standards through which employees are evaluated."[7]

The NYPD top brass has denied the existence of a quota as it would be in violation of New York State Labor Law § 215-a and would be an overall unpopular measure with the public. Even in the absence of quotas, however, police officers are quantitatively evaluated on their performance.

The NYPD Patrol Guide, an official document detailing the duties associated with each rank in the police department, contains an extensive process for evaluation of police officers. The following summarizes selected parts of this document.

Police officers and detectives must submit their Officer Profile Report, which measures their performance levels, to the designated supervisor (often sergeants) for a monthly assessment by the second day of the following month. The supervisor's assessment includes an evaluation of uniformed officers' performance by assessing "the quality and caliber of the member's efforts by carefully

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[6] Joel Rose, "Despite Laws and Lawsuits, Quota-Based Policing Lingers," *NPR*, April 4, 2015, https://www.npr.org/2015/04/04/395061810/despite-laws-and-lawsuits-quota-based-policing-lingers.

[7] Sarah Wallace, "I-team: More NYPD Officers Say There's Proof of Quota-Driven Arrests," *NBC New York*, April 1, 2016, https://www.nbcnewyork.com/investigations/NYPD-Officers-Arrest-Quota-Exclusive-Interview-Pressure-Numbers-374077091.html.

reviewing activity." This activity is also compared with other officers with similar duties. At the end of the evaluative report, positive feedback is provided for "proactive and quality activity" or "guidance and direction for improvement" with "regular follow-ups, when a deficiency is identified." In case of unsatisfactory performance, the guide specifies that "appropriate steps" be taken in order to "improve the uniformed member's performance." If these steps do not resolve the performance issue, officers are to "confer with [their] platoon commander/special operations lieutenant or next higher supervisor." Following this protocol, their supervisor delivers the Officer Profile Report to the platoon commander (often lieutenant) or another reviewer by the fifth day of the month. The platoon commander reviews the report and forwards it to the operations coordinator by the seventh day for filing. At the end of this monthly evaluation process, the commanding officer (often captain) reviews the report and logs the information that it contains into the Performance Evaluation System. Commanding officers are ultimately the ones responsible for "determining performance standards within their respective commands and resolving all issues within their command relative to the Monthly Performance Review."

Police officers who repeatedly fail to meet acceptable performance standards are placed under performance monitoring, with "possible impositions of sanctions by the Personnel Review Board concerned." This board can take corrective actions including, but not limited to, a "change of assignment within the command, intraborough or interborough transfer, transfer from administrative command and/or disciplinary action."[8]

On the other hand, police officers' who continually demonstrate exceptional performance have their exemplary conduct noted on the Performance Evaluations. Such commendations, when

[8] "Once you get in that program, they got you," said police Sergeant Cyress Smith, a 19-year veteran of the NYPD, referring to the Performance Monitoring program for those who do not meet the performance standards. He continues, "no matter how well you perform, it's not going to be good enough. The Performance Monitoring program and evaluation is supposed to be tools to measure performance whether cop is doing his job or not. They are both used as weapons of retaliation and weapons of abuse. They don't do stuff by the books," (Crime + Punishment).

considered alongside other factors listed in the Patrol Guide, can be used for promotional decisions, lucrative reassignments, and additional overtime. Overall, rewards are granted to those who "consistently perform their assignments in an exceptional manner."

Police officers, therefore, are rewarded or punished based on their performance which is agglomerated over time intervals as short as one month. The chronology of this performance appears to start on the first of the month and conclude at the end of the month.[9]

The evaluative standards are established in line with the average performance of the unit, which is not the same as the establishment of a numerical quota. Whereas the average performance will vary as a reflection of the current crime conditions, a quota sets a minimum floor on productivity regardless of existing conditions. The latter creates an undesirable potential scenario where police officers may be compelled to issue more summonses and make more arrests than crime conditions warrant. To do so, police officers may resort to improper measures that violate the fourth and fifth amendments, such as false summonses, groundless arrests, and unreasonable searches.

Although, arguably, the formal measure of performance is preferable to a quota, it still may incentivize some police officers to make up the numbers if they are falling behind their peers. Even in the absence of realized underperformance, a forward looking and motivated police officer may anticipate the risk of not meeting the average. This too can lead to over-policing in the earlier periods. Excessive policing, in turn, can lead to a higher incidence of the use of force as unnecessary stops might lead to worsened interactions with the public. In addition, worrying about making the numbers on a monthly basis can detract from the quality of policing in pursuit of a quantitative outcome. These concerns are only exacerbated by additional presence of a quota. And, although the existence of a

[9] Although this information is taken from the 2016 version of the Patrol Guide, it appears to be in line with the Patrol Guide from the year 2000. In the earlier years, there is an additional mention of a Police Officer Monthly Performance Report (PD439-1414) which is used for monthly assessments. The 2016 document suggests that this monthly report is now a part of the Officer Profile report. Taken together, these reports show the existence of monthly assessments between the years 2000 and 2016.

quota system has officially been denied, many believe that the NYPD surreptitiously operates under an evaluative process that considers both average performance and quotas.

B. Quota System

The earliest accusations of the NYPD adhering to a quota system extend back to 1957 in a lawsuit filed against New York City over an alleged quota on the issuances of traffic summons.[10] In the early 1970s, the Knapp Commission (a commission charged with investigating corruption within the NYPD) concluded that elements of corruption in the Department could be attributed to the existence of quotas on narcotics and gambling arrests, and as part of its recommendations to reduce corruption, advocated for the elimination of such quotas (Bronstein, 2015). The allegations of the existence of quotas did not disappear with time and have only gained traction in the 21st century.

The Patrolmen's Benevolent Association (PBA), a labor union representing New York City's police officers, maintain the position that such quotas continue to persist. In 2016, an organizational survey conducted by the PBA found that 89% of its members believe that supervisors mandate quotas.[11] This belief parallels the statement by Patrick Lynch, the union's president, in reference to claims of excessive policing in the city, "… end illegal quotas and the issue will be resolved."[12]

Although clandestine in nature, the effects of a quota are experienced by those who must adhere to it. As discussed previously, quota systems could incentivize improper police actions, which could lead to violations of individuals' rights and deteriorated relations between the police and the public they serve. Many residents of New York City feel that their rights have been infringed upon

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[10] "Kennedy Summoned Over Ticket Quotas," *New York Times*, October 18, 1957, http://query.nytimes.com/mem/archive/pdf?res=F40B15FE3A5C127A93CAA8178BD95F43 8585F9.

[11] "New York Patrolmen's Benevolent Association Membership Study," McLaughlin (Mar. 15, 2016).

[12] Daniel Beekman, "Ivy League Law Professor to Help Implement Stop-and-Fisk Reforms," *New York Daily News*, September 19, 2013, http://www.nydailynews.com/news/crime/ivy-league-law-professors-implement-stop-and-frisk-reforms-article-1.1459589#ixzz2fJhclXYo.

when dealing with the police, presumably due to police pressure to meet a quota, and as a result have filed series of lawsuits against the city and the department. These lawsuits include Floyd v. City of New York, Ligon v. City of New York, Stinson v. City of New York, Daniels v. City of New York, and Davis v. City of New York.[13] Some of the litigation was initiated by the NYPD's own police officers. In 2006, arbitrator ruled that the NYPD maintained a traffic citation quota in violation of the state labor law (Case #A-10699-04, 2006). In 2015, an NYPD officer was awarded a $280,000 settlement from a federal lawsuit in which he alleged retaliation from his superiors over his exposing the existence of a quota system (Matthews v. City of New York).

Since then, more members of the NYPD have come forward as whistleblowers alleging the existence of quota such as Officers Pedro Serrano, Adil Polanco, and Adrian Schoolcraft, among many others. Renegades to this system, they claim to have been persecuted as a result. Some of them have provided secret audio recordings of their supervisors calling for numbers. "If you think 1 and 20 is breaking your balls, guess what you're going to be doing. You're going to be doing a lot more, a lot more than what they're saying," said an officer in the 41st precinct referring to 1 arrest and 20 summonses over the course of a month. "Next week, 25 and 1, 35 and 1, and until you decide to quit this job to go to work at a Pizza Hut, this is what you're going to be doing till then," uttered another 41st precinct officer on a different date.[14,15]

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[13] The most prominent among them is Floyd v. City of New York (2013). In this class action lawsuit, the plaintiffs alleged that the defendants, which included police commissioner Raymond Kelly and mayor Michael Bloomberg, maintained an organizational practices resulting in unconstitutional and unreasonable stops and frisks based on race and national origin. In August 2013, Judge Scheindlin ruled that the plaintiffs' 4th and 14th Amendment rights were violated by the police department due to the prevalence of unreasonable searches and discriminatory stops. Similar allegations were made against the city a decade earlier, Daniels v. the City of New York (1999). The plaintiffs in Stinson v. City of New York alleged that police officers issued summons that were deficient in the necessary probable cause. Davis, Ligon v. City of New York cases claimed that police officers were abusing trespass laws in housing areas.

[14] Jim Hoffer, "NYPD Officer Claims Pressure to Make Arrests," *ABC New York*, March 2, 2010, https://abc7ny.com/archive/7305356/.

[15] There are other recordings mentioning concrete numbers. Al Baker and Ray Rivera, "Secret Tape has Police Pressing Ticket Quotas," *New York Times*, September 9, 2010, https://www.nytimes.com/2010/09/10/nyregion/10quotas.html. Graham Rayman, "The NYPD Tapes: Inside Bed-Stuy's 81st Precinct," *Village Voice*, May 4, 2010, https://www.villagevoice.com/2010/05/04/the-nypd-tapes-inside-bed-stuys-81st-precinct/.

Although not all of the 77 NYPD precincts were involved in quota scandals, then-PBA president Patrick Lynch believed that quotas were "a department-wide problem," echoing the sentiment shared by the overwhelming majority of police officers from the aforementioned PBA survey (Fisk and Richardson, 2016).

III. Economic Implications

The conditions faced by New York's police produce economic implications for policemen as well as the community they patrol. The following section provides a possible framework for interpreting the empirical findings of preproperation and the subsequent reduction in efforts.

A. Conditions

Police officers operate in an environment that calls for attaining a certain level of output by the end of each month. Such output counts the number of arrests, summonses, and stops conducted. This requirement, in addition to salary, creates a nonlinear compensation schedule for a typical police officer. Nonlinearity arises from discrete returns to an officer's performance relative to expectations on minimum levels of productivity in monthly performance. Failure to reach this expectation results in punitive measures. Consistent satisfactory and exceptional monthly performance, on the other hand, might be rewarded. Therefore, end-of-the-month performance can result in either a positive or negative shock to the utility of the police officers.

For a police officer, ex ante monthly productivity is unknown. Among many factors, it will depend on "market" conditions, which are semi-random. Positive shocks can be thought of as exogenous increases in crime during some days of the month. These shocks improve the likelihood that costly efforts translate to valuable outcomes such as arrest and summons. Furthermore, the monthly distribution of crime may not be entirely random. Early days of the months may correspond to an increase in certain criminal activities that are positively correlated with the temporarily augmented financial resources of welfare recipients.

Therefore, given the above conditions, a representative police officer decides how to optimally allocate his labor efforts with respect to dynamic conditions within a month.

B. Behavioral Response

Given the scarcity of time as a resource, a police officer's intra-month effort allocation will depend on many factors, such as monthly goals or quotas, monthly compensation with subjective response to it, uncertainty of output, prevailing crime conditions, preference for leisure over work, and time preferences.

Conventional literature, whether it analyzes salespersons' responses to quotas or the efforts of representative agents faced with time-sensitive tasks, predicts an unequal allocation of effort where the amount of work performed increases as the deadline approaches. The reason for procrastination stems from individuals' disutility of work coupled with positive time discounting, leading to an immediate undiscounted gratification with discounted delayed costs.

There is no reason why police officers should deviate from the described behavior under the assumptions that typify the literature. They too prefer leisure and exhibit time preferences. Therefore, absent of any uncertainty, each day a representative police officer would balance the costs of efforts against the chosen level of output such that the difference between the expected monthly target and the police officer's accumulated monthly output approaches zero by the end of a month.[16] This leads

[16] In this case, police officers maximize their utility over a month by choosing to allocate their time between leisure and work:

to intertemporal effort-smoothing consistent with the time-preference parameter of the officer. In this case, a police officer will always meet the expectations by the end of each month by choosing to work harder closer to the deadline. To invert this pattern and observe more efforts in early periods, the existence of a strong countervailing behavioral responses would be required.

A nonlinear compensation scheme at the conclusion of each month invites a different equilibrium behavior in the presence of uncertainty. Depending on the random distribution of crime and the form of the functional relationship that transforms efforts into output, continual deferral of effort in each month will yield a series of unmet monthly goals in the long run resulting in utility-decreasing penalties. And, procrastination behavior becomes suboptimal when the sum of the discounted disutilities outweighs the accumulated ex ante benefits of delaying work. As a result, a forward-looking police officer might exert more efforts in the beginning of the month as a precautionary measure.

Moreover, the Patrol Guide stresses that benefits are likely to be given to those who consistently, from month to month, provide the department with satisfactory performance. This system of penalties and rewards leads to the existence of two potential levels of compensation corresponding to two mutually exclusive states, which thereby creates a sizeable difference between the two outcomes in terms of utility lost or gained. This additionally incentivizes a police officer to

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$$\max_{a_t \in [0,h]} U(Q,T) \text{ where } U(Q,T) = \sum_{t=1}^{T} \delta^{t-1} u(h - a_t) - \lambda_t (Q - \sum_{t=1}^{T} a_t),$$

where $t = 1, \ldots, T$(with T representing the final day of the month); Q is the monthly arrest quota; a_t is the number of arrests performed in period t with $a_0 = 0$; $l_t = (h - a_t)$ is leisure in period t under the assumption that there are h hours available in a work day, and each 1 hour spent working deterministically leads to 1 arrest; λ_t is the shadow value of another hour to the work day; $\delta^{t-1} < 1$ is a time consistent discount rate in period t. Utility is assumed to be increasing and concave. The solution to this utility maximization problem implies a rule for the optimal exertion of efforts (or alternatively, leisure):

$$U'(l_t)\delta^{t-1} = \lambda_t \text{ such that } \lim_{t \to T} (a_t - \frac{Q - \sum_{t=1}^{T} a_{t-1}}{T - t + 1}) = 0.$$

According to this equality, the marginal utility of leisure will be growing with t: $\frac{\partial \lambda}{\partial t} > 0$. This means that arrests derived from efforts will grow monotonically, and hence efforts will increase closer to the end of the period.

reach the numbers and minimize the risk of failure, an incentive which is only exacerbated in the presence of risk-aversion.

If an officer chooses to front-load their efforts to the early days of a month, a high level of output is likely to be achieved in these early periods. And if the officer were to maintain their early-period effort level for the entire duration of the month, they would be likely to exceed the minimum quantitative requirements imposed by the performance standards or quota.[17] Given that there are fewer incentives to exceed required performance targets, a police officer will adjust efforts each day in a way that continues to keep the probability of a failure to an acceptable minimum while avoiding exerting more costly efforts than are required. Therefore, as police issue more summonses in the early days of the month than the period-proportional target mandates, the risk of underperformance drops, allowing officers to reduce their efforts and enjoy leisure. If this behavior characterizes a representative police officer in New York City, then it would be captured in the SQF data in which a greater number of arrests, summonses, and overall stops occur in the first half of the month followed by a scaling down in these numbers as a month progresses.

Such a phenomenon could also be explained by the formal evaluation standards used by the NYPD management whereby an officer's performance is compared against the average performance of the unit. Officers that exert a high level of effort would raise the bar for the rest of the officers. Provided that officers' efforts are visible to other officers, this raising of the unit's evaluative standards could be met with punishment from coworkers who are unable or unwilling to meet the unit's heightened standards. The retaliation enacted by such coworkers would lead to high-effort officers internalizing the negative externality stemming from their hard work. This creates a disincentive for

[17] If this is not the case on average, then it implies that the standards call for the maximum effort exertion for the full month. Given the observed data, it would mean that the average police officer does not meet his goal by the end of each month as the numbers fall off closer to the end. In this case, the NYPD would have a difficult time attracting and retaining officers. Such a scenario is unlikely.

high-effort officers to go "above-and-beyond." Such a disincentive, coupled with the lower returns following the attainment of the monthly target, will induce an even larger reduction in efforts.

An important consideration in analyzing the behavior described above is the potential existence of a non-random intra-month variation in crime. If crime increases at the start of the month, it incentivizes police officers to exert more efforts in that period due to higher returns on their work. This mechanism could be complementary to the precautionary work or could entirely override it, rendering it unnecessary. Even in the absence of these strategic effort responses, higher crime rates in early periods could lead to similar empirical results even under the presence of procrastination. Consider a scenario where a police officer allocates an increasing sequence of efforts $\{e_1, e_2, e_3\}$ over three periods such that $e_1 < e_2 < e_3$. It is possible to observe a decreasing number of arrests under certain assumptions on the functional form of the transformation function. Assume that the production function is $a_t = e_t t^{-\alpha} + \varepsilon_t$ where a_t is number of arrests in period $t \in \{1,2,3\}$ and ε_t is a period-specific random shock such that $E(\varepsilon_t) = 0$. This production function represents higher returns to efforts in earlier periods as a result of the prevalence of crime. On average, the observed numbers of arrests will be decreasing in t, $a_1 > a_2 > a_3$, as long as $2^\alpha e_1 > e_2 > 2^\alpha 3^{-\alpha} e_3$. Therefore, the presence of intra-month crime cycles allows for multiple potential effort allocation levels while generating a larger amount of output in the earlier days of the month. Later sections provide a careful examination of these possibilities and conclude that the front-loading of efforts as a precautionary measure persists even when considering these other factors.

IV. Data and Primary Methodology

The primary data used in this paper comes from the NYPD Stop, Question, and Frisk (SQF) database which documents daily interactions between NYPD officers and the community.[18] The SQF collects information on New York City's "stop and frisk" program which emerged as a controversial strategy in the 1990s with the appointment of William Bratton as New York's Police Commissioner.[19] The SQF program was aggressively used to expand community policing by increasing focus on lower level criminal violations accompanying the department's new focus on order-maintenance and adoption of CompStat crime mapping (Spitzer, 1999).

Pedestrians are stopped by a police officer and questioned during an SQF interaction. A frisk of the suspect is warranted and may lead to search if the officer reasonably suspects that a suspect may inflict physical harm.[20] The officer can either release the individual without further action, issue a criminal summons, or make an arrest following the interaction. Arrest is the most severe of these outcomes, as an arrest involves placing a suspect into police custody and is generally conducted for more egregious crimes. A criminal summons, unlike an arrest, does not lead to the suspect being taken into custody. Similar to an arrest, an individual receiving a summons is accused of a criminal infraction and is required to appear in court to answer for the alleged charges.

At the conclusion of the interaction, an officer fills out a UF-250 form recording which of the aforementioned actions was performed. This includes additional details describing the characteristics

[18] Since 2008, the data is publically available following a Freedom of Information Law and court order (NYCLU v. NYPD, 2008). It can be accessed at https://www1.nyc.gov/site/nypd/stats/reports-analysis/stopfrisk.page

[19] Brief individual detentions by police, absent of probable cause, were ruled not to be in violation of the United States Constitution by the United States Supreme Court in Terry v. Ohio (392 U.S. 1, 1968). Henceforth, police were allowed to conduct stops and frisks on articulable suspicion that the suspect was, currently is, or will be involved in a criminal act.

[20] Stops and searches are governed by the New York Criminal Procedure Law §140.50 (1) and (3), respectively. During a frisk, a police officer runs his hands over a suspect's clothing. If the officer suspects that an object concealed on the person could be a weapon, a search is allowed in which it is permissible for the officer to put their hands in the interior parts of the suspect's clothing (Patrol Guide 2016).

of the individual, the exact timing of the stop, the area of the incident, the circumstances leading to the stop, and the offense with which the individual was charged if appropriate.

Police officers are not required to record each interaction with the public. All police interactions based on factors that fall short of a reasonable suspicion of a criminal act are legally permissible, but are exempt from needing to be documented (such encounters are classified as level 1 and level 2). Any summonses and arrests resulting from immediately observed probable cause (considered as a level 4 encounter) do not need to be recorded. Only stops involving level 3 encounters, also known as "Terry stops," require completion of a UF-250. These stops require a reasonable suspicion that the detained person has committed, is committing, or intends to commit a criminal act. Table 1.1 provides detailed information on the distinction between these various categories of encounters.[21]

Measurement errors due to recording practices are a concern. The boundaries between permissible interactions are often thought to be vague despite their formal definitions. This can cause confusion for officers with regard to the necessity of recording an interaction. This would not pose a serious concern if such errors occur randomly throughout the course of the month.

Systematically misreported records, on the other hand, would present an obstacle to accurately identifying effort allocations. One such misreport could involve the record of the date on which an interaction took place. If police officers are able to transpose their numbers between months, they might move their surplus output (numbers exceeding expectations) from the final days of a month towards the next month. However, this possibility is unlikely to arise with regard to the NYPD's data on arrests and summonses. Ever since the introduction of CompStat, a computer system for the recording of information on police activities, the real-time entry of information on crime statistics is

[21] Additional guidelines specify that if level 1 and 2 encounters escalate to level 3, records are made. A level 4 outcome of an arrest or summons is also recorded as long as the encounter involved a level 3 interaction during the process. In addition, stops are recorded if force was used to stop a person, a frisk or search was conducted, or a person failed to identify themselves (USCCR Report, 1999).

TABLE 1.1: LEVELS OF PERMISSIBLE INTERACTIONS WITH THE PUBLIC

TYPE OF ENCOUNTER	LEVEL OF KNOWLEDGE REQUIRED	NATURE AND EXTENT OF PERMISSIBLE QUESTIONING	AUTHORITY TO SEARCH	FORCE AND DETENTION
I. Request for Information	An objective, credible reason to approach. Suspicion of criminality is not required. However, the UMOS must be able to articulate a basis beyond mere whim and caprice.	Non-accusatory questions concerning the reason for the approach.	At this level of suspicion, there is no basis to search. A request for consent to search the person or a bag, pocketbook, luggage, or other item of personal property is improper.	Force may not be used to detain a subject at this level of suspicion. The subject is free to walk away from the UMOS if they so desire. They need not answer questions.
II. Common-Law Inquiry	A founded suspicion that criminality is afoot. This could be triggered by false responses to questions posed during the request for information, as well as observations by the UMOS.	UMOS may conduct more extensive questioning. Accusatory-type (guilt-seeking) questions may be asked.	A subject may be asked to consent to the search of an item of personal property. This consent must be voluntary on the subject's part.	Force may not be used to detain a subject at this level of suspicion. The subject is free to leave if they desire. They need not answer questions.
III. Stop, Question, And Possible Frisk	An officer has *individualized, reasonable suspicion that the subject is committing, has committed, or is about to commit a crime*. The New York State Legislature has limited the term crime, for purposes of a stop, to mean a felony or a misdemeanor in the Penal Law. (CPL § 140.50(1)). Reasonable suspicion exists when the information known to the UMOS is of such weight and persuasiveness as to make the UMOS reasonably suspect criminality on the part of the person being stopped.	The UMOS may stop the subject, ask for his or her name and address, an explanation of conduct, and detain the person while an expeditious investigation is conducted to determine if there is probable cause to arrest the subject.	In addition to the consent search described above, the UMOS may frisk the subject for a deadly weapon or any instrument or article readily capable of causing serious physical injury, and of a sort not ordinarily carried in public places by law-abiding persons, if the UMOS reasonably suspects the person is armed and dangerous.	A stop occurs whenever *a reasonable person would not feel free to disregard the officer and walk away*. A UMOS is permitted to use reasonable force to stop and question a subject. The type and amount of physical force used must be objectively reasonable under the circumstances facing the UMOS.
IV. Arrest	Probable cause to believe that (a) an offense was committed and (b) that the subject arrested committed it. Probable cause requires the existence of facts and circumstances which when viewed together would lead a reasonable person possessing the expertise of the arresting officer to conclude that an offense has been committed.	An UMOS may engage in constitutionally permissible custodial interrogation (i.e., *Miranda* waiver must be lawfully obtained. *Miranda* waiver is not required to obtain pedigree information).	"Search incident to arrest" (i.e., a search of a subject conducted immediately after the arrest to secure weapons, prevent evidence destruction). "Inventory," etc.	A UMOS is permitted to use reasonable force to arrest and detain a subject.

Notes: The information in this table is copied from NYPD's *Investigative Encounters Reference Guide* that was used for training conference in 2015. http://nypdmonitor.org/wp content/uploads/2016/02/InvestigativeEncountersRefGuideSept162015Approved.pdf

required. This forces the numbers to be entered in a central computer system within a short period of time (Silverman 1999, 97–124). Nonetheless, this could be a problem for recorded stops that yield no criminal outcome. Such stops would be of no relevance to the recording of statistics on committed crimes and offer no additional evidence of police activity taking place, unlike arrests and summonses where suspects are formally charged.

Notwithstanding concerns about recording practices, this data provides a significant advantage in that it records high-frequency interactions between police and the community. This makes it possible to identify, albeit noisily, the effort allocations on the part of police officers.

Over five million stops were recorded across all 77 precincts in New York City between January 2003 and December 2016 (all available SQF years). For the main analysis, stop-level observations (which comprise SQF data) are converted into day-precinct observations by counting the daily total precinct-level number of stops without a criminal outcome, stops involving summonses, and stops leading to arrests (denoted henceforth as non-criminal stops, summonses, and arrests, respectively). This produces 358,708 distinct daily precinct-level observations over the duration of sample.

The following precinct-level model is estimated using OLS to find evidence for intra-month labor efforts cycles:

$$(1)\quad ActivityRate_{dmyp} = \beta_L LastTwoWeeks_{dmyp} + \boldsymbol{X}'_{dmyp}\gamma + \varepsilon_{dmyp}$$

Equation (1) measures the temporal variation in recorded intra-month police activity where $d = 1,\ 2, \dots,\ 31$ corresponds to the days in a month; $m = 1,\ 2,\ \dots,\ 12$ represents the months of the year, $y = 2003,\ 2004,\ \dots,\ 2016$ the years in the sample; and $p = 1, 2, \dots, 77$ denotes each of New York City's police precincts. The spatial unit of analysis is the precinct due to it being the unit at which enforcement policies are set. Errors are likely to correlate over time within precincts, and therefore standard errors are clustered at the precinct level.

The dependent variable $ActivityRate_{dmyp}$ is constructed using the following formula:

$$ActivityRate_{dmyp} = \frac{Activity_{dmyp}}{\sum_{d=1} Activity_{dmyp}},$$

where $Activity$ is a placeholder for arrests, summonses, and non-criminal stops. Arrests are also broken down between financially motivated, violent, and controlled-substance-related types to see if any particular types of crime drive the results.[22] These dependent variables measure precinct-specific and temporally distinct daily activity shares relative to officers' monthly activities.

Consider one of the six dependent variables:

$$ArrestRate_{dmyp} = \frac{Arrest_{dmyp}}{\sum_{d=1} Arrest_{dmyp}}.$$

This dependent variable calculates the fraction of total monthly arrests within a precinct that occur on a particular day of the month.[23] The remaining five dependent variables (summonses, non-criminal stops, and fragmented arrests) are defined analogously.

Given the construction of the dependent variables, this model mechanically includes precinct-month-year fixed effects which control for unobserved heterogeneity across precincts and time, and also account for the unequal number of days across months. These fixed effects are important to include since commanding officers set the goals and practices of the precincts as reflections of the current socio-economic and crime conditions, which vary across New York City and change over time. Furthermore, the way in which SQF was used underwent a substantial change during the years covered by the data. Police activity peaks in the year 2011 with 686,056 stops and drops to its lowest level in 2016 with 33,983 stops. This signals temporal changes in police practices resulting from public

[22] For the purposes of this paper, all crimes that are expected to produce material gains for the perpetrator at the expense of victim(s) are considered as financially motivated crimes. By this definition, these crimes include robbery, burglary, as well as petty and grand larceny. This definition excludes other crimes that might be financially motivated but lacking victims such as unlicensed vending or gambling. The reason for exclusion of the latter activities is to limit the confounding effects of welfare payments on this cycle. Welfare payments produce a shock to the availability of financial resources that enables crimes such as gambling and encourages illegal vending due to positive demand shocks. The former definition attempts to restrict the analysis to crime driven by scarcity as opposed to crime driven by abundance. Violent crimes are considered to be those that harm or threatens to harm another person. These include all degrees of assault, sexual assaults, menacing, harassment, kidnapping, and homicide. Controlled substance crimes include all violations of the New York City and the state of New York penal laws governing narcotics. These include consumption, possession, and distribution of all illegal substances.

[23] A hypothetical example: June of 2005 had 30 days during which a total of 30 arrests took place in the 5th precinct. Assume that each day in that month (and precinct) is responsible for 1 arrest. In this case, the dependent variable takes on a value of $0.03\overline{3}$ for each day.

outcry over excessive policing. For robustness, separate analyses were considered in Section V omitting the years of low SQF utilization. No substantive changes were observed.

The main explanatory variable is $LastTwoWeeks$. To divide each month in a symmetric fashion (given that some months have more days than others), this variable divides a month into periods corresponding to the first and last two weeks of the month. Therefore, this binary variable equals one if a day belongs to the last 14 days of the month and zero if it belongs to the first 14 days. Similar 28-day time windows were used for analysis in Stephens (2003) and Dobkin and Puller (2007).

If $E(ActivityRate_{dmyp}) = E(ActivityRate_{(d+1)myp}) \approx 0.033 \;\; \forall \; d$, then it suggests that crime is uniformly distributed and yields an equal response throughout a month, in which case coefficient β_L would be equal to zero. This would indicate no strategic and unequal allocation of police efforts.

$\boldsymbol{X'}$ is a vector of control variables. Continuous controls include average daily temperatures, lunar luminosity, rainfall, snowfall, and daylight. Other control variables include indicators for the days of the week and holidays.[24] These variables can potentially influence both the commission of crime and apprehension of criminals.

Daylight measures the number of minutes of available light emitted from the sun in a day. Lunar luminosity ranges from zero to one, encompassing all possible linear combinations of luminosity between the new and full moon; both of the above variables influence visibility throughout a full day, and visibility is a fundamental element in the decision to commit a crime given that darkness helps to conceal the act. The data on daylight and lunar luminosity comes from the United States Naval Observatory.[25]

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[24] *Holiday* is a dummy variable indicating days such as federal holidays and other publically celebrated occasions. These dates include all federal holidays and adjacent weekends and Fridays. If a federal holiday fell on a Sunday, the following Monday is included due to its "in lieu of" observance (the U.S. Office of Personnel Management). In addition, Saint Patrick's Day, New Year's Eve, Cinco de Mayo, Halloween, Super Bowl Sunday, and Christmas Eve are also included with their weekends and Fridays if those days were adjacent. These holidays differ with regard to how they are celebrated and, therefore, have varying relationships with prevailing levels of crime. A consideration of these differences is provided in Section V.

[25] Data is taken from http://aa.usno.navy.mil/data/docs/RS_OneDay.php.

Snowfall and rainfall are measured in inches of precipitation. Temperature is measured in degrees Fahrenheit. The variables can affect the number of potential victims, perpetrators, and officers on the streets and act as an impediment to interactions between these agents. The data on rain, snowfall, and temperature is taken from the National Weather Service Forecast Office.[26]

The importance of weekdays and holidays is explained through the routine-activity theory (Cohen and Felson, 1979). Weekends and specific holidays may lead to excessive drinking and a greater incidence of interactions between the police and the public. In addition, many people are paid weekly with paychecks disbursed on Fridays, further altering incentives for crimes across days of the week. These variables can also affect police presence given that more police officers might be deployed over weekends in anticipation of public disorder, or conversely, might have a lower presence during certain holidays.

Table 1.2 contains summary statistics of the control variables and the activity levels that were used in the creation of the rate dependent variables. The number of arrests range from 0 (days without a single arrest) to 222 arrests on a day of unusually high activity. Average daily stops leading to arrests (60 stops) or summonses (60.62) comprise only 5.97% and 6.03% of daily stops respectively. Most stops (872.76) result in neither of these outcomes.[27] A quarter of all arrests are made over controlled substances, representing the largest category of crime committed. Within this category, 59.9% of arrests involve marijuana (not shown in Table 1.2).[28]

The indicator variable representing monthly divisions of first and second halves has a mean of 0.5. This indicates a symmetrical division with equal number of days in the first and the second half of each month. The mean of 0.117 on the holiday dummy indicates that over ten percent of all days

[26] Data is taken from http://w2.weather.gov/climate/xmacis.php?wfo=okx.

[27] The literature refers to the likelihood of a stop resulting in a tangible outcome as the hit-rate. Given a small (12%) hit-rate, police officers in New York City were criticized for excessive use of SQF (Ridgeway, 2007).

[28] Identification of different types of arrests is not trivial in the SQF data. Police officers, using their own words, summarize the violations for which arrests occur. These summaries are string variables that include typographical errors, abbreviations, acronyms, and other challenges to accurate classification. Diligent steps were taken to ensure accuracy.

TABLE 1.2: SUMMARY STATISTICS

Variables	Mean	SD	Min	Max
Daily counts of activity levels				
Arrests	60	42.22	0	222
Summonses	60.62	48.42	0	281
Stops (non-criminal outcome)	872.76	629.31	2	2,869
Financially motivated arrests	10.62	8.25	0	56
Violent arrests	5.1	4.52	0	31
Controlled substance arrests	14.44	12.6	0	69
Explanatory variables				
Last two weeks	0.5	0.5	0	1
Each day of week	0.142	0.349	0	1
Holiday	0.117	0.322	0	1
Temperature (in °F)	55.19	17.33	4	94
Rainfall (in inches)	0.144	0.407	0	7.57
Snowfall (in inches)	0.102	0.903	0	27.3
Lunar luminosity	0.5	0.351	0	1
Daylight (in minutes)	731.87	120.23	555	906

Notes: Financially motivated crime includes robbery, burglary, and all types of larceny. Violent crimes include homicide, assault, sexual assault, kidnapping, menacing, and harassment. Controlled substance crimes include possession, consumption, and distribution of all narcotics prohibited in New York City. The total number of unique day-precinct observations is 358,708 based on 4,704 unique days.

are considered celebratory. The inclusion of the adjacent weekend in addition to the actual day of the holiday is responsible for the large mean (see footnote 24).

V. Main Results

This section estimates the model in equation (1) which considers the intra-month variation of labor efforts on the part of NYPD's rank-and-file. If there exists an unequal display of performance throughout a month, it will be captured by the coefficient on the indicator variable separating a month into two halves. This unequal performance could be a product of unequal distributions of efforts, cyclical crime supply shocks driven by disbursements of welfare payments, or a mixture of both. The main results presented here are only partially able to discern between these explanations, though a later discussion attempts to distinguish between the two.

Table 1.3 presents the estimates of equation (1) for arrests, summonses, and non-criminal stops. Columns (1) and (2) differ with regard to their inclusion of particular control variables. The following discussion focuses exclusively on columns (2) as the results are similar across both columns.

The first row in Table 1.3 summarizes the main results of interest. The coefficients presented across columns in Table 1.3 depict the differences in arrests, summonses, and non-criminal stops between the first and the second halves of a typical month. All three coefficients are statistically significant at the 1% level, negative, and sizable in their magnitudes. These results translate to 10.1% fewer arrests, 6.9% fewer summonses, and 3.3% fewer non-criminal stops during the last two weeks of a month relative to its first two weeks. These results suggest that officers make more arrests, issue more summonses, and conduct more unproductive stops early in the month, consistent with the strategy of front-loading efforts and a discretionary decision to reduce efforts following the attainment of monthly expectations.

Arrests and summonses are likely to be valued more highly than simple stops due to their successful apprehension of criminals, which could lead to safer streets and additional revenue generation for the city. Therefore, police officers' behavioral responses should be primarily driven by achieving these outcomes. This might explain larger cyclical effects for arrests and summonses in contrast with the attenuated cycle of non-criminal stops.

The control variables have similar impacts across the three dependent variables. More daylight leads to fewer arrests, summonses, and non-criminal stops. This is presumably because more hours of daylight limits the available time for committing crimes under the cover of darkness.[29] More light

[29] In addition, more daylight may lead to improved detection by the police or public which, in turn, should increase the likelihood that a suspect engaged in a crime will be apprehended. Given the associated decline of 3.1%, the former effect of a drop in crime is likely to outweigh this possibility.

TABLE 1.3: OLS ESTIMATES OF STOP OUTCOMES

Explanatory variables	(1) Arrests	(2) Arrests	(1) Summonses	(2) Summonses	(1) Non-criminal Stops	(2) Non-criminal Stops
Last two weeks	-0.00344***	-0.00348***	-0.00231***	-0.00234***	-0.00109***	-0.00111***
	(0.000261)	(0.000321)	(0.000308)	(0.000314)	(0.000148)	(0.000175)
Holiday		-0.00376***		-0.00226***		-0.0026***
		(0.000459)		(0.000461)		(0.000278)
Tuesday		0.0153***		0.00742***		0.011***
		(0.000628)		(0.00077)		(0.000467)
Wednesday		0.0191***		0.00995***		0.0143***
		(0.000674)		(0.000737)		(0.000564)
Thursday		0.0173***		0.00997***		0.0129***
		(0.000642)		(0.000701)		(0.000478)
Friday		0.0169***		0.0141***		0.015***
		(0.000648)		(0.000676)		(0.000542)
Saturday		0.012***		0.0149***		0.0113***
		(0.000788)		(0.000892)		(0.00063)
Sunday		0.00114*		0.00631***		0.0017***
		(0.000644)		(0.000866)		(0.00054)
Temperature		0.000064***		0.000067**		0.000044***
		(0.000019)		(0.000026)		(0.000013)
Lunar luminosity		-0.00102**		-0.000784		-0.000642***
		(0.000456)		(0.000501)		(0.000222)
Rainfall		-0.00259***		-0.00376***		-0.00303***
		(0.000341)		(0.000353)		(0.000176)
Snowfall		-0.00106***		-0.00116***		-0.00098***
		(0.000125)		(0.000155)		(0.000058)
Daylight		-0.000017**		-0.000016*		-0.000009*
		(0.000008)		(0.000008)		(0.000004)
Constant	0.0311***	0.0298***	0.0317***	0.0323***	0.0323***	0.0277***
	(0.000179)	(0.00536)	(0.000215)	(0.00574)	(0.000102)	(0.0032)
Observations	338,968	338,968	301,000	301,000	356,860	356,860
Month×Year×Precinct FEs	Y	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the precinct level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

reflected by the moon similarly reduces criminal activity. Interestingly, the coefficients on daylight and lunar luminosity are largest for arrest outcomes and lowest for non-criminal stops. One possible explanation for this is that perpetrators of serious crimes are most sensitive to potential exposure due to greater adverse legal risks of their actions when visibility is high.

Precipitation of rain and snow both decrease activities. This could be explained through several channels, for instance, the reduction of the number of potential victims, aversion to precipitation by criminals, or similar aversion by police officers who might view inclement weather as an inconvenience, leading to lower apprehensions.

Days that fall on holidays or their adjacent weekends are associated with lower arrests (11.5%), summonses, and non-criminal stops. The explanation for this is ambiguous. Some holidays are spent quietly within the walls of one's home (e.g. Thanksgiving or Christmas) whereas other holidays (St. Patrick's Day or Cinco de Mayo) induce people to venture out and partake in alcohol consumption. The former types of holiday should be associated with a lower incidence of the commission of crimes while the latter should be associated with the opposite. Crime apprehension could additionally be reduced owing to the efforts of the police if officers view holidays as days associated with higher leisure and decreased efforts. Separate regression analyses were performed (not shown here) which introduced a holiday dummy variable based on the public's inclination to engage in drinking in an effort to explore whether the latter effect of decreased police efforts drives the above results.[30] Holidays associated with drinking retain the qualitative result of lower arrest rates (6.9% fewer arrests relative to non-holiday days). This effect was larger for non-drinking holidays (12.1% fewer arrests), consistent with an additional drop in crime due to the less boisterous nature of these holidays. In addition, there was no discernible change in summonses issued or non-criminal stops conducted on the days of drinking holidays. This might contrast with what one might expect of the "holiday effect," which is associated with greater public interactions characterized by excessive drinking potentially leading to additional criminal conflicts. These results suggest that the drop in police officers' efforts (or a more judicious choice of apprehensions) are primarily responsible for the reduction in activities.

Lastly, warmer temperatures and weekends are associated with a greater number of criminal interactions as recorded by the SQF.

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[30] The holidays associated with drinking included St. Patrick's Day, Cinco de Mayo, Halloween, Super Bowl weekend, New Year's Eve, and the Fourth of July. The non-drinking holidays included the remainder of holidays listed in footnote 24.

It is worth noting the unequal number of observations between the dependent variables used in equation (1). During some months, some of the precincts did not record any instances of the associated activities (arrests, summonses, or non-criminal stops), and therefore, these precinct-month observations cannot be included (as the denominator of the dependent variable for such observations is equal to zero). Such precinct-month observations with zero instances of a particular activity being recorded constitute 5.5%, 16.1%, and 0.5% of the full sample for arrests, summonses, and non-criminal stops, respectively. Of these observations with zero recorded activities within a month, around 90% fall in the interval of time between July 2013 and December 2016. The overabundance of zero-valued observations in this period can be attributed to procedural reforms in response to a series of accusations against the city and the department over its excessive use of SQF tactics (Mummolo, 2017), and an ensuing reduction in police interactions with the public involving SQF. Figure 1.3 illustrates this drastic reduction in the number of monthly stops following the changes, with a vertical line (July, 2013) representing a stabilized new trend. To address this break in the data, equation (1) was re-estimated by excluding this period of lower monthly activities. Restricting the sample in such a way preserves statistical significance and does not substantially change the magnitude of the main results (not formally presented).[31]

The next table explores whether specific types of crime are responsible for the observed patterns. Table 1.4 presents results of equation (1) using dependent variables that disaggregate arrests into three categories of financially driven, violent-in-nature, or controlled-substance-related.[32] All

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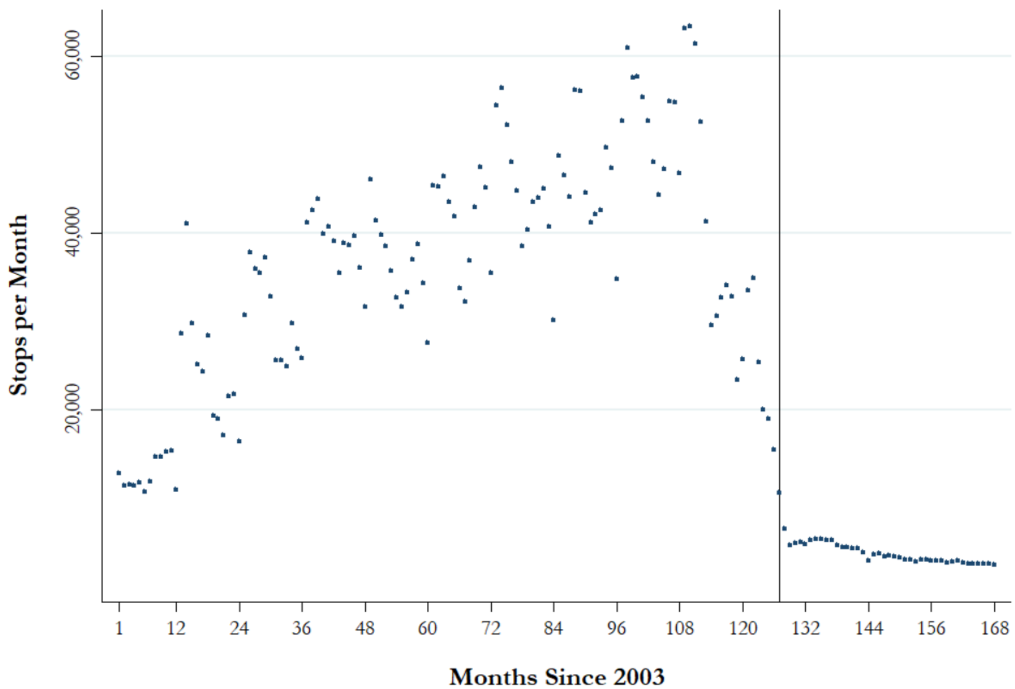
[31] When equation (1) is re-estimated excluding years post-SQF reforms, the magnitudes on the last two weeks become somewhat lower for arrests (0.00073 percentage points lower relative to the coefficient found using the full sample, representing a 21.1% difference in magnitudes) and non-criminal stops (0.0006 percentage points), and slightly higher for summonses (0.000046 percentage points).

[32] Similar to the explanation provided with regard to Table 1.3, the difference in the number of observations is due to precincts making zero arrests for particular crimes during some months. Analyses were again performed excluding post-reform SQF years. The results were qualitatively unchanged, with similar statistical significance and magnitudes for financially-motivated and substance-related crimes but not for violent crimes (*p*-value: 0.18).

FIGURE 1.3: TOTAL NUMBER OF STOPS PER MONTH



Notes: Number of stops per month recorded in SQF data, 2003–2016 (New York City). The vertical black line indicates July, 2013.

coefficients on the $LastTwoWeeks$ variables are again statistically significant and negative. Arrests are 4.9%, 3.9%, and 13.6% lower for financial, violent, and controlled substance crimes respectively during the second half of a month. These results suggest that there is less overall activity in the last two weeks irrespective of crime composition.

These findings suggest the existence of both: the intra-month cyclical nature of crime and discretionary adjustments of labor efforts on the part of police officers, which exists independently of the former. The largest intra-month cycle in arrests is found in the illicit narcotics category. This discovery is consistent with the literature connecting welfare disbursements to illegal substance use. A liquidity-constrained individual is financially enabled to procure drugs upon receiving a welfare check, leading to increased consumption and possession of such substances. This might also expand the

TABLE 1.4: OLS ESTIMATES OF DISAGGREGATED ARREST RATES

Explanatory variables	Financially Motivated	Violent	Controlled Substance
Last two weeks	-0.00162***	-0.0013**	-0.00481***
	(0.000474)	(0.000593)	(0.00052)
Holiday	-0.00387***	-0.000626	-0.00477***
	(0.000828)	(0.000993)	(0.000659)
Tuesday	0.015***	0.0065***	0.0179***
	(0.000909)	(0.00113)	(0.000897)
Wednesday	0.0185***	0.00674***	0.024***
	(0.00106)	(0.00119)	(0.000953)
Thursday	0.0152***	0.00813***	0.0213***
	(0.000913)	(0.00116)	(0.000955)
Friday	0.0134***	0.00947***	0.0216***
	(0.00103)	(0.00136)	(0.0011)
Saturday	0.00684***	0.0133***	0.0128***
	(0.00115)	(0.00138)	(0.000986)
Sunday	-0.00227***	0.00827***	0.000692
	(0.000813)	(0.00135)	(0.000815)
Temperature	0.000059	0.00015***	0.000115***
	(0.000036)	(0.000044)	(0.000037)
Lunar luminosity	-0.000922	0.000201	-0.00182**
	(0.000688)	(0.000942)	(0.000717)
Rainfall	-0.00189***	-0.00178**	-0.00323***
	(0.000468)	(0.00072)	(0.000488)
Snowfall	-0.00113***	-0.000669*	-0.00107***
	(0.000278)	(0.000381)	(0.000182)
Daylight	-0.000013	0.000007	-0.000009
	(0.000014)	(0.000014)	(0.000013)
Constant	0.0299***	0.0112	0.0185**
	(0.0106)	(0.0102)	(0.00928)
Observations	277,256	212,884	262,164
Month×Year×Precinct FEs	Y	Y	Y

Notes: Standard errors are clustered at the precinct level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

presence of narcotics merchants on the streets, who are eager to capitalize on favorable demand conditions. This further increases the number of apprehensions of substance-related violators.

The intra-month cycle in arrests for violent crimes follows a similar trajectory of that for substance-related arrests by exhibiting an intra-month decline. It is hard to conclude what drives this result. It could reflect the effort adjustments of police officers, or it could be complementary to the drug-related cycle where substance consumption is positively correlated with risk-taking behavior leading to violent crime. Another plausible channel for this is the increased competition between drug dealers over ephemerally larger markets. The methods with which such conflicts are settled are notoriously violent due to the unavailability of formal property rights or dispute settlement mechanisms for conflict resolution (Goldstein, 1985).

The final result on the declining intra-month cycle of financially motivated crimes is inconsistent with the previous literature connecting crime to the welfare disbursement schedule. The end-of-month scarcity of resources owing to the exhaustion of welfare funds should produce a higher marginal utility of consumption due to lower levels of consumption.[33] This creates an incentive for some to obtain resources through crime. More arrests would therefore be expected during the ending days of a month, but in fact, fewer are recorded. This declining number of arrests nonetheless parallels the decline in the number of arrests for other crimes. This is strong evidence for the idea that police undertake a lower effort level as a month progresses, and further, this mechanism is independent of the type of crimes that officers deal with.

VI. Exogeneity of Police Officers' Efforts Adjustments with Respect to Crime Levels

This section presents more direct evidence of a conscious decision behind effort adjustments and the immateriality of non-random welfare disbursements in affecting the behavior of police officers. It also further extends the original analysis by considering police officers' aversion to difficult

[33] The consumer goods also include behavior-altering substances. Given that some fraction of welfare recipients struggle with addiction, their marginal utility of consumption for these drugs will be immense.

tasks and the discretionary nature of effort adjustments, and testing for differences in police behavior across precincts with high and low rates of welfare participation.

A. Complexity of the Task at Hand

Police enforcement is a series of temporal interactions with tasks, often criminal in nature. These tasks are not homogenous and vary in complexity. If there exists a reduction in effort on the part of a police officer, then some of the more difficult tasks may be ignored. One dimension of such difficulty lies in the physical attributes of suspects. Larger individuals pose additional risk to officers' safety and to the prospect of a successful detainment. As a result, a reduction in effort may materialize in aversion towards individuals possessing such attributes.

The SQF data contains variables describing the physical attributes of those stopped, including the individual's weight, height, and physical build. Unfortunately, the data does not report the physical attributes of the officer that conducted the stop; therefore, estimating the officer-specific difficulty of a stop is not possible. Nonetheless, on average, the difficulty of a stop should increase with the degree with which individuals possess the aforementioned physical attributes. As a result, within each of these three variables on physical characteristics, two different subdivisions were employed to create a total of six separate binary variables. Each division characterizes stops as belonging to one of two categories of lower or higher difficulty with the second division further intensifying the severity of a higher difficulty group.

Variables $Heavy$ and $Tall$ are constructed using suspects' body weight and height information. In the first division, the variables $Heavy$ and $Tall$ are equal to one if the suspect's reported weight or height were at least one standard deviation above the sample mean and zero otherwise, respectively. In the second division, variables $Heavy$ and $Tall$ are equal to one if the suspect's reported weight or height were at least two standard deviations above the sample mean and zero otherwise, respectively.[34] Thus, the second divisions potentially indicate a more difficult stop.[35]

The variable $Large$ is initially constructed from the information on the physical build of a suspect. At first, it is defined as an indicator equaling one if a suspect's body build was described as muscular or heavy and equaling zero if medium or thin. In the second specification, the variable's construction considers information on all of the three physical characteristics. $Large$ equals one if the suspect was considered either muscular or heavy, with both weight and height being at least one standard deviation above their mean values.

A linear probability model is used to estimate a change in likelihood of stopped individual possessing unfavorable physical attributes during the second half of a month relative to the first half:[36]

$$(2) \quad AdversePhysique_s = \beta_L LastTwoWeeks_s + \boldsymbol{X}'_s\gamma + \varphi_{ymp} + \varepsilon_s$$

In contrast with equation (1), the unit of analysis is an individual stop s recorded in the SQF data. $AdversePhysique_s$ is a binary variable equaling one if stop involved an individual possessing an "unfavorable" physique and zero otherwise.

The main explanatory variable of interest is $LastTwoWeeks$, a binary variable indicating whether the stop occurred during the last or first two weeks of a month, similar to model (1). Vector

34 The cutoffs for these measures are 197 pounds and 72 inches for one standard deviation above the mean for weight and height; 228 pounds and 76 inches for two standard deviations.

35 When these variables are instead defined as representing individuals being above or below average height or weight rather than standard deviations above the mean, no pattern in the relationship between physical characteristics and daily effort levels emerge. This is not surprising given that an average police officer might not view a smaller deviation above the sample mean as a substantive increase in difficulty, especially if an average police officer possesses above average values of the aforementioned physical attributes.

36 A logit model was also estimated. The logit estimates were quantitatively similar to those generated by the linear probability model.

TABLE 1.5: SUMMARY STATISTICS FOR PHYSICAL CHARACTERISTICS OF SUSPECTS

Variables	Mean	SD	Min	Max
Weight (in lbs.)	168.6	29.14	50	600
1 SD above mean	0.142	0.349	0	1
2 SD above mean	0.0342	0.181	0	1
Height (in inches)	68.59	3.28	24	99
1 SD above mean	0.191	0.393	0	1
2 SD above mean	0.0111	0.105	0	1
Large				
Body type descriptions: muscular or heavy	0.0891	0.285	0	1
"Large" body type with height and weight 1 SD above mean	0.0239	0.153	0	1

Notes: Body type consists of four categories: muscular, heavy, medium, and thin. The "large" body type includes muscular and heavy builds.

$\boldsymbol{X}$ contains all other controls included in model (1). φ_{ymp} is a year-month-precinct fixed effect. The standard errors are clustered at the precinct level.

Table 1.5 provides descriptive statistics for the six dependent variables considered and the continuous variables used in their construction. Initially, the variables weight and height had unreasonably high and low ranges, reflecting inaccuracies in the recording of the data.[37] Their minimum and maximum values represent the adopted cutoffs. These cutoffs were based on historical records on minimum and maximum heights and weights. For robustness, equation (2) was also re-estimated using more restrictive limits on permissible values for heights and weights, as well as unrestricted ranges. There were no substantive changes in the results (not shown here).

Table 1.6 reports the results for equation (2). The difference in the number of observations across the Heavy, Tall, and Large columns reflect incidences of missing and misreported values.[38] The first two columns consider weight as a potential determinant of difficulty. The first column labels an individual heavy if his or her weight is one standard deviation above the mean or greater. The

[37] Weight ranged between 0 and 20,000 lbs. Height ranged between 0 and 162 inches, approximately the height of an atom and a full size elephant.

[38] These instances do not correlate with the days of the month. Correlations between the occurrence of missing values for body build, weight, height and whether such observations fall in the first two weeks of the month are all approximately equal to zero.

TABLE 1.6: OLS ESTIMATES OF STOPS INVOLVING INDIVIDUALS WITH ADVERSE PHYSIQUES

Explanatory variables	Heavy		Tall		Large	
	Weight 1 SD above	Weight 2 SD above	Height 1 SD above	Height 2 SD above	Body type	Weight, height, and body type
Last two weeks	-0.00152***	-0.000975***	-0.000523	-0.000294**	-0.00126***	-0.000443***
	(0.000363)	(0.000191)	(0.000338)	(0.000125)	(0.000293)	(0.000138)
Holiday	-0.00151**	-0.000603**	-0.00183**	-0.000299	-0.00137***	-0.000784***
	(0.000593)	(0.00029)	(0.000756)	(0.000218)	(0.00045)	(0.000238)
Constant	0.146***	0.0303***	0.195***	0.00832***	0.081***	0.0229***
	(0.00592)	(0.00339)	(0.00709)	(0.00154)	(0.00528)	(0.0028)
Observations	4,627,886	4,627,886	4,657,513	4,657,513	4,656,386	4,562,656

Notes: Other included controls are temperature, lunar luminosity, rainfall, snowfall, daylight, dummies for days of the week, and month-year-precinct fixed effects. Standard errors are clustered at the precinct level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

coefficient of interest is equal to -0.00152 and is statistically significant at the 1% level. Given that 14.3% of all stopped individuals in the first two weeks of the month had recorded weights of at least one standard deviation above the mean, this coefficient indicates that the probability of a stop involving such an individual is 1.1% lower in the second half than in the first half of a month. Similarly, the second column shows that the probability of stopping an individual whose weight is at least two standard deviations above the mean is 2.8% lower in the last two weeks of a month.

The third and fourth columns consider the height of a suspect. There is no evidence that the likelihood of stopping a person whose height is one standard deviation above the mean is different throughout the month. In the fourth column, a person is considered tall if his or her height is more extreme, at least two standard deviations above the mean. The estimate on the second half of the month is statistically significant at a 5% level and reflects a 2.6% decreased chance of a stop involving a tall person during the second half relative to the first half.

The fifth column presents results for body type description. A person is considered large if his or her body build is described as muscular or heavy. The results show that the probability of stopping a large individual is 1.4% lower in the second half at the 1% significance level. The final column classifies an individual as large if he or she possesses comparatively extreme attributes for all of the physical characteristics considered. During the first two weeks, only 2.4% of all stops involved such individuals. The coefficient of -0.000443, therefore, translates to 1.9% fewer stops of large individuals during the last two weeks of a month.

To better conceptualize the above magnitudes, it is worth noting the coefficients on the holiday dummy across columns. The magnitudes and signs of these coefficients are similar to the ones observed on the second half of the month and with the exception of only one column, the coefficients on the holiday dummies are negative and statically significant. This shows that heavier, taller, and larger people are less likely to be stopped during holidays, the days that are typically associated with leisure and reduced labor efforts.[39] The magnitude of the aversion to potentially difficult stops during these days is comparable to the level of aversion observed in the second half of a month.

These results show that individuals with potentially threatening physical attributes are less likely to be stopped during the last two weeks of a month. Furthermore, a higher degree of such a threat further lowers the likelihood of being stopped during the second half. These findings suggest that the more difficult the task is, the more likely it is to be skipped as a month progresses. This observed relation between difficulty and aversion provides evidence that the intra-month criminal cycle could in part be driven by reduction in policing efforts. This conclusion of course hinges on the assumption that the distribution of crimes committed by heavier, taller, and larger people does not systematically differ from the rest of the criminals throughout the month. That is, as long as larger criminals do not commit more crime during the first half than the rest of the criminal population, then the results imply a change in the allocation of efforts on the part of police.

[39] It is possible that these holidays are associated with less crime overall which would produce a similar effect. However, as the discussion of the main empirical results suggests, these observations are likely to be driven by the effort reduction of police.

B. *The Possibility of Discretion*

If voluntary discretion to exert less effort is one of the mechanisms behind lower rates of criminal apprehension later in the month, then the tasks possessing less leeway in the potential range of efforts level should exhibit an attenuated cycle.

In the SQF data, the decision to initiate a stop can come from two different sources. The first source occurs when a police officer conducts a self-initiated stop during his patrol. The second source of a stop occurs when a police officer responds to calls for service from the public. These calls for service are communicated to a police officer via police radio, are assigned a job number, and are generally considered more urgent due to the immediacy of the assistance request. Logically, police officers' discretion with respect to whether to initiate an interaction is more limited during these "radio runs."[40]

Nonetheless, calls for service do not have to be equal in their severity and immediacy. Some calls could involve minor public infractions or delayed reports of past crimes. These calls, due to their lesser importance, allow for a greater degree of effort adjustments.[41] One way to narrow down the list of tasks which further deprive police officers of the latitude to shirk is to consider the outcome of the stop. Service calls resulting in arrests are, on average, an indication of their importance and immediacy. Therefore, to estimate this effect, model (3) is estimated, which takes as its unit of analysis a stop involving arrest:

$$(3)\quad RadioRun_a = \beta_L LastTwoWeeks_a + \boldsymbol{X}'_a\gamma + \varphi_{ymp} + \varepsilon_a$$

[40] One of the assigned duties to police officers is "monitor portable radio" which further limits the discretion even about being informed of the existence of service calls (Patrol Guide).

[41] Reporting a crime which happened days ago might cause an officer to delay his arrival at the scene. Reported acts that are not readily evident in their illegality, or crimes that are minor, might produce lower quality of investigative involvement on their part of the police officer.

The dependent variable is $RadioRun_a$, which equals one if arrest a was made due a service call and zero if it was made due to self-initiation by an officer. Given the binary nature of the dependent variable, equation (3) is a linear probability model.

Given that arrests resulting from service calls are harder for an officer to avoid than arrests originating from an officer-initiated interaction, the probability of an arrest being generated due to a "radio run" would be higher in the second half of a month if police officers were indeed voluntarily scaling down on their efforts.[42] This conclusion relies on the assumption that the fraction of crime discovered through patrolling in the second half is not lower than in the first half[43] and that the fraction of crime reported by the public does not increase in the second half. This assumption is not necessarily true. It is possible that during the earlier days of the month different types of crimes are committed. These types might differ in their discovery and reporting rates from the rest of crimes. Controlled substances related offenses are prime examples of this. If early-in-a-month welfare disbursements induce recipients to purchase these substances, more illegal transactions and drug consumption may happen in the plain view of a police officer, leading to a higher general discovery rate. This will lead to a higher number of self-initiated apprehensions early in the month. Such offenses are also likely to have a lower reporting rate by the public due its victimless nature.[44] If there is a lower incidence of substance use in the second half of a month, the general report rate by the public will be higher. This would bias the interpretation of results that show a higher fraction of "radio run" arrests occurring later in the month by erroneously attributing the full effect to the reduced efforts narrative.

[42] Arrests are used as a proxy for importance of the call. A similar analysis was done for summonses as well. Although the coefficient on this analysis was positive as expected, it had a large standard error; therefore, nothing conclusive can be stated. It is not unexpected given the fact that these summonses ordinarily involve simple quality-of-life violations and fall short of the severity of the violations involving arrests.

[43] It is important to stress the difference between *discovered* and *apprehended*. It is the goal of this paper to demonstrate a lower apprehension rate in the second half. Discovered crimes represent all visible crimes to the police officers under a constant amount of efforts without making a statement on whether they are formally dealt with.

[44] 18% of all arrests in the data were a result of service calls by the public compared to only 7.5% of arrests involving controlled substances.

TABLE 1.7: OLS ESTIMATES FOR SERVICE CALLS RESPONSES

Explanatory variables	Among arrested	Among non-criminal stops
Last two weeks	0.00761***	0.00213**
	(0.00199)	(0.000978)
Constant	0.164***	0.213***
	(0.0388)	(0.0168)
Observations	280,721	4,097,359

Notes: Other included controls are temperature, lunar luminosity, rainfall, snowfall, daylight, dummies for days of the week, holiday dummies, and month-year-precinct fixed effects. Standard errors are clustered at the precinct level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To avoid conflating the above effect with the discretionary reduction in efforts, equation (3) is reconsidered for the subsample of stops which did not record any criminal activity. This, of course, comes at the expense of identifying which calls were potentially important, hence partially lowering the ability to determine the extent to which police officers are able to exhibit discretion in how they deal with calls.

Table 1.7 presents the results of equation (3). The first column looks at the probability that arrests were generated as a result of service calls as opposed to self-initiative. The coefficient of interest shows a 0.0076 percentage point increase in such arrests during the last two weeks of the month, and is statistically significant at the 1% level. Given that 18.5% of all arrests in the first two weeks were a result of service calls, arrests during the second half have a 4.1% higher probability of being radio-call generated. The second column considers stops without criminal outcomes. Considering that 23.1% of such stops during the first two weeks of a typical month arose from service calls, the coefficient on the last two weeks translates to a 0.9% higher probability of a stop being radio-call generated in the second half of the month.

These results show that a higher fraction of non-criminal stops and arrests are generated as a result of service calls—calls for assistance that are harder to ignore—during the last two weeks. This conclusion is consistent with less efforts being exerted in the last two weeks of the month as captured by attenuated monthly cycles in activities that are harder to skip due to reduced leeway in officers' ability to practice discretion.

C. *Welfare Differences Across Precincts*

The results in the preceding subsections demonstrate that efforts are reduced later in the month as indicated by a demonstrated greater aversion to difficult or less pressing tasks as a month advances. These results, however, do not rule out the possibility that police officers are simply working more in earlier days, reflecting higher returns on their efforts due to a larger supply of criminals engendered by the disbursement of benefits. This rational behavior would not require the existence of front-loading efforts as conscious precautionary measures.

To test whether this economic decision on the part of police officers drives all of the empirical results, precincts are divided into two groups of high and low welfare participation by their residents. To identify which precincts are characterized by lower or higher welfare participation, a variable is constructed which calculates the fraction of households receiving welfare within each precinct.

The data on welfare participation comes from the 2000 U.S. Decennial Census and American Community Survey (ACS) 5-year estimates for the years 2005–2009 (the earliest available 5-year estimates) and 2010–2014. Some of the information collected in the 2000 U.S. Census is incomparable to the information gathered in the ACS because of "differences in the universe, question wording, residence rules, reference periods, and the way in which the data are tabulated" (U.S. Census Bureau). A direct comparison of variables on welfare participation is possible only for public assistance[45] and SSI.[46] The values from the ACS 5-year estimates were attributed to their middle years (2007 and 2012) for the regression analysis. The values on welfare participation for the years 2003–2006, 2008–2011, and 2013–2016 were calculated using linear interpolation between the values for the years 2000, 2007 and 2012.

For robustness, analyses were also performed using an alternative method. Values for welfare participation from the 5-year estimates were assigned to each of the years in the 5-year intervals, rather than just the middle year. That is, the value of welfare participation assigned to a particular precinct was constant over the years 2005–2009 and 2010–2014, as based on the 5-year estimates. In this alternative case, linear interpolation was utilized only for the years 2003, 2004, 2015, and 2016. The results (not shown here) were virtually identical.

The above data was obtained on census tract levels. Due to their larger geographical areas, precinct-level jurisdictions encompass many census tracts. In addition, some of the census tract boundaries encompass multiple precincts. Given this non-bijective association between the boundaries of tracts and precincts, ArcGIS was utilized for geographical matching. The data on geographical coordinates of NYPD precincts' and tracts' boundaries come from the NYC Department of City Planning and the US Census Bureau, respectively.

Precinct-level variables on welfare participation were created by identifying the fraction of a tract's area belonging to a particular precinct, then using this fraction as a weight for variables collected at the tract level, iterating the process for each of the remaining tracts that have common area with a

[45] "Public assistance income includes general assistance and Temporary Assistance for Needy Families (TANF) … [this] does not include Supplemental Security Income (SSI)" (U.S. Census Bureau, 2000 Census). Although "ACS/Census Table Comparison" states that the public assistance variable is identical in its comparison across years and surveys, denoted P064 to B19057 in the respective resources, the Census Bureau definitions of public assistance appear to differ in later versions. "Public assistance refers to assistance programs that provide either cash assistance or in-kind benefits to individuals and families from any governmental entity. There are two major types of public assistance programs; social welfare programs and social insurance programs … [some] of the major federal, state, and local social welfare programs are: Supplemental Security Income (SSI), Supplemental Nutritional Assistance Program (SNAP), … , General Assistance (GA)…" https://www.census.gov/topics/income-poverty/public-assistance/about.html. Further reading suggests that even social security is included. Overall, the comparability of variables measuring "public assistance" across these surveys is inconsistent.

[46] Public assistance corresponds to the variables P064 and B19057 in the 2000 Census and ACS, respectively. SSI income corresponds to the variables P063 and B19056 in the 2000 Census and ACS, respectively.

precinct, and aggregating their values. Lastly, the estimated number of households receiving welfare is divided by the estimated total number of households in a precinct, producing a variable that measures the fraction of households receiving welfare for each precinct.[47]

Using the above precinct-level information, the binary variable $HighWelfare_{yp}$ was constructed indicating whether a precinct p was considered to have a high or low welfare participation in year y. The division was based on the average fraction of all households in New York City receiving welfare assistance in a particular year. Therefore, $HighWelfare_{yp}$ is equal to one for precincts where the fraction of households receiving welfare exceeds the sample mean in a particular year. Delineating precincts in such a way allows for the consideration of temporal changes in welfare participation rates from year to year.

The above classification was also performed separately based on information on public assistance, which includes TANF and SNA along with "general assistance," and SSI. It is not clear from the information provided whether a household received only public assistance, only SSI, or both. In addition, there appears to be ambiguity in the comparability of the public assistance variables used in the 2000 Census and the ACS, as discussed in footnote 45. To avoid double counting and allowing for reliable comparison across precincts, output of the empirical analysis will present results using both types of welfare assistance.[48]

Table 1.8 presents summary statistics for welfare variables. Average welfare participation across all years and precincts ranges from 5.2% to 7.8%. Within a specific precinct, SSI participation goes as high as 22.9% in the year 2016. About 38% of all precincts are considered high welfare

[47] The variable transformation was done through the following formula:

$$Welfare\ Participation_{j,y} = \frac{\sum_i \left(W_{i,y} \frac{Area(i \cap j)}{Area(i)}\right)}{\sum_i \left(HH_{i,y} \frac{Area(i \cap j)}{Area(i)}\right)}$$

Where $Welfare\ Participation_{j,y}$ is the fraction of total households, HH, receiving assistance from the government, W, in precinct j throughout year y. $Area(i \cap j)$ is the shared area between precinct j and census tract i.

[48] The two measures appear to capture the welfare characteristics of precincts somewhat similarly. The correlation between the two welfare classifications is 0.71.

TABLE 1.8: SUMMARY STATISTICS FOR PRECINCT–LEVEL WELFARE PARTICIPATION

Variables	Mean	SD	Min	Max
Supplemental Security Income (SSI)	0.0775	0.0466	0.00609	0.229
High welfare precinct	0.387	0.487	0	1
Public Assistance	0.0523	0.039	0.00294	0.209
High welfare precinct	0.389	0.487	0	1

Notes: Public assistance includes welfare from TANF, SNA, and "general assistance." High-welfare precincts have a mean participation rates of 12.6% and 8.9% for SSI and public assistance, respectively. Low-welfare precincts have a mean participation rates of 4.7% and 2.8% for SSI and public assistance, respectively.

reflecting skewness in the distribution of welfare intensity.

The following regression specification is used to analyze whether the cycles differ between precincts with lower and higher welfare participations:

$$(4)\quad Y_{dmyp} = \beta_L LastTwoWeeks_{dmyp} + \beta_D (LastTwoWeeks \times HighWelfare)_{dmyp} + \boldsymbol{X}'_{dmyp}\gamma + \varepsilon_{dmyp}$$

This specification is identical to equation (1), with the only difference arising from the interaction variable $LastTwoWeeks \times HighWelfare$. Each of the six dependent variables from equation (1) are considered.

The standalone indicator variable for high-welfare precincts is not included in equation (4) due to it being perfectly collinear with the month-year-precinct fixed effects. Given this specification, the coefficient on $LastTwoWeeks$, β_L, captures the difference in activities between the second and first halves of a month for low-welfare precincts, while the coefficient on the interaction variable, β_D, captures the difference in the effect of $LastTwoWeeks$ arising from precincts belonging to the high-welfare category. Both of these coefficients are of interest to this section's analysis as the former reveals if the cycle still persists in the regions with low welfare participation rates and the latter identifying if the cycle is dependent on the welfare participation intensity.

If the cycles are observed exclusively in precincts with higher welfare participation rates, then welfare-induced-crime and consequent efforts responding to such crime might be the driving forces behind the results. Alternatively, it could be that these high-welfare precincts have disproportionally higher precinct-specific quotas or performance standards (or low-welfare precincts do not have quotas in the first place), corresponding to higher crime statistics in these precincts, which could produce similar results. Although it is not easy to disentangle these two explanations from each other, it is not necessarily needed as long as the intra-month cycles of police activities are also present in the lower welfare precincts. This would suggest a presence of other behavioral mechanisms, such as precautionary measures, behind front-loading of efforts.

Table 1.9 presents results from estimation of equation (4) using SSI and public assistance information. Given the similarities across these two variables on welfare participation, the discussion focuses mainly on the results based on SSI. The difference in the number of observations across the columns largely follows the explanation of the difference in the number of observations found in the main results, as described in Section V. Additional differences in this exercise arise from the omission of the 22nd precinct section due to its jurisdiction exclusively covering Central Park, a non-residential area where the relevance of welfare participation is not applicable.

The first row shows that precincts with lower rates of welfare participation evince differences in police activity rates between the first and second halves of the month. This is true across each of the various dependent variables under consideration, and demonstrates that even when high-welfare precincts are excluded, the principle result of decreasing police apprehensions persist. The "first-of-the-month" confounder, therefore, is not likely to be the driving force behind the results presented in Section V. This conclusion is further corroborated by the second row of coefficients in Table 1.9. These coefficients test for whether the differences in apprehension cycles are amplified by the intensity

TABLE 1.9: OLS ESTIMATES USING WELFARE PARTICIPATION BY PRECINCT

Explanatory variables	Arrests	Summonses	Non-criminal Stops	Financially Motivated Arrests	Violent Arrests	Controlled Substance Arrests
Using Supplemental Security Income (SSI)						
Last two weeks	-0.00347***	-0.00225***	-0.00085***	-0.00183***	-0.00188**	-0.00439***
	(0.000469)	(0.000402)	(0.000234)	(0.000634)	(0.000809)	(0.000769)
(Last two weeks)×(high-welfare)	-0.000066	-0.000232	-0.00065**	0.000458	0.00135	-0.000974
	(0.000644)	(0.00067)	(0.000316)	(0.000954)	(0.00111)	(0.00104)
Constant	0.0286***	0.0324***	0.027***	0.0293***	0.0104	0.0172*
	(0.00527)	(0.0058)	(0.00316)	(0.0106)	(0.0101)	(0.00922)
Observations	336,280	298,144	352,324	276,304	212,436	260,764
Using public assistance						
Last two weeks	-0.00319***	-0.00223***	-0.000849***	-0.00172***	-0.00163**	-0.0038***
	(0.000492)	(0.000431)	(0.000239)	(0.000611)	(0.000771)	(0.000717)
(Last two weeks)×(high-welfare)	-0.000771	-0.00028	-0.00065*	0.000188	0.000699	-0.00237**
	(0.000597)	(0.000629)	(0.000351)	(0.00102)	(0.00112)	(0.00102)
Constant	0.0286***	0.0324***	0.027***	0.0293***	0.0104	0.0172*
	(0.00527)	(0.0058)	(0.00316)	(0.0106)	(0.0102)	(0.00923)
Observations	336,280	298,144	352,324	276,304	212,436	260,764

Notes: Other controls include temperature, lunar luminosity, rainfall, snowfall, daylight, dummies for days of the week, holiday dummies, and month-year-precinct fixed effects. Standard errors are clustered at the precinct level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of welfare participation. For the specification using SSI information, only one coefficient is statistically significant across any of the six columns. From the specifications using public assistance information, another one emerges. This suggests that the welfare intensity is not entirely responsible for these cycles.

Examining the first two columns, it is apparent that arrests and summonses in lower welfare precincts follow a cycle that is almost identical to the ones found using all precincts (presented in Table 1.3). The difference in magnitudes is miniscule, corresponding to differences of 0.1% and 3.9% for arrests and summonses, respectively. Large standard errors on the interaction terms prevent any conclusion on the possibility of larger cycles in high-welfare precincts.

The third column, which uses non-criminal stops as the dependent variable, depicts a somewhat different story. Lower welfare precincts have an attenuated cycle because higher welfare precincts experience an additional decrease of 0.00065 percentage points in non-criminal stops during the last two weeks of the month. This drop is 76.5% larger compared to the one experienced by the lower welfare precincts. Although the percentage difference appears large, it is worth keeping in mind that these unproductive stops exhibited the weakest cycle, with a difference of 3.5% between the two halves of a month. Notwithstanding this smaller variation, it appears that unproductive efforts undergo a larger decline in the later days of the month within high-welfare precincts. This could potentially be explained by additional aversion towards policing these areas by officers, due to their disorder, once the numbers are met.

The fourth and fifth columns differentiate arrest rates across financially driven and violent-in-nature crimes, respectively. The coefficients are larger (12.7% and 44.4%, respectively) for lower welfare precincts than the ones presented in Table 1.3. However, the absence of statistical significance on the interaction term precludes any definite conclusion. The absence of a discernable effect across low and high-welfare precincts for financially-motivated crimes is of particular importance given the previously mentioned literature linking the incidence of such crimes to the timing of welfare payments. The absence of any such association here further discredits the "first-of-the-month" explanation.

The sixth and final column considers arrests for controlled substance crimes. For the low-welfare precincts, a cycle pattern in police efforts persists, albeit with a 8.7% lower magnitude compared with Table 1.4. The results in this column suggest a major divergence between the results derived using SSI versus public assistance. Using public assistance information, precincts with higher welfare participation rates experience an additional 62.3% drop-off in drug-related arrests during the last two weeks of the month. This is plausible considering the financial constraints face by welfare recipients by the end of the month. As police officers scale down their efforts, and fewer people abuse drugs, fewer drug-related arrests will be manifested. This last column shows that, as expected, welfare-induced crime still plays a role in explaining some of the empirical results.

The analysis of this subsection suggests that welfare difference across precincts do not explain away the main empirical results. Cycles in arrests, summonses, and non-criminal stops appear to be driven in part by cycles in police efforts. Furthermore, allocations of efforts are not solely contingent on the temporality of their returns. If they were, larger cycles would have been observed in precincts with higher fractions of households receiving assistance from the government.

VII. Conclusion

Analysis of the SQF data establishes the existence of criminal apprehension cycles in New York City and allows for the magnitude of these cycles to be quantified. This exercise reveals an intertemporal disparity in the way that members of the police force and the community interact. More arrests, summonses, and non-criminal stops are conducted in the earlier days of a typical month. When arrests are disaggregated along several dimensions, a similar trajectory is revealed for financially motivated, violent-in-nature, and controlled-substance-related crimes.

The findings highlight the role of behavioral mechanisms in how police officers determine their optimal allocations of effort in the presence of formal performance standards or a system of quotas. While these two evaluative regimes are subtly different in what they require of officers, "[i]n terms of the effect on police operations, the two ideas are virtually indistinguishable" (Sparrow 2016, 68).

Faced with a requirement to produce a certain number of summonses and arrests by the end of a month, police officers preproperate efforts in order to minimize the risk of not meeting expectations. Following the completion of a satisfactory performance, they are faced with fewer incentives to maintain high efforts, rendering police officers to reduce their work load in the later days of the month. These conclusions are supported by the evidence of discretionary effort adjustments on the part of police officers. This evidence includes greater aversion to difficult and discretionary tasks during the last two weeks. Furthermore, the main empirical results are not explained by the differences in the concentration of welfare recipients across police precincts.

This paper does not attempt to entirely rule out intra-month variation in crime as the mechanism that generates this cycle. In general, however, it demonstrates the existence of an intra-month criminal apprehension cycle that is driven, at least in part, by the temporal disparity in efforts undertaken by NYPD officers.

A concern over external validity is warranted. The findings of this paper are concentrated within New York City, reflecting the behavior of NYPD police officers. The attributes of this police organization and the characteristics of its workers may depart from the standards of other occupations, including those of other police departments. Notwithstanding this concern, the novel finding of the front-loading of efforts (and the expected finding of effort reductions to lower-return tasks) might manifest itself in other organizational settings whose participants face a similar incentive structure of uncertainty, deadlines, and corresponding returns on performance.

This work adds to the literature on the dynamic allocation of labor efforts by presenting evidence of preproperation and discretionary reduction in efforts. It also suggests a potential pitfall faced by future researchers studying intra-month relationships who fail to account for their phenomena of interest potentially being influenced by the intertemporality of effort allocation. This pattern is of particular relevance for researchers investigating police or criminal behavior.

Furthermore, this research reveals potentially concerning welfare implications that stem from the existence of public policies that mandate or expect a minimum level of productivity from law enforcement. Such policies induce behavioral responses not consistent with an equal distribution of police activities over time. Such a status quo might engender suboptimal police protection during the later days of the month and/or excessive policing in the earlier days. The former could be capitalized on by savvy criminals who strategically allocate their criminal activities towards the days with a predictably lower police presence, whereas the latter might delegitimize law enforcement institutions in the eyes of the public. A full consideration of such effects is essential for designing and implementing policies concerning performance standards that encourage effective policing procedures.

Chapter 2

One Man's Treasure is Another Man's Salvage: The Criminal Response to a Change in Missouri's Salvage Law

I. Introduction

Crime inflicts a substantive social cost. Anderson (2012) estimates that in the U.S. alone, these costs amount to $3.2 trillion, or $1.7 trillion net of involuntary transfers between victims and criminals, in year 2012.[49] Contending this number (and complementing to it), the U.S. is a global leader in rates of incarceration with prison populations of 716 per 100,000 of the national population (Walmsley, 2013).

Because of the social costs engendered by crime, the application of economic principles to the causes and consequences of crime emerged as an active field of research as early as Becker (1968) and Ehrlich (1973) with the application of a rational choice model to explain why people commit crimes. In its basic form, an individual commits a crime if the subjective expected benefits of a crime exceed the expected costs. At the broadest level, the factors that shape this decision include the potential gains to be obtained from committing the crime, the likelihood of criminal apprehension and the associated costs, and the foregone net benefits from non-criminal activities.

Many of the public policies designed to deter crime directly attempt to reduce the supply of criminals by either increasing the probability of capture (Di Tella and Schargrodsky, 2004; Prescott and Rockoff, 2011; Doleac, 2017), increasing the severity of punishment (Levitt, 1998; Drago et al., 2009; Hansen, 2015), or reducing the returns to crime (Vollaard and van Ours, 2011; Vollaard and van Ours, 2014).

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[49] In his calculation of the costs of crime, Anderson (2012) "include(s) all costs that would not exist in the absence of illegal behavior under current U.S. law."

Other public policies indirectly deter crime by enhancing the availability of alternative economic activities (Gould et al., 2002; Lin, 2008; Deming, 2011). Conversely, some policies inadvertently bolster the incentives to commit crimes (DiNardo and Lemieux, 2001; Lott and Whitley, 2001; Hornik et al., 2008; Iyengar, 2008).

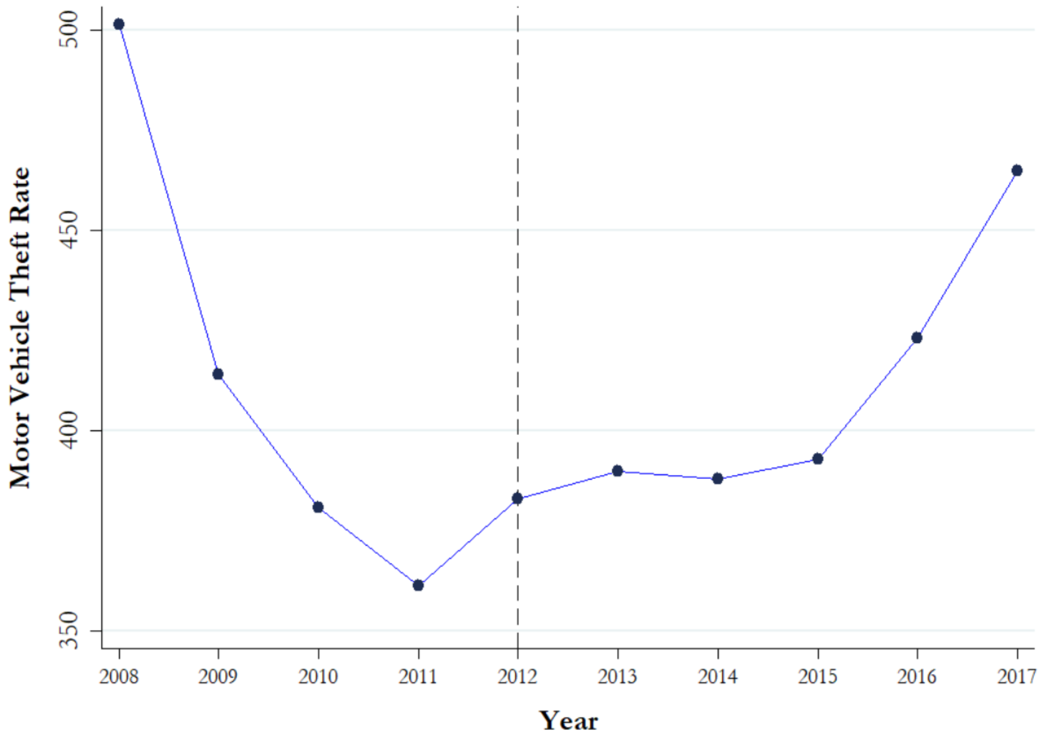
One such policy that gave rise to such unintended consequences was the 2012 inclusion of a clause into Missouri's House Bill 1150 which allowed for the sale of inoperable vehicles ten years or older to salvage yards without the seller possessing title. When the new law went into effect, it altered the economic incentives underlying the theft of older vehicles by facilitating the sale of stolen vehicles, thereby making such crime more lucrative.

The purpose of this paper is twofold. First, this paper formally tests for a causal relationship between the 2012 change in Missouri's law on the rate of motor vehicle theft (MVT). Second, having established the causal relationship between the change in law and rates of MVTs, the magnitude of the effect on rates of MVT is quantified.

Using the FBI's Uniform Crime Reporting Program data, Figure 2.1 plots the trajectory of MVTs in Missouri over the years of 2008 to 2017. Following years of steady decline in rates of MVT, an abrupt spike is evident for 2012 and is followed by a reversal in the trend. Many of Missouri's law enforcement agencies blame the 2012 policy change for this phenomenon.[50] Notwithstanding the ostensible association, the temporal relationship alone is not a proof of causality. Rates of MVT in Missouri might have followed broader national trends, or could have resulted from other factors that had broader effects on a wide array of property crimes.

[50] Sam Zeff, "Why A Missouri Scrap Metal Law Is To Blame For Soaring Car Thefts In Kansas City," KCUR 89.3 Radio, Kansas City, MO: KCUR, Nov 15, 2018. http://www.tinyurl.com/y899ez5s.

FIGURE 2.1: MOTOR VEHICLE THEFTS PER 100,000 IN MISSOURI



Notes: Information on motor vehicle thefts comes from the FBI's UCR. The vertical line indicates the year of the change in Missouri's law. The annual rate is calculated for the balanced sample of cities, c, in Missouri during years 2008−2017, following the formula: $100{,}000(\sum_c Motot\ vehicle\ theft_c)(\sum_c Population_c)^{-1}$.

Using a panel of crime data from the FBI's Uniform Crime Reporting Program and time-series crime data from the National Incident-Based Reporting System, difference-in-difference approaches are employed to help establish the causal effect of the change in law by accounting for contemporaneous trends in MVT across other states and by accounting for contemporaneous trends in other types of larceny-thefts. These techniques provide for more definitive causal inference and allow for the quantification of the short and long-run effects arising from the change in Missouri's law.

The results support the causal impact of the 2012 change in law on the increase in rates of MVT in Missouri. The estimates suggest an increase of 8% to 14% in rates of MVT within one year of the change in law. The effect continues to grow after one year with the rate of MVT increasing to 30% to 43% within five years after the change.

These results are of particular interest to policymakers in the state of Missouri. Although the specific details of this study relate to Missouri and MVT, the effects on crime arising from a failure to provide appropriate legal safeguards for transactions in secondary markets are more general.

Furthermore, this paper contributes to the literature on changes in economic incentives—particularly the emerging research studying the impacts of changes in the returns to criminal activities—on observed crime levels (Reilly and Witt, 2008; Harbaugh et al., 2011; Brabanec and Montag, 2018; Draca et al., 2018). The economic returns to crime has been "… the most understudied element of crime determinants that arise from the basic economic model of crime" (Draca and Machin, 2015), presumably because of "… the practical difficulty in eliciting good information on the actual or potential returns from crime" (Draca et al., 2018). This case study from Missouri offers a unique opportunity to explore the effects of an exogenous change in the resale potential of stolen older vehicles.

The remainder of the paper is organized as follows. The next section provides institutional information on the change in Missouri's law and briefly discusses the changes in economic incentives. Section III describes the data. Section IV discusses the primary empirical methodology used to establish the causal relationship between the change in law and Missouri's rates of MVT. Section V presents the main results. Section VI concludes.

II. Institutional Background and Economic Incentives

In August 2012, Missouri House Bill 1150 went into effect which, among other items, repealed Section 301.227 of the Missouri Revised Statutes (RSMo) under the chapter on the "Registration and Licensing of Motor Vehicles." Enacted in its place was a revised version stipulating the legal process for the sale of inoperable[51] vehicles that are "at least ten model years old."[52] The adoption of Section 301.227.9 allowed for the purchase of qualified vehicles by scrap metal operators without having received the title (or other legal substitutes), provided that the buyer verifies that the vehicle is not subject to a lien. Upon purchase of a vehicle, a buyer must submit a copy of the seller's state identification and a bill of sale to the Missouri Department of Revenue within 10 days. Furthermore, it stipulates similar procedures for the sale of vehicles 20 years and older, with the exception that in these cases the buyer is not required to verify the lien status on the vehicle.[53]

Such a change in the law alters the economic incentives underlying the theft of older vehicles. It raises the expected criminal returns by liberalizing the market for stolen vehicles by facilitating their purchase—absent of any verification of ownership—by salvage yards. Provided that the majority of car thieves have some existing relation with a salvage yard (Mullins and Cherbonneau, 2010), the change in law influentially enhances the dynamics between car thieves and salvage buyers. The law also eliminated the cost to car thieves of forging the title. Considering that "most scrapped cars fetch $200 to $500,"[54] the prior full set of costs might have been prohibitively high for a large share of older vehicles.

Other states have similar relaxed legal provisions for salvaging older vehicles, however, they offer additional safeguards against the sale of stolen vehicles such as requirements for VIN verifications by local government agencies, a period of delay before salvaging, or additional

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[51] Inoperable is defined as "[a] motor vehicle that is in a rusted, wrecked, discarded, worn out, extensively damaged, dismantled, and mechanically inoperative condition and the vehicle's highest and best use is for scrap purposes." Cpl. Nate Bradley with the Missouri Highway Patrol states that: "crooks will simply take off a wheel and that is enough for some scrap yards to judge the car inoperable."
[52] MO Rev Stat § 301.227 (2012). See Appendix (B) for the exact language of the revised provisions.
[53] Representative Kevin Engler, who authored the legislation, did so with the intent of making it easier for rural car owners to dispose of their derelict vehicles.
[54] Sam Zeff, "Why A Missouri Scrap Metal Law Is To Blame For Soaring Car Thefts In Kansas City," KCUR 89.3 Radio, Kansas City, MO: KCUR, Nov 15, 2018. http://www.tinyurl.com/y899ez5s.

documentation connecting the seller to the vehicle being sold—typically copies of the registration or proof of insurance under a name that matches the seller's ID.[55]

In 2018, Kansas City, Missouri adopted similar additional safeguards as a result of Ordinance 180606 after officials cited an increase in auto thefts and "a correlation between auto theft, theft of metal and the towing, salvage yards and secondary metal recycling industries."[56]

III. Data

The crime data used in this paper comes from two sources: the FBI's Uniform Crime Reporting (UCR) Program and the FBI's National Incident-Based Reporting System (NIBRS). Both the UCR and NIBRS data are voluntarily reported to the FBI by local law enforcement agencies. The data on iron and steel scrap prices comes from the U.S. Bureau of Labor Statistics.

Empirical estimations using each set of data will consider two alternative time intervals. First, to estimate the short-run effects of the 2012 change in Missouri's law, the sample will be based on the time periods immediately before and after the policy treatment. Second, to analyze the long-run effects of the policy, and to assess prior-to-treatment trends, the sample will cover a more extended period of time.

55 States that maintain similar laws include Alabama, Georgia, Indiana, Iowa, Kentucky, Louisiana, Mississippi, New York, North Carolina, Ohio, South Carolina, and Tennessee. Steve Levetan, "State Laws Dealing with End-of-Life Vehicles and NMVTIS," *American Association of Motor Vehicle Administrators.* https://www.aamva.org/uploadedFiles/MainSite/Content/EventsEducation/Event_Materials/2016/2016_Workshop_and_Law_Institute/LEVETAN%20Salvage,%20Damaged,%20Junk%20Vehicles.pdf.

56 The correlation cited is found in the "Fact Sheet" of the Amendment to Chapter 54 that was introduced on August 16, 2018, which states: "[s]tate Statute 301.227.9 took effect on August 28, 2012 and it allows a secondary metal recycler or salvage yard business to purchase or acquire a motor vehicle that is inoperable and is at least ten model years old without receiving the original certificate of ownership, salvage certificate of title, or junking certificate from the seller of the vehicle or parts. Since this law went into effect Kansas City has seen a 14% increase in auto theft."

A. UCR

The UCR data is compiled annually for each reporting agency, and tallies total counts of each offense in the Part I and Part II categories. The analyses of this paper employ the information on motor vehicle theft (MVT)[57], larceny-theft, and city populations from each reporting agency.[58]

Many local agencies do not report consistently, in which cases the FBI imputes missing observations when aggregating agency-level statistics to the county and state levels. This produces large measurement errors leading some researchers to conclude that "until improved methods of imputing county-level crime data are developed, tested, and implemented, they should not be used, especially in policy studies" (Maltz and Targonski, 2002). To avoid this issue, this paper uses city-level data as directly reported by the cities' law enforcement agencies and makes no imputations for missing values.

The sample is constrained to only include cities that report in each year during the range of years examined. This constraint is critical for the extended time period model in which observations in each year are compared against a referent year—this ensures that the results are not driven by changes in the sample.[59]

The short-run analysis is based on the years 2011 to 2013 (the years around the 2012 treatment year).[60] In 2012, there were a total of 9,484 police city-agencies reporting whose jurisdictions covered approximately 198 million people across the U.S. Of these cities, 7,942 consistently report each year

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57 It would be ideal if the data on MVT included the age of each stolen vehicle, but unfortunately, this is not the case.
58 See Appendix (C) for definitions of each crime.
59 This rule also minimizes measurement errors if the excluded non-reporting police agencies are characterized by changes in internal procedures or overall inconsistencies in productivity.
60 The law changed in August of 2012, therefore, not all of the 2012 year was "treated." Year 2013 is included to allow for more time since the change.

TABLE 2.1: SUMMARY STATISICS FOR CITIES

Variables		Mean	SD	Min	Max
2011−2013 Sample					
Missouri	N=404				
Population		9,046	31,538	52	465,514
MVT (per 100,000)		148.3	216.6	0	2,551
Larceny-theft (per 100,000)		1,968	1,771	0	16,667
Midwestern states (excluding MO)	N=1,607				
Population		20,713	80,746	229	2,720,554
MVT (per 100,000)		102.1	157.8	0	5,628
Larceny-theft (per 100,000)		1,908	1,792	0	52,147
U.S. States (excluding MO)	N=7,538				
Population		24,247	130,016	5	8,396,126
MVT (per 100,000)		157.9	1,527	0	105,405
Larceny-theft (per 100,000)		2,372	45,831	0	6,850,000
2008−2017 Sample					
Missouri	N=292				
Population		11,246	37,126	93	484,948
MVT (per 100,000)		174.7	239.5	0	4,481
Larceny-theft (per 100,000)		2,156	1,814	0	34,873
Midwestern states (excluding MO)	N=801				
Population		24,833	108,694	449	2,848,431
MVT (per 100,000)		111.3	147.6	0	2,772
Larceny-theft (per 100,000)		1,955	2,245	0	85,011
U.S. States (excluding MO)	N=5,150				
Population		29,127	157,112	5	8,616,333
MVT (per 100,000)		187	1,889	0	177,778
Larceny-theft (per 100,000)		2,602	57,456	0	8,062,500

Notes: N=number of cities. Balanced panel of cities in each sample using the FBI's UCR. Larceny-theft includes all other types of larceny listed as Part I offenses.

between 2011 and 2013. These cities encompass roughly 186 million people and will comprise the sample used to estimate the immediate changes in Missouri's rate of MVT following the policy change.

The long-run analysis extends the sample to the years between 2008 and 2017.[61] There are 5,442 cities that report in each year of this interval with a total of 152 million residents (in 2012).

[61] The choice for 2008 as a starting year is because Kansas City, MO did not report in year 2007. The year 2017 is the last year of available UCR data.

Table 2.1 contains summary statistics for the key variables used in the main estimations, broken down across both of the time periods analyzed. Some of the rate variables have large maximum values due to low populations.[62] All of the regressions were re-estimated using only the cities with populations exceeding 2,499 residents, which did not qualitatively change any of the results (not shown in tables).[63]

B. NIBRS

The unit of observation in the NIBRS data is a criminal incident reported to police. Such incidents are classified as corresponding to a broad range of potential offenses, allowing for a discrete division between MVT and all other types of thefts (OTT) that are likely to be independent of MVT. The OTT category includes all of the larceny-theft offenses in Group A (as defined by the FBI) aside for the thefts from motor vehicle, and theft of motor vehicle parts or accessories.[64] Since these crimes involve a vehicle, they might be correlated with the instances of MVT.[65] Using this data, MVT and OTT crime counts are aggregated into monthly time intervals to reduce bias arising from time-series autocorrelation between adjacent days.

The short-term analysis examines monthly crime rates for 12 months before and 11 months after August, 2012.[66] The years considered in the extended analysis span from 2010 to 2016.[67] Only seven Missouri cities consistently report statistics for each month of this period, and among them,

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[62] City of Industry, California had a rate of MVT in 2012 of 105,405 per 100,000 residents, suggesting that a car is statistically guaranteed to be stolen. Humor aside, the incredible rate can be attributed to City of Industry's status as an industrial suburb with a low population but a large number of daily commuters into the city.

[63] These results are available from the author upon request.

[64] The OTT category includes the following types of larceny-thefts: pocket-picking, purse-snatching, shoplifting, theft from building, theft from coin-operated machine or device, and all other larceny.

[65] MVT could be a substitute to the theft of auto parts and a failed MVT could be a complement to theft of the contents of a vehicle.

[66] From August, 2011 to July, 2013.

[67] 2010 is the first year available for Kansas City and the year 2016 is the last year for which the NIBRS data is available.

TABLE 2.2: SUMMARY STATISTICS FOR KANSAS CITY, MO

Variables	Mean	SD	Min	Max
Population	468,868	6,471	461,458	483,191
MVT (per 100,000)	65.5	10.8	45.8	88.1
OTT (per 100,000)	136.8	19.9	96.3	177.3

Notes: Dates: July, 2010−July, 2016. Data is based on the FBI's NIBRS. OTT−all other larceny-theft crimes in Group A offenses except for thefts from motor vehicle and theft of motor vehicle parts or accessories.

Kansas City was responsible for 95% of all MVT in 2010.[68] Because of this large share, the analysis exclusively focuses on Kansas City, Missouri.

Table 2.2 reports summary statistics for Kansas City's population, MVT and OTT rates. The MVT rate of 65.5 corresponds to 786 stolen vehicles each year per 100,000 residents, which is above Missouri's average but not atypical for a large city in the FBI's UCR data. The number of instances of OTT are approximately double the number of instances of MVT.

IV. Methodology

As shown in Figure 2.1, the downward trend in MVTs reversed around the time of the change in Missouri's law. This relationship is not necessarily causal, however. The following empirical models help establish the nature of causality, in addition to providing estimates of the magnitude of the policy's effect.

Two distinct difference-in-difference models are estimated. The first model explores annual changes in cities' rates of MVT by exploiting variation across states and assuming that only cities in Missouri received the treatment in 2012. The second model exploits the variation in MVT relative to the OTT throughout the sample period for Kansas City, Missouri.

[68] The seven cities are: Chillicothe, Grain Valley, Kansas City, Laclede, Oak Grove, St. Peters, and Ste. Genevieve.

A. *Causal Inference Using City-Year Observations from UCR data*

The first model relies on the critical assumption that US cities located outside of Missouri present suitable counterfactuals relative to cities within Missouri. That is, absent the 2012 policy change, MVT in cities in Missouri would follow the path of cities outside of Missouri. This may not be the case if the cities in other states experienced confounding shocks to the trajectories of MVT rates during the period analyzed, or if rates of MVT adhered to a different trend prior to the policy change. It is infeasible to directly control for the full set of idiosyncratic confounding shocks or eliminate each city that does not yield a valid comparison. So long as cities outside of Missouri are not systematically subject to some unobserved shock, the model will capture the differences in rates of MVT engendered by the policy change. Since such confounders are more likely to affect cities at the state level and that differences between cities could possibly increase in their spatial distance, the model is re-estimated using a sample comprised solely of Midwestern states (U.S. Census Bureau, 2010).[69] Furthermore, in addition to a sample restriction, pre-treatment trends are analyzed after the estimation of main results.

The first difference-in-difference is estimated using a two-way fixed effect model for the years 2011 to 2013:

(1) $$MVT\_Rate_{cy} = \gamma_c + \lambda_y + \beta(M_c * A_y) + \varepsilon_{cy},$$

[69] Midwestern states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

where MVT_Rate_{cy} is the total number of motor vehicles stolen (per 100,000 residents) in city c during calendar year y. City fixed effects, denoted by γ_c, control for time-invariant differences across cities, while year fixed effects, denoted by λ_y, control for annual variation in auto theft common to all cities in the respective samples. The variable A_y is an indicator variable equaling one in the years 2012 and 2013, and zero in 2011. The indicator M_c equals one if city c is in Missouri and zero otherwise. Their product ($M_c * A_y$) indicates whether the city experienced the policy change. Therefore, the coefficient β captures the treatment effect of the change in Missouri's law on the MVT rate in Missouri's cities. ε_{cy} is an error term. Observations are likely to be correlated within cities (and within states), however, equation (1) includes only three observations per city; therefore, standard errors are clustered at the state level. Since the unit of observation is a city-year, the regression is weighted by city-year population to correct for population related heteroscedasticity and to ensure that the estimates are representative of the overall population.[70]

A potential threat to obtaining an unbiased estimate of the causal effect of policy change on rates of MVT is the idiosyncratic time-variant differences across cities which might exert influence on the frequency of MVT. To control for such factors, model (1) is re-estimated using the ratio of MVT to all other larceny-thefts under the assumption that these time-variant differences affect all types of thefts similarly.[71]

The discrete short-run specification (1) does not offer any insights on the dynamics of the change in the long run. The full treatment effect might materialize over time in the wake of the law's adoption. Furthermore, a more important task is to analyze the trends in thefts prior to the change in

[70] Absent of the population weights—changes in a city such as Doolittle, Missouri (population under 1,000) would have an equal influence on the estimates as Kansas City, Missouri (population just under 500,000).

[71] This assumption is reasonable for many unaccounted time-variant confounders that are idiosyncratic to cities. A good example is change in incomes per capita across cities. Cities experiencing a decline in income are also likely to see a rise in property crimes. This effect is likely to extend to both MVT and other types of thefts, since both types are driven by the prospects of gains in the face of pressing scarcity.

law. If the difference in MVT between Missouri and other states is increasing prior to the treatment year, then it obscures any inference on causality. That is, factors in existence prior to 2012 could be responsible for the continued divergence in thefts. Therefore, the model is augmented to include four leads and six lags[72] of the treatment effect, spanning the years 2008 to 2017:

$$(2) \quad MVT\_Rate_{c\tau} = \gamma_c + \lambda_\tau + \sum_{\substack{\tau=-4 \\ \tau\neq-1}}^{6} \beta_\tau(M_c * \lambda_\tau) + \varepsilon_{c\tau},$$

where λ_τ is an indicator for years with $\tau = 0$ corresponding to year 2012. In this specification, the 2011 difference in rates of MVT between Missouri and non-Missouri cities is used to compare the differences (measured by β_τ) in the years before 2011 ($\tau \in [-4, -2]$), in the year of the policy change ($\tau = 0$), and in the years following the policy change ($\tau \in [1,6]$).[73]

Increasing coefficients on leads in τ would indicate a pre-treatment divergence in the trends of cross-state rates of MVT. A divergence in pre-treatment trends works against a causal interpretation of the estimates as it signals that even in the absence of the policy change, the trends are expected to continue diverging.

If the coefficients on β_τ are positive for $\tau \geq 0$, then the difference in MVT across treated and non-treated cities is greater compared to the difference in the year preceding the policy change. Furthermore, if β_τ increases in τ in the post-treatment period, then the treatment effect shows signs of a delayed response to the policy change.

The augmented model (2) is also re-estimated for the ratio of MVT to non-MVT in order to confirm that the time-variant differences across cities do not lead to the misattribution of the origin of the policy effect.

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[72] Due to a larger number of observations per city, the standard errors are clustered on city.
[73] This estimation is identical to the equation (1), for the exception that the "treatment effect" of each year is individually analyzed using the year 2011 as a comparison.

B. *Causal Inference Using Monthly Observations for Kansas City from the NIBRS Data*

An alternative difference-in-difference approach is to estimate Missouri's changes in rates of MVT relative to the change in all other types of thefts (OTT) that are independent of MVT following the 2012 change in law. The non-MVT considered in the re-estimated model (1) includes all types of larceny, some of which may not be independent of MVT. Such thefts include theft from a motor vehicle and theft of motor vehicle parts or accessories.[74] The OTT measure omits these categories.

Some additional strengths of this version of the analysis are that the FBI's NIBRS data allows for a better delineation between time periods around August of 2012, and further that it does not rely on the assumption that other cities outside of Missouri are good counterfactuals. Instead, the critical assumption here is that rates of OTT represent a good counterfactual to MVT. That is, absent the 2012 policy change, rates of MVT would follow the same path as rates of OTT. This assumption is reasonable, given that these types of crimes are likely to be driven by similar motivations relating to material gain. General factors that alter these motivations should extend to both MVT and OTT. Furthermore, the 2012 change in law should not produce any direct effect on OTT, making any relative deviations in MVT around the treatment date a product of augmented incentives to steal a car. An analysis of pre-trends is considered after the estimation of main results.

The second difference-in-difference model is estimated for 12 months prior and 11 months after the treatment month, and takes the form:

$$(3) \quad \log(Count_{ot}) = \delta_t + \beta_1 MVT_o + \beta_2 (MVT_o * A_t) + P_t + \varepsilon_{ot},$$

[74] The collected data from the FBI UCR used in model (1) aggregates all types of thefts together, which precludes the exclusion of certain types of thefts.

where $Count_{ot}$ is the total count of incidences of a particular type of offense o in time period t.[75] t ranges from 1 to 24 representing the 24 months of analysis in model (3). Time fixed effects, denoted by δ_t, capture time-variant differences that are common to both types of offenses.[76] The variable MVT_o is an indicator equaling one if offense o is MVT and zero if it belongs to the OTT category. This variable controls for the mean difference in the counts of offenses that arises due to time-invariant unobserved factors. The variable A_t is an indicator variable equaling one if the time t falls on or after the treatment date (August, 2012) and zero if before. The coefficient of interest is β_2 which captures the additional change in MVT relative to the change in OTT, following the date when the law was changed. P_t controls for monthly prices of scrap metal due to its potential to heterogeneously affect MVT. ε_{ot} is an error term.

Analogous to the extended model (2), model (3) is augmented to include two leads and three lags, each with year intervals, of the treatment effect:

$$(4) \quad \log(Count_{o\tau}) = I_\tau + \beta_{-1}MVT_o + \sum_{\substack{\tau=-2 \\ \tau\neq-1}}^{3} \beta_\tau MVT_o * I_\tau + P_\tau + \varepsilon_{o\tau},$$

where I_τ is an indicator for synthetic years centered around the treatment date, $\tau = 0$. These years are indicators for the groups of 12 consecutive months starting with the month of August in the calendar year of 2010.[77] In this specification, the variable MVT becomes the second lead referent category to all other synthetic years. Therefore, the coefficient β_{-1} measures the average difference in monthly incidents between the MVT and OTT throughout the 12-month period preceding the date of policy

[75] Given that there are twice as many instances of OTT, a log transformation of the dependent variable is used.

[76] Seasonality is not necessarily purged by δ_t since different calendar months may affect MVT differently from OTT. To account for these potentially heterogeneous effects, every regression employing the NIBRS data uses time periods symmetrical around treatment date in a way that includes equal number of each calendar month in all periods of comparison.

[77] The agglomeration of monthly data on a wider time interval smooths out any random monthly shocks, and, most importantly, obviates the need for the presentation of 71 different coefficients.

change. If the coefficient $\beta_{-2} < 0$, then the relative frequency of MVT was increasing before the policy change, which prevents a causal interpretation.

V. Results and Discussion

A. Estimation of Short-Run Effects Using City-Year Observations from the UCR Data

Table 2.3 reports the results for estimating equation (1) which considers the years immediately before and after the year of the policy change. The four columns differ with respect to the dependent variables and the sample of states analyzed.

The coefficient on the interaction term in column (1) captures the change in the rate of MVT for cities in Missouri relative to the change occurring in all other U.S. cities, following the change in law. The coefficient is positive, as expected, and statistically significant at the 5% level. During the years 2012 and 2013—relative to year 2011—the MVT (per 100,000) in Missouri increased by 27 thefts in addition to the concurrent change in MVT rates of other states.

In 2012 and 2013, cities in other states recorded an average decrease of 4.7 thefts per 100,000 residents in annual MVT rates (a decrease of 1.7% relative to their mean value in 2011). The predicted change in Missouri's MVT rate implied by the estimates, absent the 2012 policy intervention, would be a decrease of 1.7% as in other states. In actuality, the rate of MVTs in Missouri increased by 22.3 thefts (an increase of 6.5%).[78] It might be the case, however, that unobserved idiosyncratic time-variant city-level attributes systematically differ between cities in Missouri and cities in other states. If these

[78] In 2011, the population-weighted rate of MVT was 345.3 in Missouri and 279.8 across all other states.

TABLE 2.3: CROSS-CITIES DIFFERENCES IN THE SHORT-RUN

Explanatory variables	(1) U.S. **MVT Rate**	(2) U.S. **MVT/Larceny**	(3) Midwest **MVT Rate**	(4) Midwest **MVT/Larceny**
(City, MO) × Post	27**	0.0093*	43.3**	0.014**
	(11.9)	(0.0047)	(14.5)	(0.0051)
Year 2012	-0.141	-0.001	-14.5	-0.0056
	(11.6)	(0.0039)	(8.1)	(0.0033)
Year 2013	-9.3	-0.0021	-27.7	-0.0065
	(12.5)	(0.0055)	(21.5)	(0.0071)
Constant	279.8***	0.129***	287.6***	0.113***
	(7.8)	(0.0031)	(8.7)	(0.0031)
R^2	0.975	0.94	0.98	0.957
Observations	23,826	23,351	6,033	5,893
City FE	Y	Y	Y	Y

Notes: Table 2.3 reports short-run estimates of the effects of Missouri's House Bill 1150 in equation (1) using WLS, using city-year populations as weights. Years: 2011−2013. The units of observations are (balanced) city-years from the FBI's UCR. Cities not reporting in each year are excluded. The dependent variables in columns (1) and (3) are motor vehicle thefts per 100,000 city residents. The dependent variables in columns (2) and (4) are the ratios of motor vehicle thefts to other larceny-theft offenses. The sample in columns (1) and (2) are all U.S. states. The sample in columns (3) and (4) are Midwestern states (U.S. Census Bureau). Standard errors (in parenthesis) are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

differences exert any influence on the frequency of MVTs, then the estimate of the coefficient on the interaction term is biased. To account for this possibility, the MVT rate is divided by the larceny-theft rate and equation (1) is re-estimated using this new dependent variable, the results for which are shown in column (2).[79] This technique should entirely purge out any effect from unobserved city-level factors as long as these factors have proportional influences on the frequency of both types of thefts. The caveat is that changes in larceny-theft may not be fully independent of changes in MVT, as discussed in the data section.

The coefficient on the interaction term in column (2) is interpreted analogously to the coefficient in column (1), with the difference being that the changes are now estimated for the ratio of MVT to larceny-theft. The coefficient is positive and statistically significant at the 10% level. For every 1,000 incidents of larceny-theft, MVT in Missouri increased by 9.3 occurrences in addition to

[79] Columns (1) and (2) differ slightly in the number of observations because some cities did not report any instances of larceny-theft.

the common change across all states following the change in Missouri's law. Converting this to percentages, the ratio of MVT to larceny-theft in Missouri increased by 7.2% while other states saw a decrease of 1.3%.[80] These estimates are comparable to the ones found in column (1). Therefore, the results suggest that any unobserved time-variant differences between cities in Missouri and cities in the rest of the country are not likely to bias the estimate in column (1).

Columns (3) and (4) repeat the estimations in columns (1) and (2) for a restricted sample of Midwestern states. The coefficient of interest in column (3) implies an effect that is 16 thefts higher than the estimate in column (1) and is more precisely estimated. This increase in magnitude is due to Midwestern states (besides Missouri) experiencing a larger average annual decline—a reduction of 21.1 thefts (a decrease of 7.3%) relative to 2011—in rates of MVT.

Column (4), which analogously to column (2) presents estimates using the ratio of MVT theft to larceny-theft, shows that the effect persists in the Midwestern sample even after accounting for changes in the trajectory of larceny-thefts. These estimates imply that the ratio of these thefts declined by 5.3% in Midwestern states compared to an increase of 7.2% in Missouri.

Columns (1) and (3) offer the smallest and the largest estimated effects (measured in percentage point difference) across the four sets of estimates. These columns differ in the sample of states used for counterfactual. It is not clear whether the U.S. average or Midwestern average is a better reference for the change in the rate of MVT in Missouri. Hence, their results may represent plausible bounds of 8.2% and 13.8% on the true effect.[81]

[80] In 2011, the population-weighted ratios of MVT to larceny-theft was 0.1069 in Missouri and 0.1285 in other states.

[81] The lower bound on the effect from column (1) suggests a 6.5% increase in Missouri and 1.7% decrease in U.S. states, corresponding to an 8.2 percentage point difference. The upper bound on the effect from column (3) corresponds to a 13.8 percentage points difference (6.5% + 7.3%) in MVT rates between Missouri and other Midwestern states. Assuming that the rate of MVT in Missouri would otherwise follow the same percent decline observed in the comparison group, percentage point differences represent the change in MVT rates in Missouri resulting from the policy change.

B. Long-Run Effects Using the UCR Data

Table 2.4 presents results from estimating equation (2), which augments equation (1) to include leads and lags. The results allow for an assessment of the appropriateness of the various counterfactuals and also shed light on the dynamics of the policy effect.

Across all four columns, the omitted group captures the difference in rates between Missouri and other states in each of the respective samples for the year 2011.[82] Therefore, each coefficient in Table 2.4 presents the respective year's net change in Missouri's MVT rate,[83] controlling for the mean differences in the year 2011—the year immediately preceding the treatment year.[84]

Before turning to column (1), it is useful to consider Figure 2.2 Panel A. This figure shows that MVT rates were decreasing prior to 2012 across the U.S., including in Missouri. Notwithstanding the differences in average rates across years, the pre-treatment trends of MVT rates appear to be parallel or even slightly convergent. In the year of Missouri's policy change, the rate of MVT abruptly jumps in Missouri whereas the U.S. sees only a slight increase.[85] Following the year 2012, the trends diverge in most of the years.

Column (1) in Table 2.4 quantifies the effect observed in Figure 2.2 Panel A. Prior to 2012, the differences in rates of MVT between Missouri and U.S. states were similar to the 2011 difference, as indicated by the lack of statistical significance on any of the leads.[86] The first significant deviation relative to the difference in 2011 occurs in the year of the policy change. The coefficient is positive

[82] In 2011, Missouri was 71 and 23 thefts higher in its rates of MVT relative to the rest of the U.S. and other Midwestern states, respectively. In the same year, Missouri was 0.028 and 0.026 lower in its ratios of MVT to larceny-theft relative to the rest of the U.S. and other Midwestern states, respectively. These differences are obtained using a more restrictive sample that excludes cities that did not report crime statistics for every year between 2008 and 2017.

[83] Net of other states' changes in MVT rates.

[84] The design here is identical to the one in equation (1), except that each year is individually compared against the year 2011.

[85] A minor disconnect between the graph and the coefficient on the year 2012 dummy in column (1) of Table 2.4 is due to different samples employed in equation (1) and equation (2)

[86] The coefficient on the lead for 2008 appears to be large. Even if the estimate were significant, it would indicate a convergence in trends prior to 2011. An *F*-test fails to reject the hypothesis that the coefficients on the leads are different from one another.

TABLE 2.4: CROSS-CITIES DIFFERENCES IN THE LONG-RUN

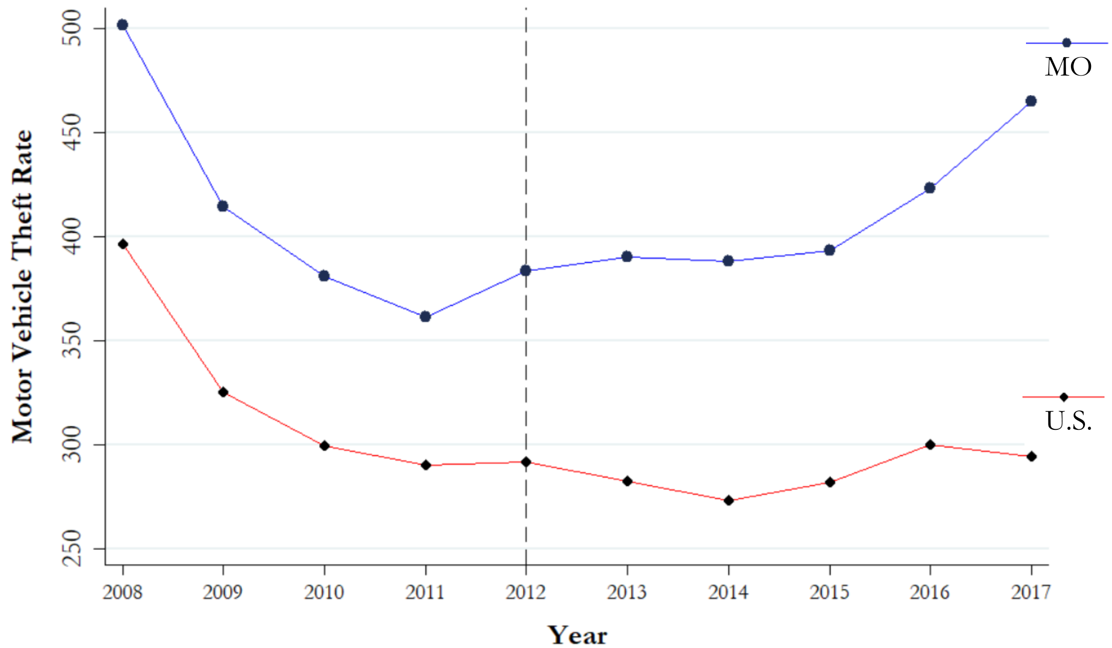
Explanatory variables	(1) U.S. MVT Rate	(2) U.S. MVT/Larceny	(3) Midwest MVT Rate	(4) Midwest MVT/Larceny
2008 Lead	27	-0.0062	70	0.0088
	(57.1)	(0.012)	(60)	(0.017)
2009 Lead	7.6	0.00021	61.3	0.019*
	(37)	(0.0068)	(43.5)	(0.011)
2010 Lead	1	-0.0042	23	0.00091
	(21.7)	(0.007)	(23.5)	(0.0073)
2012 Treatment Year	21.2***	0.007	38.2***	0.011*
	(7)	(0.0047)	(13)	(0.0064)
2013 Lag	38.3	0.016	68.9*	0.022
	(25.1)	(0.012)	(40.3)	(0.015)
2014 Lag	46.1**	0.024**	84.2*	0.028
	(18.5)	(0.01)	(48.2)	(0.019)
2015 Lag	43.1**	0.023**	114**	0.039*
	(18.5)	(0.012)	(52.6)	(0.023)
2016 Lag	56.5**	0.026**	113.1**	0.037**
	(26.1)	(0.011)	(46)	(0.018)
2017 Lag	105**	0.037***	151.3***	0.048**
	(43.9)	(0.014)	(58.2)	(0.021)
Constant	395.3***	0.168***	403.6***	0.149***
	(8)	(0.0035)	(15.5)	(0.0093)
R^2	0.885	0.867	0.927	0.891
Observations	54,420	53,917	10,930	10,738
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Notes: Table 2.4 reports long-run estimates of the effects of Missouri's House Bill 1150 in equation (2) using WLS, using city-year populations as weights. Years: 2008−2017. The units of observations are (balanced) city-years from the FBI's UCR. Cities not reporting in each year are excluded. The dependent variables in columns (1) and (3) are motor vehicle thefts per 100,000 city residents. The dependent variables in columns (2) and (4) are the ratios of motor vehicle thefts to other larceny-theft offenses. The estimates represent treatment effects relative to year 2011. The sample in columns (1) and (2) are all U.S. states. The sample in columns (3) and (4) are Midwestern states (U.S. Census Bureau). Standard errors (in parenthesis) are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

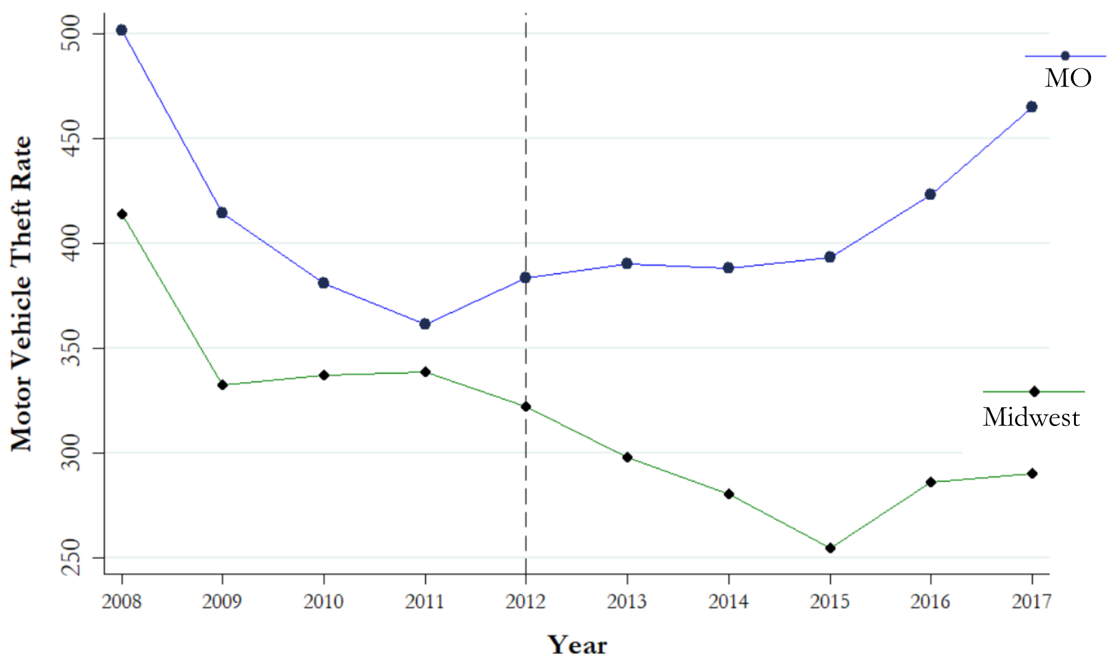
and statistically significant at the 1% level, and translates to an increase of 21 additional vehicles stolen (per 100,000) relative to other states' changes since 2011. Subsequent years all show larger coefficients that increase almost monotonically in the years following 2012. Such results are consistent with a delay in the realization of the full effects of the change in Missouri's law.

Figure 2.2: Motor Vehicle Thefts per 100,000 Population

Panel A. Missouri and U.S. states

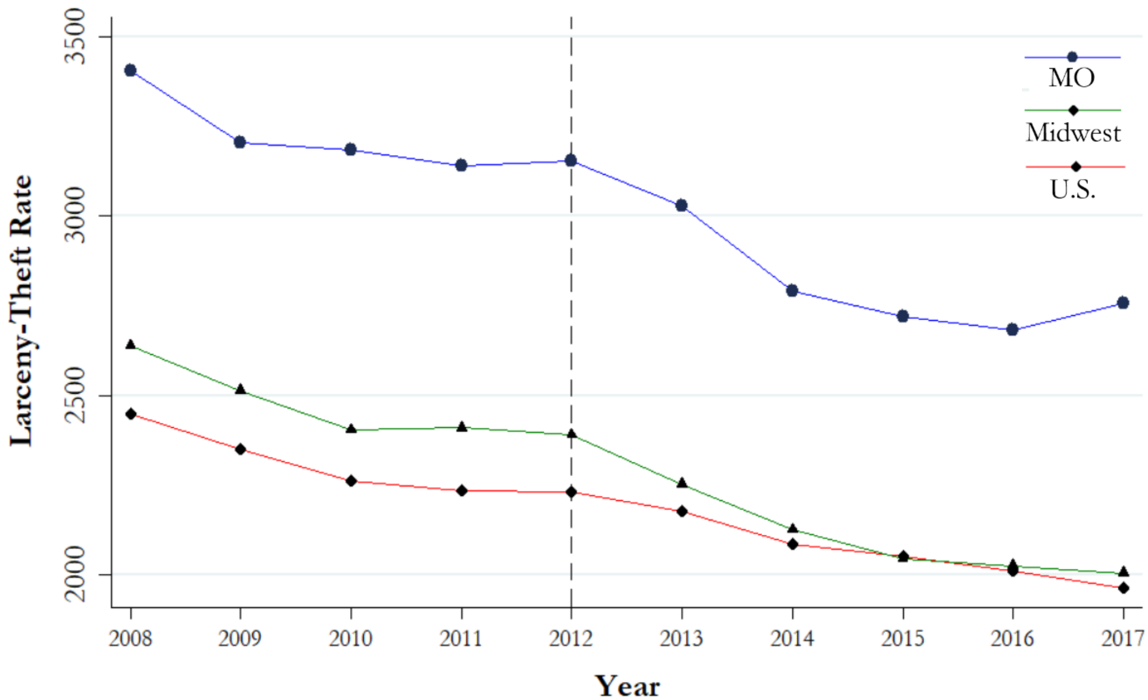


Panel B. Missouri and Midwestern states



Notes: Information on motor vehicle thefts comes from the FBI's UCR. The vertical line indicates the year of the change in Missouri's law. The annual rates are calculated for the balanced sample of cities, c_i, per group i during years 2008−2017 with i = Missouri in the upper curves of Panel A and B, i = U.S. states (excluding Missouri) in Panel A, and i = Midwestern states (excluding Missouri) in Panel B. All of the rate calculations follow the formula: $100{,}000\left(\sum_{c_i} Motot\ vehicle\ theft_{c_i}\right)\left(\sum_{c_i} Population_{c_i}\right)^{-1}$.

FIGURE 2.3: LARCENY-THEFT PER 100,000 POPULATION



Notes: Information on larceny-thefts comes from the FBI's UCR. The vertical line indicates the year of the change in Missouri's law. The annual rates are calculated for the balanced sample of cities, c_i, per group i during years 2008−2017 with i = Missouri in the upper curve, i = Midwestern states (excluding Missouri) in the middle curve, and i = U.S. states (excluding Missouri). All of the rate calculations follow the formula: $100{,}000(\sum_{c_i} Motot\ vehicle\ theft_{c_i})(\sum_{c_i} Population_{c_i})^{-1}$.

Skipping to column (3), a similar pattern is manifested when comparing Missouri to Midwestern states. All leads are statistically insignificant whereas the coefficients on the year of treatment and each of the following years are positive and statistically significant. The coefficients are larger in magnitudes relative to column (1) due to a larger decline in MVT rates in other Midwestern states.

Figure 2.2 Panel B illustrates the dynamic changes in MVT rates for other Midwestern states relative to those for Missouri. The curves converge in each successive lead year before starting to diverge in year 2012.

Columns (2) and (4) analyze the pre and post-treatment trends for ratios of MVT to larceny-thefts. The results are less precisely estimated, but overall, show an increase in the ratios beginning around 2012 and growing since then. Figure 2.3 plots larceny-theft instances (per 100,000) for U.S., other Midwestern states, and Missouri. The rates appear to follow a similar trajectory, suggesting the absence of unobserved differential shocks across states.

The results across all four columns provide justification for the parallel trend assumptions. The average U.S. and Midwestern cities appear to be a reasonable comparison for cities in Missouri with regard to the dynamics of their own MVT rates. Furthermore, the results provide evidence that the full effect of the policy was only revealed over time. Criminals may need time to learn about the changes, existing salvage yard owners might be initially hesitant to accept a vehicle without a title, and the entrance of new salvage firms over time could delay the realization of the full effect.[87]

The largest effects across each of the specifications are found for the year 2017.[88] Following the subsection A, columns (1) and (3) are used to construct possible bounds on the long-run effect arising from the policy. A lower bound of 28.8% is found using the U.S. sample and an upper bound of 42.5% is obtained using the Midwestern sample.[89]

C. *Estimation of Short-Run and Long-Run Effects Using Monthly Kansas City Observations from NIBRS Data*

The empirical results in subsections A and B (accompanied by graphs) provide strong evidence for a fundamental change in the trajectories of Missouri's MVT rates starting in year 2012. This subsection attempts to further establish the causal effect of the 2012 policy change by restricting the

[87] Another possibility involves unaccounted confounding shocks since 2012. Provided that the ratio of MVT to larceny-theft continues to grow over time, these shocks must either disproportionally (and positively) affect the rate of MVT or disproportionally (and negatively) affect the rate of larceny-thefts.
[88] The *F*-test rejects the hypothesis that the effects in 2017 are equal to the effects in earlier years at least the 5% level for the U.S. and at least the 10% level for the Midwest.
[89] Since 2011, U.S. states saw an increase of 4.1 in rates of MVT (an increase of 1.4%) while Missouri experienced a 109.1 (30.2%) increase, and Midwest saw a decline of 42.1 (-12.3%).

analysis to only consider within-Missouri variation and by avoiding some of the limitations of the preceding subsections. Namely, equation (3) allows for a more nuanced examination of the effect around the treatment date (August, 2012) by not counting months prior to August as treated observations. Also, it employs a larceny-theft category which does not include thefts that could be correlated with the frequency of MVT.

Column (1) in Table 2.5 presents results from estimating equation (3), which captures the short-run effects of the policy change by comparing the average changes in MVT and OTT over a one-year period following the treatment relative to their differences in means in the one-year period preceding August, 2012. This comparison is measured by the coefficient on the interaction term. The estimate translates to a 12.3 percentage point increase in the occurrence of MVT in addition to the percent change in occurrence of OTT and is statistically significant at the 5% level.[90] This increase is sizable and interpreted as an additional 91.8 vehicles stolen in Kansas City per 100,000 population, during the first year of the law going into effect.[91]

The second column in Table 2.5 presents results for estimating equation (4), which augments equation (3) to include leads and lags. The coefficient on MVT_{-1} captures the log difference between MVT and OTT for the 12 months preceding the treatment month.[92] The coefficients on the remaining variables measure the percentage point change in MVT in addition to the percent change in OTT, for their respective synthetic years against the referent 12 months. The coefficient on $lead_{-2}$ is statistically no different from zero, showing that the trends in MVT and OTT were parallel prior to policy change. Starting from the treatment year, the changes in MVT disproportionally exceed the changes in OTT

[90] OTT increases by 0.4%.
[91] Kansas City's rate of MVT for the 12 months preceding August, 2012 is 745.68.
[92] As it has in equation (3). Hence the identical coefficients between column (1) and column (2).

TABLE 2.5: CROSS-CRIME DIFFERENCES

Explanatory variables	**Log Count** (1)	**Log Count** (2)
MVT × Post	0.123**	
	(0.053)	
MVT	-0.893***	
	(0.051)	
Lead $_{-2}$		-0.00044
		(0.083)
MVT $_{-1}$		-0.893***
		(0.058)
Treatment year $_0$		0.123*
		(0.071)
Lag $_1$		0.254***
		(0.081)
Lag $_2$		0.285***
		(0.086)
Lag $_3$		0.26***
		(0.08)
Constant	6.9***	6.4***
	(0.239)	(0.079)
R^2	0.979	0.893
Observations	48	144

Notes: Columns (1) and (2) report OLS estimates of the effects of Missouri's House Bill 1150 corresponding to equation (3) and equation (4) respectively. Column (1) includes month FE. Colum (2) includes synthetic year FE. Both columns include controls for the monthly price of scrap metal. Dates: July, 2011−July, 2013 in column (1); July, 2010−July, 2016 in column (2). The units of observations are months from the FBI's NIBRS for Kansas City, Missouri. The dependent variable in both columns is the log of the monthly crime incident count. Robust standard errors are reported in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

each year as compared to their difference in the 12 months prior to the policy change. The treatment effect gains full force by the second year after the law went into effect.[93] Considering the largest coefficient as a plausible upper bound for the long-run effect, the 0.285 percentage difference translates to an additional 212.52 vehicles stolen per year in Kansas City (per 100,000 residents) within four years of the change in law.

[93] An *F*-test fails to reject the hypothesis that the coefficients on lags are different from each other. The *F*-test does reject (at the 5% level) that the coefficient on the treatment year is equal to either of the lags' coefficients.

FIGURE 2.4: LOG CRIME COUNTS OF MVT AND OTT

Notes: Monthly crime is plotted for Kansas City, Missouri using the FBI's NIBRS. The upper curve is OTT defined as all larceny-theft offenses except for theft from a motor vehicle and theft of motor vehicle parts or accessories. The bottom curve is motor vehicle theft (MVT). The vertical line indicates the date of the change in Missouri's law.

Figure 2.4 traces out the trends in MVT and OTT (in logs) over the six years in the analysis, and overall accords with the findings in this subsection.

VI. Conclusion

This paper evaluates the impact of the change in Missouri law that facilitated the sale of older vehicles to salvage yards, finding that the introduction of the new statute on vehicle sales set in motion a significant increase in rates of MVT.

Analysis of the FBI's UCR and NIBRS data establishes the causal relationship between the 2012 passage of Missouri House Bill 1150 and the following increase in MVTs. Difference-in-difference models—accounting for broader trends—find an estimated 8% to 14% increase in the theft of vehicles within one year as a consequence of the change in law. Five years after the change, the effect is estimated to range between 30% and 43%, reflecting the cumulative effect of the law on rates of MVT.

The findings highlight the response to changes in the returns to crime by exploring the introduction of a policy that had an immediate impact on the potential resale value of stolen vehicles. By liberalizing the market for stolen vehicles, Missouri House Bill 1150 increased the net gain from theft of older vehicles, leading to a higher incidence of such thefts. Concerns for external validity are warranted, but the results align with the predictions of a rational choice model and are of relevance in other policy contexts that might affect criminal net gains.

The unintended social cost imposed by this law is amplified by the possibility that the increased number of stolen vehicles are likely to be scrapped instead of used for transportation (or sold to someone for that purpose), therefore, the loss to victims are likely to extensively exceed the gains to criminals. In addition, an increase in MVT is typically accompanied by a corresponding increase in gun theft due to the prevalence of guns stored inside of stolen vehicles, which carries its own social cost.[94]

A plausible solution to the MVT problem in Missouri is to either repeal the Section 301.227.9 (RSMo) or introduce safeguards that impose additional costs to dispose of stolen vehicles in salvage yards.

[94] Kelly Eckerman, "Car thefts are skyrocketing across the Kansas City area," *KMBC 9 News*, July 12, 2018, https://www.kmbc.com/article/car-thefts-are-skyrocketing-across-the-kansas-city-area/22134313.

Chapter 3

Alphabetism: The Effects of Surname Initial and the Cost of Being Otherwise Undistinguished.

"It all started in first grade … I became dimly aware of a curse that would follow me throughout life. Along with Martin Perlmutter, Schwartz, Chester Woczniewski, Helen Weathers, and poor old Zynzmeister, I was a member of the Alphabetical Ghetto, forever doomed by the fateful first letter of our last names to squat restlessly, hopelessly, at the very end of every line known to man, fearfully aware that whatever the authorities were passing out, they would run out of goodies by the time they got to us." (Shepard, 1973).

I. Introduction

Individual experiences of life, and of economic success in particular, depend on many individual characteristics. Human capital is the most prominent among them. Its role has been the subject of extensive study. Other salient characteristics may include non-cognitive skills, personality traits, height, and appearance. The role of identity, defined by ethnic or racial affiliation, national origin, or gender has also received substantial attention.

Names are central to identity.[95] A small literature has exploited names to proxy for unobserved ethnic, racial and socio-demographic characteristics. Another small literature has examined the role of alphabetization in academic publishing and in a few other domains.

Although this latter literature is narrow in scope, intuition may suggest that the effects of alphabetization on resource allocation are much more extensive. Deaton (2010, 446) fears that alphabetical assignments of experimental treatments may be non-random, on the grounds that "(r)esources are often allocated alphabetically because that is how many lists are presented".

This intuition also appears frequently in the popular press. For example, The Economist (30

[95] "There is no single human culture or society that does not bestow personal names on its members … personal naming is an inherently human activity" (Mateos, 2014, 36). "Every human society has a naming system for identifying individuals within it" (Hanks and Parkin, 2016, 214).

August 2001) wrote that "(o)ne theory … is that the rot sets in early. At the start of the first year in infant school, teachers seat pupils alphabetically from the front, to make it easier to remember their names. … the alphabetically disadvantaged may think they have had a lucky escape. Yet the result may be worse qualifications, because they get less individual attention, as well as less confidence in speaking publicly."[96]

However, there appear to be no previous attempts to assess the more general effects, if any, of alphabetization. This paper presents a unique and extensive analysis of the effects of surname initial alphabetic rank on life outcomes. These outcomes span the period from late adolescence through middle age. They measure experiences in high school, investment in further accumulation of human capital through tertiary education and labor market success in early and mid-adulthood.

This paper demonstrates that men with surname initials ranked further from the beginning of the alphabet experience significantly, and often cases substantively, worse outcomes through early adulthood. These effects are concentrated on those who are of ordinary intelligence and appearance. They seem to dissipate by mid-adulthood, but may persist for those who are most susceptible.

The results here are, essentially, estimates of the "intent to treat" effects of surname initial assignment. The available data do not identify the precise mechanisms through which they arise. However, Shepherd (1973), The Economist (2001), and Deaton (2010) suggest one that is plausible: the mundane and repeated experience, throughout primary and secondary school, of alphabetized allocations of attention, resources, and opportunities. Under these allocations, those with surnames towards the end of the alphabet receive less. Consequently, they achieve less. The plausibility of this

[96] Similar descriptions of the origins and consequences of alphabetism appear in popular publications. They include Slate (http://www.slate.com/articles/business/the_customer/2011/01/tyranny_of_the_alphabet.html), Teen Ink (https://www.teenink.com/nonfiction/academic/article/471358/Alphabetical-Disorder), The New Republic (https://newrepublic.com/article/40632/stop-insidious-alphabetism-now), Draw Curiosity (http://drawcuriosity.com/2016/08/why-browns-do-better-than-smiths/), and Odyssey (https://www.theodysseyonline.com/truth-about-always-being-last). Buzzfeed (https://www.buzzfeed.com/christianzamora/ways-your-end-of-the-alphabet-name-has-ruined-your-chance?utm_term=.vgE3qRgx1#.wq1vzYgEG) presents a particularly lurid video description.

mechanism is reinforced by the apparent absence of alphabetic effects for those who might have increased access to these allocations because of their distinctive cognitive abilities and appearances.

Section II summarizes the literature that analyzes the economic effects of the information embedded in names. Section III reviews the literature that investigates the economic effects of orderings, and particularly those that are alphabetic. Section IV describes the econometric models employed here, their motivation, and the data to which they are applied. These data include 12 dependent variables that describe high school experiences, tertiary education accomplishment and labor market outcomes through mid-adulthood. Section V estimates sample-wide effects of surname initials on these outcomes. Section VI distinguishes between these effects on individuals who are and are not distinctive in terms of cognitive ability. Section VII extends the exploration of section VI to incorporate facial attractiveness. Section VIII concludes.

II. Names, Identities and Economic Outcomes

Names convey a substantial amount of information. Given names, surnames and their combination may be indicative of ethnicity (https://www.census.gov/data/developers/data-sets/surnames.html) or ancestry (Collado, et al., 2013; Clark, 2014; Mateos, 2014, section 3.4; Clark and Cummins (2015); Güell, et al., 2015 and Clark, Leigh and Pottenger, 2017). They may be correlated with socioeconomic status (Fryer and Levitt, 2004; Collado, et al., 2008; Aura and Hess, 2010; Olivetti and Paserman, 2015), longevity (Pena, 2013; Cook, et al. 2016), residence (Pelham, et al., 2002) and political involvement (Jurajda and Kova, 2016).

Opportunities depend on the identities suggested by names. Names may affect expectations in school (Figlio, 2005), Uber service (Ge, et al., 2016) and cooperative behavior (Fershtman and

Gneezy, 2001). Responses to job applications depend on the ethnic identities associated with different names (Bertrand and Mullainathan, 2004; Carlsson and Rooth, 2007; Wood, et al., 2009; Widner and Chicoine, 2011; Derous, et al., 2012; Baert, et al., 2015). The same is true for responses to rental housing applications (Carpusor and Loges, 2006; Ahmed and Hammarstedt, 2008; Ahmed, Andersson and Hammarstedt, 2010; Bosch, Carnero and Farré, 2010; Hanson and Hawley, 2011; Ewens, Tomlin and Wang, 2014; Edelman, Luca and Svirsky, 2017) and investments in mutual funds (Kumar, et al., 2015). Economic status changes in response to changes in given names (Biavaschi, et al., 2017) and in surnames (Arai and Skogman Thoursie, 2009).[97]

III. The Economic Effects of Orderings

In the results summarized above, names have substantive importance because they are correlated with other characteristics that may be relevant, but are unobserved. However, orderings by name can themselves have substantive importance, even if the ordering principles are random with respect to the relevant outcomes. Search outcomes depend on these orderings. Consequently, orderings can affect the allocation of resources and opportunities.

Individuals with disadvantageous ranks in these orderings may respond strategically. They may alter their ranks by manipulating their names. They may also limit participation in search-based allocation mechanisms. Furthermore, the allocative effects of alphabetic rank may be overridden by individual distinction in the relevant domains.

[97] Suggestive evidence indicates that the intrinsic attractiveness or popularity of names may also have behavioral effects. Those with greater regard for their own full name may have higher self-esteem (Gebauer, et al., 2008). The attractiveness of given names may affect both own behavior and perceptions by others (Erwin and Calev, 1984, 223). Younger people may associate names common in older generations with reduced popularity and intelligence (Young, et al., 1993). However, Hassebrauck (1988) finds no effect of first name attractiveness on perceptions of physical or emotional attractiveness. Erwin (1995, 49) suggests that conclusive results in this domain probably require more rigorous analytical designs.

A. Ordering and Search

In environments with multiple options that are evaluated sequentially and whose characteristics are ex ante uncertain, theory predicts that search must balance the cost of delaying choice against the potential benefit of identifying a superior option. The optimal stopping rule consists of identifying a minimum acceptable, or "reservation" quality for the choice, and concluding the search with the first option that meets or exceeds that quality (Kohn and Shavell, 1974; Albrecht, 2011).

Generally, the probability that an acceptable choice has appeared increases as search progresses.[98] Consequently, the probability of being sampled declines with rank.[99] For example, more votes accrue to the choice in the first position on an electoral ballot, even though that position is assigned randomly (Ho and Imai, 2008).

This prediction is also consistent with the results of multiple studies of academic publishing. Papers that appear first in a randomly-ordered online listing are significantly more likely to be downloaded and cited (Haque and Ginsparg, 2009; Feenberg, et al., 2017). They are also more likely to be viewed (Feenberg, et al., 2017). Experiments with long lists of papers demonstrate that those listed earlier are more likely to be downloaded (Novarese and Wilson, 2013). Papers that are randomly listed first in online lists (Dietrich, 2008) and in print (Berger, 2016) receive more citations.

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[98] When all alternatives must be considered, search incentives are irrelevant. In these cases, later placement may not be prejudicial. In the musical competition studied by Ginsburgh and van Ours (2003), the first position was at the greatest disadvantage. In the arts performance competition studied by Page and Page (2010), the last position was at the greatest advantage.

[99] Arbatskaya (2007) presents a model in which ordered, costly consumer search implies that, in equilibrium, prices for a homogeneous good also vary systematically with search order.

B. Alphabetic Orderings and Alphabetic Effects

Groups are often ordered and searched by alphabetic rank of initial. In alphabetic orderings, the probability of identifying an acceptable choice increases as search proceeds to letters with greater numerical "rank" – those more distant from the beginning of the alphabet. Therefore, those with higher alphabetic rank experience fewer economic opportunities and poorer outcomes.

Stock markets present multiple examples. Stocks with names ranked earlier in the alphabet experience higher trading volumes and liquidity (Jacobs and Hillert, 2016). Stocks with names ranked earlier in the alphabet experience higher trading volumes, and may have higher valuations (Itzkowitz, et al., 2016). Within a portfolio, the stock with the initial closest to the front of the alphabet is most likely to be sold (Hartzmark, 2015).

Alphabetic bias arises in other business domains, as well. The positive correlation between surname initial rank and secondary school test scores in Czechoslovakia suggests that these schools admit marginal students in alphabetical order (Jurajda and Münich, 2010). Potential donors with surname initials further from the beginning of the alphabet are less likely to make charitable donations, apparently because they are less likely to receive personal solicitations (Rosen and Meer, 2011). Law school faculty with surname initials closer to the beginning of the alphabet are more likely to receive invitations to visit other institutions (Merritt, 1999).

More extensive examples of alphabetic bias appear in academic publishing. Journals disproportionately request reviews from referees with surname initials towards the beginning of the alphabet (Richardson, 2008). Authors whose surname initials are ranked towards the front of the alphabet are more likely to be cited (Arsenault and Larivière, 2015). The tendency to disproportionately cite papers by these authors is greater in disciplines where reference lists tend to be longer, perhaps because citations are generated by alphabetical search procedures that favor papers encountered earlier (Huang, 2015).[100]

Alphabetic ordering effects are exploitable. The difference in value between company shares that are equivalent with the exception of differential voting rights is less when the shares with inferior rights are designated as "A" shares and those with superior rights are designated as "B" shares than when the designations are reversed (Ang, Chua and Jiang, 2010). Businesses that adopt artificial names for the purpose of appearing at the front of alphabetical listings target infrequent customers and are able to charge higher prices for inferior service (McDevitt, 2014).[101] In alphabetic roll calls, U.S. Senators with surname initials towards the front of the alphabet are more likely to vote against party policies (Spenkuch, Montagnes and Magleby, 2018).

Alphabetical ordering effects in academic publishing create incentives to respond strategically. Authors with surname initials towards the front of the alphabet have an incentive to shirk because their effort will not affect their rank in the listing. However, if authors with surname initials towards the end of the alphabet are to accept coauthors with earlier surname initials, they have an incentive to choose those who do not shirk (Ackerman and Brânzei, 2017).[102]

In publication regimes where alphabetical author listings are conventional but listings by contribution occur intermittently, authors with surname initials towards the front of the alphabet have an incentive to enforce and preserve the norm. In these regimes, alphabetical listings convey no information regarding contribution. If some co-authors agree to list authorship by contribution, and those with early surname initials have contributed most, the resulting ordering may be sufficiently

[100] Author lists in economics are disproportionately ordered alphabetically (Frandsen and Nicolaisen 2010, 613; Waltman, 2012; Levitt and Thelwall, 2013). This exacerbates alphabetic inequities. Moreover, despite alphabetical author ordering, economists tend to assign slightly less credit to authors in later positions (Maciejovsky, et al., 2009). Perhaps as a consequence, faculty with initials that occur earlier in the alphabet are more likely to be tenured in highly ranked economics departments (Einav and Yariv, 2006). Ray ® Robson (2018) propose "certified random" ordering of authors, indicated by "®", in order to reduce these biases.

[101] Steve Wozniak quotes Steve Jobs as preferring "Apple" for the name of their company because, in part, "it got us ahead of Atari in the phone book" (Chea, 2011). High prices may have been another element in his business strategy, though perhaps not inferior service.

[102] Similarly, orderings by contribution create an incentive to contribute only slightly more than the author ranked just behind. In some circumstances, this incentive can lead to greater shirking than under alphabetic ordering (Ackerman and Brânzei, 2017).

similar to alphabetical ordering so as to be indistinguishable. Therefore, the true contributions of those with surname initials towards the beginning of the alphabet cannot be revealed in lists by alphabet and can only be revealed in lists by contribution if they are minor (Efthyvoulou, 2008).

As a first strategic response, alphabetical authorship listings across multiple scholarly fields have become less common. Waltman (2012) demonstrates that the frequency of alphabetical authorship listings in multi-authored papers diminished across all areas of scholarship from 32.2% in 1981 to 15.9% in 2011.

Waltman (2012) also attributes this, in part, to increasing numbers of co-authors.[103] Frandsen and Nicolaisen (2010) confirm that alphabetical orderings become less common as the number of co-authors increases. This reduction occurs, in part, because, with more authors, alphabetical orderings are less likely to coincide with other ordering principles. In addition, authors with surname initials far from the beginning of the alphabet prefer collaborations where authorship lists follow some non-alphabetic ordering (van Praag and van Praag, 2008).

As a second strategic response, authors with surname initials far from the beginning of the alphabet strategically choose their co-authorships. Economists with surname initials ranked further from the beginning of the alphabet avoid participating in papers with more than three authors (Einav and Yariv, 2006; Kadel and Walter, 2015).

Moreover, among authors with surname initials that are farther from the beginning of the alphabet, those with greater skill have a greater incentive to author singly. This reduces the risk that they will share credit with an author who contributes less, but who would nevertheless precede them in alphabetical order. Consequently, single-authored papers receive more citations if their authors have surname initials that are farther from the beginning of the alphabet (Ong, et al., 2018).

[103] As examples, Frandsen and Nicolaisen (2010) demonstrate that the shares of papers in both economics and information science with multiple authors increased from approximately one-third in 1978 to approximately two-thirds in 2007. The share of co-authored papers in high energy physics increased from approximately 72% to approximately 83%.

In contrast, among authors with surname initials that are closer to the beginning of the alphabet, those with greater skill have a greater incentive to co-author. They are more likely to find a co-author who can contribute usefully but who is nevertheless content to receive second listing. Correspondingly, double-authored papers receive more citations as the first author's surname initial moves closer to the beginning of the alphabet (Ong, et al., 2018).

As a third strategic response, economists with surname initials further from the beginning of the alphabet tend to be less productive (van Praag and van Praag, 2008). This may be an endogenous response to systematic disadvantage. Those consistently in later ranks will have fewer incentives to invest in the skills necessary to take advantage of opportunities, should they arise.

C. Primary Effects Dominate Name Effects

In business contexts, the primary characteristic of interest would be economic returns or value. In academic publishing, it would be article quality. In all of the examples of alphabetic ordering above, the ordering itself is not correlated with either. Nevertheless, it is influential, presumably because the important characteristics are costly to assess or appear to be similar across options.

As examples, the ballot effects in Ho and Imai (2008) are most important in races and for candidates that attract little attention. The trading volume and liquidity effects in Jacobs and Hillert (2016) are most important for stocks in companies that are of lesser prominence. The effects associated with paternal and father-in-law origin in Rubinstein and Brenner (2014) are markedly stronger for individuals whose imputed skin tone is less indicative regarding this origin.

Conversely, Hamermesh and Pfann (2012) find no significant relationship between alphabetical rank of surname initial and membership in the Econometric Society, or receipt of honors from the American Economic Association, the John Bates Clark Award or the Nobel Memorial Prize in Economic Sciences. In the comparisons among outstanding economists, records of accomplishments are substantial and the numbers of such records are relatively few. In contexts such as these, where searches are over fewer options, each characterized by extensive relevant information, alphabetic orderings may be irrelevant.

IV. Motivations, Models and Data

The examples in the previous section include many in which alphabetic designations and orderings clearly occur, such as stocks of different classes in the same company, telephone listings, author names and reference lists. However, they also include situations in which outcomes are consistent with search based on alphabetical orderings, but where there is no direct evidence that alphabetical orderings take place. Examples include groups of stocks and mutual funds, secondary school students in Czechoslovakia, philanthropists, law school faculty and referees for academic journals.

This paper expands the investigation of surname initial effects beyond the limited domains described in the previous section. The situation analyzed here is another in which alphabetization is likely to occur, but is not directly observed. As in other situations that share this observational limitation, the analysis here assumes that a substantial amount of activity is alphabetically ordered – in this case, daily activity in primary and secondary school and in other organized childhood settings.

If so, then individuals with surnames towards the end of the alphabet would have the repeated experience of participating later or not at all, as described in the epigraph. Moreover, the reduced probability of participating could discourage investment in the skills that would be required for successful participation. Consequently, individuals with surnames towards the end of the alphabet would achieve less and aspire to achieve less.[104] The next sections estimate the relationships between rank of surname initial and 12 measures of individual achievement in high school, college and the labor force.

Section V estimates common effects of surname initial on all members of the sample described here. The regression equation employed for this purpose is model 1, where y_j represents any of the 12 dependent variables and *j* indexes sample members:

$$(1) \qquad y_j = \beta_0 + \beta_\alpha \alpha_j + \boldsymbol{X}_j^{'} \gamma + \varepsilon_j$$

The explanatory variable of interest is α_j, the index for surname initial. The coefficient of interest is β_α, the effect of surname initial. $\boldsymbol{X}_j$ represents a vector of covariates that may also affect y_j.

As discussed at the end of the previous section, alphabetic rank may not matter for individuals who are distinguished in more relevant or salient characteristics. With regard to the experience of accumulating human capital, cognitive ability would be the most important example. Those with especially high levels of cognitive ability may earn opportunity regardless of their placement in alphabetic rankings. The same may be true for those with especially low levels of cognitive ability, whose deficits may demand or require enhanced support.

Section VI explores the hypothesis that those who are undistinguished bear a greater burden of alphabetic effects with equation 2. It expands equation 1 to distinguish three IQ strata:

[104] Similarly, "children with surnames that begin with a letter near the beginning of the alphabet enjoy privileged treatment. They are at the beginning of lines, they sit in the front of the class, and they often get first choice when opportunities arise. Those with surnames late in the alphabet face parallel disadvantages. These differential experiences throughout the early formative years of childhood may have implications for behavior throughout one's life." (Carlson and Conrad, 2011, 300).

$$(2) \qquad y_j = \sum_{i \in I} \beta_i(i_j) + \sum_{i \in I} \beta_{i,IQ}(i_j) IQ_j + \beta_{M_I,\alpha}(M_I)\alpha_j + \sum_{\substack{i \in I \\ I \setminus M_I}} \beta_{i,\alpha}(i_j)\alpha_j + \boldsymbol{X}_j^{'}\gamma + \varepsilon_j$$

Set I = $\{L_I, M_I, H_I\}$ consists of three hierarchical strata of IQ.

The strata *i* for individual *j* is i_j. Each strata *i* has its own intercept, $\beta_i(i_j)$, its own IQ coefficient $\beta_{i,IQ}(i_j)$ and its own surname initial coefficient $\beta_{i,\alpha}(i_j)$. The effect of interest is that of surname initial for those with intermediate IQ scores, $\beta_{M_I,\alpha}$.

Section VII attempts to further localize the effects of surname initial rank by subdividing each of the three IQ strata into three substrata based on facial attractiveness, as in model 3:

$$(3) \qquad \begin{aligned} y_j = & \sum_{i \in I} \sum_{r \in R} \beta_{ir}(i_j r_j) + \sum_{i \in I} \sum_{r \in R} \sum_{k=1}^{2} \beta_{ir,k}(i_j r_j) x_{k,j} + \beta_{M_I M_R,\alpha}(M_I M_R)\alpha_j \\ & + \sum_{\substack{i \in I \\ (I \times R) \setminus \{M_I M_R\}}} \sum_{r \in R} \beta_{ir,\alpha}(i_j r_j)\alpha_j + \boldsymbol{X}_j^{'}\gamma + \varepsilon_j \end{aligned}$$

Set R = $\{L_R, M_R, H_R\}$ consists of three hierarchical strata of facial attractiveness scores. The interaction between the partitions by IQ and facial attractiveness yields nine substrata, comprising all combinations of low, intermediate and high IQ with low, intermediate and high facial attractiveness.

In model 3, $\beta_{ir}(i_j r_j)$ represent substrata-specific fixed effects. $\beta_{ir,k}(i_j r_j)$ represent substrata-specific coefficients for $x_{k,j}$, where $x_{1,j}$ and $x_{2,j}$ are IQ and facial attractiveness measures of individual *j*, respectively. $\beta_{ir,\alpha}(i_j r_j)$ are the coefficients for surname initial rank in the eight substrata apart from that consisting of those with intermediate IQ and intermediate facial attractiveness scores. The coefficient for this last substratum, $(M_I M_R)$, is $\beta_{M_I M_R,\alpha}$, the effect of interest.

The explanatory variables $\mathbf{X}_j$ in models 1 through 3 follow Zax and Rees (2002). As there, the analytical posture consists of observing each individual as they graduate from high school and predicting subsequent outcomes. Consequently, these variables describe individuals at that graduation.[105] While post-graduation choices may affect outcomes of interest that occurred later in adult lives, the analysis here captures the effects of these choices in the characteristics at high school graduation upon which they were based.

The Wisconsin Longitudinal Study, or WLS (Herd, et al., 2014; http://www.ssc.wisc.edu/wlsresearch) provides the data employed here. The WLS population consists of 10,137 individuals, representing a random sample comprising one-third of all seniors graduating from high school in 1957 in Wisconsin. These individuals have been surveyed intermittently from 1957 through 2011. The sample here consists of 3,281 men with complete data for all individual and family explanatory variables employed below.[106]

Table 3.1 presents summary statistics for the explanatory variables that measure characteristics of the individual. Two of the variables, IQ score and high school rank, are direct measures of human capital. A third, measuring the student's perceptions of his friends' intentions regarding college attendance, serves as an indicator of peer ambition and as a proxy for that of the individual regarding the acquisition of additional human capital.

IQ represents the individual's score on the Henmon-Nelson Test of Mental Ability, generally administered in the eleventh grade. According to table 3.1, the sample average IQ was 101.8 and the standard deviation was 15.0. This closely approximates the standard norming of most IQ tests (Gottfredson, 2009). The range of IQ scores was from 61 to 145, including individuals with limited and exceptional cognitive abilities.

High school rank measures human capital accumulation during high school. It is the individual's percentile rank in his high school class upon graduation. The average of 45.5 indicates that

[105] This construction holds constant completed education. All sample members were high school graduates at the time of observation for explanatory variables. None had yet had the opportunity to enroll in tertiary education.
[106] This analysis omits women because the high probability of marriage in this sample, coupled with the high probability that women would change surname at that time, presents analytical challenges that require separate treatment.

TABLE 3.1: SUMMARY STATISTICS FOR INDIVIDUAL EXPLANATORY VARIABLES

Variables	Mean	SD	Min	Max
Individual characteristics:				
Alphabetical rank of surname initial	11.84	6.799	1	26
IQ	101.9	15.082	61	145
Facial attractiveness	0.0793	1.303	-4.011	4.149
Relative body mass - proxy for BMI	0.0161	0.829	-2.969	3.619
High school:				
High school rank	45.5	28.115	0	99
Post-secondary education:				
Friends' plan to attend college	0.404	0.491	0	1

Notes: The sample consists of 3,281 men.

this sample is skewed slightly towards those whose high school performance was weaker, presumably because it omits women. However, the range for this variable encompasses all possible values, from zero to 99.

"Friends' plans to attend college" is a binary recode of the WLS respondent's response to the question "What are most of your friends doing after high school?" This variable assigns the value of one to any response indicating intentions to continue schooling.

"Facial attractiveness" rating and "relative body mass" measure characteristics of personal appearance that are not components of human capital. However, they may affect the experience of social interactions. These effects could arise if an individual's sense of social efficacy or if the responses elicited from others depend on these aspects of appearance. Therefore, appearance may affect returns to human capital and incentives to invest in it.

The facial attractiveness rating and relative body mass variables both derive from visual examinations of high school yearbook photographs of the WLS subjects. The facial attractiveness rating is the WLS variable "meanrat_fcoder". It is the demeaned average of facial attractiveness ratings on an 11-point scale assigned by six female raters from approximately the same age cohort as the WLS respondents. "Relative body mass" is the WLS variable "srbmi". It is the average of body mass assessments assigned by six young raters, three female and three male, on an 11-point scale and then transformed into rater-specific Z-scores.

Lastly, "alphabetical rank of surname initial" is the explanatory variable of interest.[107] It represents a simple numerical correspondence between the letters of the alphabet, ordered conventionally as "A" through "Z", and the ordered integers from one to 26. The average value of this variable, 11.8, indicates that "typical" surnames began with the letters "K" or "L".[108]

The assumption of linearity embodied in this transformation may seem restrictive. However, the intuitions that motivate this investigation are too general to imply any specific transformation. A fully non-parametric specification, consisting of letter fixed effects, is too cumbersome to be useful. Fixed effects for groups of adjacent letters relax the linearity assumption across groups but at the cost of an equality assumption within groups. The transformation here is, to some degree, validated by its performance in the regressions below.

Table 3.2 presents summary statistics for the explanatory variables that measure characteristics of the individual's family. With the exceptions of number of siblings and birth order, all variables are categorical. Apart from the measures of son's perception of parental attitudes towards college attendance[109], these variables describe the background household characteristics of household structure, parental educations and occupations, father's ethnic background and household income.

The household income variables categorize the original WLS household income variable, which is the average of parental annual incomes reported to the Wisconsin Department of Revenue

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[107] The WLS provided surname initials to this study under strict confidentiality restrictions.

[108] Einav and Yariv (2006) and Ong, et al. (2016) employ the same assignment. Efthyvoulou (2008) employs the logarithm of this assignment. van Praag and van Praag (2008) employ both. Jurajda and Münich (2010) employ the numerical assignment and the percentile of the last name by the alphabetical ranking. Spenkuch, Montagnes and Magleby (2018) use the percentile as well. Huang (2015) employs the numerical assignment and fixed effects for groups of initials and for individual initials. Hamermesh and Pfann (2012) "hold constant for alphabetical location" without further explanation. Similarly, Merritt (1999) holds constant "alphabetic placement".

[109] The omitted category consists of parents who, according to their sons, did not express opinions regarding college attendance.

TABLE 3.2: SUMMARY STATISTICS FOR HOUSEHOLD EXPLANATORY VARIABLES

Variables	Mean	Variables	Mean
Father's education:		**Parental attitude:**	
College	0.0954	Parents encouraged college	0.614
High school	0.328	Parents discouraged college	0.0305
Missing	0.0698	**Father's national/ethnic background:**	
Mother's education:		British	0.109
College	0.0933	Eastern European	0.0491
High school	0.407	French	0.0463
Missing	0.0749	German	0.489
Parental occupation:		Irish	0.0658
Father has a white collar job	0.268	Mediterranean	0.0155
Mother has a white collar job	0.145	Polish	0.0637
Household income:		Scandinavian	0.143
Bottom 25%	0.207	Minority	0.00518
Middle 50%	0.443	Missing	0.0131
Top 25%	0.226	**Household structure:**	
Below neighbors'	0.071	Both parents present	0.912
Above neighbors'	0.242	Number of siblings	3.086
		Birth order	2.416

Notes: All monetary variables are in 1992 dollars. The sample consists of 3,281 men. Standard deviations of "Both parents present", "Number of siblings", and "Birth order" are 0.283, 2.472, and 1.895 respectively

from 1957 through 1960. This is likely to be a more accurate measure of permanent incomes than are self-reported annual incomes. The omitted category consists of those with missing values.

Fewer than 10% of households contained only one parent. Fewer than 10% of both fathers and mothers had college degrees. A large majority, 61.4% of individuals, reported that their parents encouraged them to attend college.

The variables for father's national heritage differs substantially from more typical measures of race or ethnicity. The WLS, because of its geographic and temporal sampling frame, contains few individuals with African-American or Hispanic heritage. As reported in table 3.2, "minorities" in this sense comprise less than one percent of the sample. Concerns with differences in outcomes that may be attributable to substantive racial or ethnic discrimination are, therefore, not relevant here.

The important distinctions in national heritage are largely between those with different

TABLE 3.3: MOST COMMON SURNAME INITIALS BY NATIONALITY

Father's national/ethnic background:	First	Frequency	Second	Frequency	Third	Frequency	N
British	S	0.104	H	0.096	C	0.087	357
Eastern European	B	0.106	K	0.099	S	0.099	370
French	D	0.132	L	0.132	B	0.105	152
German	S	0.153	B	0.104	K	0.096	1,606
Irish	M	0.167	C	0.097	D	0.083	216
Mediterranean	R	0.137	S	0.137	B	0.117	51
Polish	S	0.196	K	0.139	B	0.100	209
Scandinavian	S	0.102	J	0.096	H	0.085	469
Minority	C	0.177	H	0.177	P	0.118	17
Missing	B	0.117	H	0.116	B	0.093	44

Notes: N = sample size. Relative frequency distribution of surname initials (Table 3.3) is derived from our WLS sample. N = 3,281

European origins. While these distinctions are not generally associated with different experiences of discrimination, they may be relevant here because they could be associated with systematic differences in names, naming conventions, and therefore surname initials.

Table 3.3 demonstrates that the most common surname initials vary substantially across categories of national origin. In order to purge estimated surname initial effects of any influence arising from other attributes associated with national origin, all models include fixed effects for these national origin categories.

In addition to the explanatory variables of tables 3.1, 3.2 and 3.3, all regressions include fixed effects for high school. Individuals in the sample attended 303 different high schools. On average, each high school contributed 10.8 students. The numbers of students from each high school ranged from one to 60 students, with a standard deviation of 11.4.

In the presence of high school fixed effects, all other coefficients effectively compare students from the graduating class of the same high school. For example, these fixed effects control for any systematic differences across high schools in the photographic techniques employed for yearbook pictures, upon which the facial attractiveness and body mass variables are based.

TABLE 3.4: SUMMARY STATISTICS FOR INDIVIDUAL DEPENDENT VARIABLES

Variables	Mean	SD	Min	Max
High school:				
Outstanding student	0.113	0.316	0	1
Favorable opinion on high school classes	0.564	0.496	0	1
Post-secondary education:				
Applied to college	0.341	0.474	0	1
Withdrew from college	0.344	0.475	0	1
Received a post-high school degree	0.444	0.497	0	1
Labor market:				
Military service	0.504	0.5	0	1
Income score for first job	270.756	236.823	0	877
Siegel prestige score for first job	396.858	165.714	144	812
1974 employment earnings ($10,000s)	4.117	2.584	0	28.458
Siegel prestige score for employment in 1974	462.359	135.313	156	812
1992 employment earnings ($10,000s)	6.242	28.435	0	999.999
Siegel prestige score for employment in 1992	465.374	139.568	154	812

Notes: All monetary variables are in 1992 dollars. The sample consists of 3,281 men.

More importantly, these effects are essential for the interpretation of high school rank. Differences in ranks across schools are meaningless because schools differ in average academic standards. Higher ranks within the same school unambiguously demonstrate superior performance. With IQ held constant as well, differences in rank probably reflect differences in chosen effort (Zax and Rees, 2002).

Table 3.4 presents summary statistics for the 12 dependent variables examined in the analysis below. Two of these variables measure outcomes of the high school experience. “Outstanding student” is a binary variable that represents the “Teacher’s evaluation of graduate” and assigns the value of one to the response “Outstanding”. “Favorable opinion of high school studies” is a binary recode of the WLS subject’s response to the question “What is your opinion of your high school studies” with the value of one representing “Interesting, want to learn more”.

Three outcome variables measure the individual’s experience with tertiary education. “Applied to college” is a binary variable indicating whether the individual had applied to college in 1957.

"Withdrew from college" is a binary variable indicating that the individual attended post- secondary school but did not report receipt of a degree. "Received a post-high school degree" is a binary variable indicating whether the individual had earned any tertiary degree as of 1992.

The remaining seven variables measure labor market experiences. Two variables, income score and Siegel prestige score for the first job, characterize the individual's first experience. Four variables, income and Siegel prestige score in 1974 and 1992, characterize the individual's employment, if any, at approximately ages 35 and 53. The seventh variable indicates whether an individual had served in the military as of 1992.[110]

V. Evidence of alphabetism

This section estimates model 1 in order to examine the sample-wide effects of surname initial rank on individual experiences in high school, participation in tertiary education, labor market activity as a young adult and in mid-career. Table 3.5 presents estimates of equation 1 for the two high school outcome variables – whether an individual was recognized as an "outstanding student" and whether a student evaluated his high school classes favorably. The first represents an external evaluation of the student's high school performance. The second represents a self-reported evaluation of the high school experience. Both dependent variables are categorical. Accordingly, both regressions in table 3.5 are linear probability models.[111]

The equation for "outstanding student" demonstrates that, as would be expected, individuals with higher IQs and with higher high school ranks were significantly more likely to be identified as

[110] Military service is a binary variable with one indicating an affirmative response to the question "Respondent ever been on active duty in the U.S. military or spent at least two months on active duty for training in the Reserves or National Guard?"
[111] Variations in sample sizes across regressions here and in the following tables are attributable, with one exception in table 3.6, to differing incidences of missing values for the dependent variables.

TABLE 3.5: ALPHABETISM IN HIGH SCHOOL

Explanatory variables	Outstanding student	Opinion on high school classes
Individual characteristics:		
Alphabetical rank of surname initial	-0.00128*	-0.00219*
	(0.000680)	(0.00122)
IQ	0.00199***	-7.22e-05
	(0.000502)	(0.000731)
High school rank	0.00354***	0.00461***
	(0.000345)	(0.000390)
Facial attractiveness	0.000555	-0.00896
	(0.00323)	(0.00680)
Relative body mass - proxy for BMI	0.00591	0.0129
	(0.00651)	(0.0111)
Friends' plan to attend college	0.0209*	0.162***
	(0.0124)	(0.0204)
Household characteristics:		
Household structure:		
Both parents present	0.0154	-0.0116
	(0.0193)	(0.0295)
Number of siblings	-0.00179	0.0105**
	(0.00222)	(0.00457)
Birth order	-0.000142	-0.0137***
	(0.00328)	(0.00515)
Father's education:		
College	0.00857	0.0496*
	(0.0250)	(0.0282)
High school	-0.00388	0.0153
	(0.0114)	(0.0207)
Missing	0.0124	-0.0194
	(0.0193)	(0.0382)
Mother's education:		
College	0.00517	-0.0138
	(0.0222)	(0.0307)
High school	-0.00973	0.0189
	(0.0108)	(0.0208)
Missing	0.00299	-0.0232
	(0.0206)	(0.0389)
Parental occupation:		
Father has a white collar job	-0.0153	-0.00443
	(0.0150)	(0.0229)
Mother has a white collar job	0.0220	0.0337
	(0.0150)	(0.0230)

TABLE 3.5: CONTINUED

Explanatory variables	Outstanding student	Opinion on high school classes
Household income:		
Bottom 25%	0.00765	-0.00365
	(0.0144)	(0.0236)
Top 25%	0.0220	0.0361*
	(0.0149)	(0.0186)
Missing	0.00798	0.0341
	(0.0171)	(0.0310)
Below neighbors'	0.0215	-0.0339
	(0.0207)	(0.0332)
Above neighbors'	0.00493	-0.00807
	(0.0125)	(0.0210)
Parental attitude:		
Parents encouraged college	0.0228*	0.215***
	(0.0120)	(0.0246)
Parents discouraged college	-0.0177	0.0678
	(0.0250)	(0.0543)
Father's national/ethnic background:		
British	0.0214	0.0651
	(0.0205)	(0.0420)
Eastern European	0.00645	0.0177
	(0.0275)	(0.0479)
French	0.0777***	0.0333
	(0.0274)	(0.0541)
German	0.0214	0.0267
	(0.0164)	(0.0350)
Irish	-0.0396**	0.0204
	(0.0196)	(0.0490)
Mediterranean	0.0215	0.0689
	(0.0399)	(0.0658)
Scandinavian	0.00638	0.0138
	(0.0174)	(0.0406)
Minority	-0.0317	0.309***
	(0.0733)	(0.0882)
Missing	0.0344	0.0307
	(0.0490)	(0.0905)
Constant	-0.288***	0.144*
	(0.0541)	(0.0851)
Observations	3,281	3,196
R^2	0.198	0.244
High school FEs	Y	Y

Notes: Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

outstanding students. The same was true for those who reported that their friends planned to attend college and that their parents encouraged college attendance.

The estimated effects of both facial attractiveness and body mass are statistically insignificant. Only two of the nationality effects are statistically significant. These characteristics, though observable, did not substantially distort recognitions as "outstanding".

However, recognition did not depend solely on ability, ambition and performance. The effect of surname initial alphabetical rank on recognition is significant, negative and substantively large. Two otherwise identical students whose surname initials differed in rank by ten places, the difference between "A" and "K", "H" and "R", or "O" and "Y", as examples, would have differed in their probabilities of designation as outstanding by 1.28 percentage points. As the average probability of designation, from table 3.4, was 11.3%, this effect reduced the probability of designation for the student with the higher-ranked surname initial by more than 10%.

The regression for "opinion on high school classes" shares important similarities with that for "outstanding student". Students with higher high school rank, who reported that friends intended to attend college and that parents encouraged college attendance, were more likely to have favorable opinions. Facial attractiveness and body mass had no effects.

However, IQ also had no effect on student opinions regarding their classes. It seems plausible that, for example, cognitive ability and appreciation for challenging courses might have been positively correlated. However, this correlation might have been of limited relevance if students of different abilities took different courses. Its relevance may have been further limited by the regression specification, which compares the effects of differences in cognitive ability for those whose high school performance and college ambitions were the same.

Regardless, the effect of alphabetic rank of surname initial on student opinions with respect to their courses was, once again, significant and negative. Substantively, though, it was less important than in the evaluation as "outstanding". Two otherwise identical students whose surname initials differed in rank by ten places would have differed in their probabilities of expressing favorable opinions of their courses by 2.19 percentage points. This effect reduced the probability of a favorable opinion by the student with the surname initial ten places farther from the beginning of the alphabet by less than 5% of the average value from table 3.4, 56.4%.

In sum, table 3.5 demonstrates that students with surname initials that were farther from the beginning of the alphabet had significantly less successful high school experiences. Moreover, these effects may be underestimates. The relationship between high school experience and rank of surname initial among those who graduated suggests that those with surname initials farther from the beginning of the alphabet may have had higher propensities to leave school prior to graduation. This would imply that, among students with such initials, those who remained through graduation had relatively positive experiences.

Teacher evaluations of high school students and students' evaluations of their high school experience could have been distorted by student characteristics that were not directly relevant to academic performance. However, the regressions in table 3.5 hold constant those that were most likely to have been salient – facial attractiveness and body mass. Moreover, it is unlikely that the alphabetic rank of surname initial was correlated with other unobserved but potentially relevant characteristics, especially in the presence of nationality fixed effects. Conditional on the other observed variables, surname initial should be, effectively, randomly assigned. Consequently, the estimated effects of surname initial are likely to capture actual effects of alphabetic rank.

The substantive differences in surname initial effects of table 3.5 may be informative regarding the behavioral mechanisms, discussed in section IV, by which those effects might arise. Teachers were responsible for designation as an "outstanding student". The large effect of surname initial on the probability of achieving this designation suggests that, for teachers, ordering effects were important.

TABLE 3.6: POST-SECONDARY EDUCATIONAL ATTAINMENT

Explanatory variables	Applied to college	Withdrew from college	Received post-high school degree
Alphabetical rank of surname initial	-0.00293***	0.00562***	-0.00267**
	(0.00106)	(0.00184)	(0.00107)
IQ	-0.000458	-0.00174	0.00256***
	(0.000634)	(0.00108)	(0.000712)
High school rank	0.00294***	-0.00493***	0.00374***
	(0.000360)	(0.000601)	(0.000395)
Facial attractiveness	0.00646	-0.000214	-0.00406
	(0.00532)	(0.00866)	(0.00666)
Relative body mass - proxy for BMI	0.0117	0.000242	-0.000610
	(0.00908)	(0.0150)	(0.00911)
Friends' plans to attend college	0.156***	-0.0654**	0.108***
	(0.0209)	(0.0253)	(0.0176)
Parents encouraged college	0.0730***	-0.0282	0.145***
	(0.0177)	(0.0420)	(0.0191)
Observations	3,281	1,610	3,280
R^2	0.161	0.182	0.226
Additional household controls	Y	Y	Y
High School FEs	Y	Y	Y

Notes: Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, students were responsible for evaluating their courses. The smaller effect of surname initial on the probability of a favorable opinion suggests that students with surname initials further from the beginning of the alphabet were able to make choices that, at least to some degree, mitigated the associated disadvantages.

Table 3.6 explores the relationships between the explanatory variables of greatest interest and tertiary education outcomes. It presents estimates from linear probability models for the probabilities of applying to college prior to high school graduation, withdrawing from college if ever enrolled prior to 1992, and receiving a college degree by 1992.[112] These estimates reinforce the themes apparent in table 3.5.

[112] The sample for the regression analyzing withdrawal from college consists only of those who ever enrolled. The authors can provide complete results for these and all subsequent regressions. Among the explanatory variables not presented in table 3.6, an individual was significantly more likely to apply to college if his father had graduated from college, significantly less likely to withdraw from college if

As in table 3.5, better performance in high school was associated with more favorable outcomes. Men with higher high school ranks subsequently accumulated more human capital: they were significantly more likely to apply to college, significantly less likely to withdraw and significantly more likely to receive a college degree. The same was true for those who believed that their friends intended to attend college. Those who reported that their parents encouraged college attendance were significantly more likely to apply and to graduate. Holding constant high school performance and proxies for college ambitions, higher IQs were significantly associated with only higher probabilities of receiving a college degree.

Facial attractiveness and relative body mass had no significant effects on college outcomes. Their absence reinforces the implication of table 3.5. Any relevance they may have had to the experience of young men does not appear to have affected their investments in human capital.

However, this again did not hold for surname initial. As in table 3.5, individuals with surname initials ranked later in the alphabet had consistently inferior outcomes. The coefficients for surname initial rank are significant in all three regressions. They imply that a difference of ten ranks in surname initial was associated with a reduction of 2.93 percentage points in the probability of applying to college, an increase of 5.62 percentage points in the probability of withdrawing after enrolling, and a reduction of 2.67 percentage points in the probability of receiving a college degree. Compared to the average probabilities from table 3.4 of, respectively, 34.1%, 34.4% and 44.4%, each of these differences was substantively large.

Table 3.7 explores the relationships between the explanatory variables of greatest interest and early employment outcomes. It presents a linear probability model for the probability of serving in the military, on the presumption that those who served were most likely to do so at the beginnings of

either father or mother had graduated from college and significantly more likely to earn a college degree if either father or mother had graduated from college. Other explanatory variables did not display consistent significant effects.

TABLE 3.7: INITIAL EMPLOYMENT

Explanatory variables	Military Service	First employment	
		Income score	Prestige score
Alphabetical rank of surname initial	0.00465***	-0.00424	-0.749*
	(0.00148)	(0.00281)	(0.390)
IQ	0.00194**	0.00760***	1.065***
	(0.000771)	(0.00175)	(0.243)
High school rank	-0.00197***	0.00810***	1.765***
	(0.000402)	(0.000821)	(0.127)
Facial attractiveness	0.000988	-0.00190	-0.163
	(0.00798)	(0.0152)	(2.191)
Relative body mass - proxy for BMI	-0.00415	0.0181	-2.170
	(0.0118)	(0.0239)	(3.312)
Friends' plan to attend college	-0.0706***	0.190***	40.47***
	(0.0231)	(0.0461)	(6.759)
Parents encouraged college	-0.0634***	0.299***	47.75***
	(0.0211)	(0.0462)	(6.375)
Observations	3,281	3,086	3,087
R^2	0.035	0.213	0.311
Additional household controls	Y	Y	Y
High school FEs	Y	Y	Y

Notes: Income score is in natural log. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

their careers. It also presents regressions that describe the natural logarithm of the income score[113] and the Siegel Occupational Prestige Score for the first job. These estimates suggest that military service was an inferior option to employment. They further support the themes apparent in table 3.5.

Students with higher high school ranks were significantly less likely to have military experience, and had significantly higher incomes and prestige scores for their first job. The same was true for students who reported that their friends intended to attend college and that their parents encouraged them to attend college. These results indicate that the more accomplished and ambitious were more likely to avoid military service and obtain better entry-level employment.

113 The WLS documentation does not offer a clear description of this variable, "ocix1" (http://www.ssc.wisc.edu/wlsresearch/documentation/waves/?wave=wls75&module=cjobh). It appears to be the median income of workers in an individual's occupation.

Holding constant high school performance and ambition, students with higher IQ scores were significantly more likely to serve in the military, and obtained first jobs with significantly higher income and prestige scores. Once again, neither facial attractiveness nor relative body mass had significant effects on any of the table 3.7 outcomes.

However, surname initial continued to confer advantages on those with initials closer to the front of the alphabet. Its coefficient is significantly positive in the linear probability model for military service and significantly negative in the regression for the prestige score of the first job. An increase of ten in alphabetic rank increased the probability of military service by 4.65 percentage points, or nearly one-tenth of the average probability of 50.4%. The same increase in alphabetic rank reduced the prestige score by 7.49 points, or approximately two percent of the average score, 396.9.

Conceptually, the effects associated with surname initial rank in tables 3.5, 3,6 and 3.7 are estimates of the "intent to treat" for those assigned surname initials farther towards the end of the alphabet. They are consistent with the hypothesis that sample members experienced alphabetized allocations of resources and opportunities throughout childhood, which conferred cumulative advantages on those with surname initials towards the beginning of the alphabet. Moreover, as the assignment of surname initial must have been essentially random, at least conditional on national origin and other observed variables, alternative explanations are not apparent.

At the same time, the actual "treatments" – the extent to which individuals actually experienced alphabetized allocations of resources and opportunities – are not recorded in the data under examination here. Therefore, the "alphabetism hypothesis" cannot be tested directly. This is a persistent issue throughout the literature on ordering effects. Explanations for why first-listed articles are more likely to be cited, first-listed stocks are more frequently traded, early-called senators are more likely to defect and authors first-listed by alphabet receive more credit all rely on hypotheses that are behaviorally plausible rather than testable in available data. Sections VI and VII present evidence

TABLE 3.8: EMPLOYMENT IN ADULTHOOD

Explanatory variables	Employment in 1974		Employment in 1992	
	Earnings	Prestige score	Earnings	Prestige score
Alphabetical rank of surname initial	-2.13e-05	0.214	0.000858	-0.203
	(0.00145)	(0.324)	(0.00238)	(0.353)
IQ	0.00294***	1.199***	0.00644***	1.432***
	(0.000920)	(0.206)	(0.00169)	(0.199)
High school rank	0.00144***	1.287***	0.00302***	0.895***
	(0.000423)	(0.107)	(0.000797)	(0.120)
Facial attractiveness	0.0131	3.359*	0.0119	0.478
	(0.00831)	(1.727)	(0.0126)	(2.080)
Relative body mass - proxy for BMI	-0.00289	-3.208	-0.00679	-4.887*
	(0.0111)	(2.614)	(0.0201)	(2.818)
Friends' plan to attend college	0.0689***	20.71***	0.0835**	22.43***
	(0.0243)	(5.445)	(0.0356)	(6.021)
Parents encouraged college	0.0686***	35.21***	0.0406	41.46***
	(0.0237)	(5.484)	(0.0381)	(6.362)
Observations	2,694	3,220	2,426	2,863
R^2	0.077	0.262	0.092	0.208
Additional household controls	Y	Y	Y	Y
High school FEs	Y	Y	Y	Y

Notes: Earnings are in natural log. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that, at least, may narrow the range of possible mechanisms for surname initial rank effects to those that pertain to individuals who are not otherwise distinguished.

Table 3.8 explores the determinants of earnings and prestige scores for employment in 1974, at approximately age 35, and in 1992, at approximately age 53. As in all previous regressions, higher high school ranks were significantly associated with better outcomes at both ages. The same was true for respondent's reports regarding friends' plans and parents' encouragement for college enrollment, with the exception of the insignificant effect for the latter in the regression for 1992 log earnings. Higher IQ scores were significantly associated with higher earnings and prestige in both years.

As before, both facial attractiveness and relative body mass make no statistically significant contributions to three of the four regressions in table 3.7. Given the absence of similar effects in all previous regressions, the two significant results probably do not indicate systematic effects.[114]

[114] In previous research, "beauty" appears to be positively associated with labor market outcomes (Hamermesh and Biddle, 1994; Fletcher, 2009; Borland and Leigh, 2014 as examples). These results are not directly comparable to those here because, most importantly,

In contrast to all previous regressions, alphabetical rank of surname initial is insignificant in the table 3.8 regressions. This implies that the effects of surname initial rank dissipated as adulthood progressed. Just as the mechanisms that created alphabetic effects earlier in life are not observable, so too are those that diminished them later in life. Once again, explanations must be hypothetical.

Conceptually, the differences between those with surname initials towards the end and towards the beginning of the alphabet in any period of the life cycle are the combination of a stock and a flow. The stock is the consequence of deficits accumulated over prior periods. The flow consists of contemporaneous inequities in the ongoing allocation of resources and opportunities.

It seems likely that adult environments are not "sustaining": they do not contribute to alphabetism because resources and opportunities are usually not allocated alphabetically. If so, the flow of additional alphabetical inequities diminishes or ceases in adulthood.[115] Moreover, the marginal return to investing in opportunities or utilizing resources would be greater for those who previously had less access. Therefore, those who experienced deficits caused by alphabetism at earlier ages might accomplish relatively more than their colleagues with more equitable treatment in adulthood.

However, it is also possible that the effects of surname initial are more persistent for those who are most likely to suffer from them. The next section explores this possibility.

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they do not control for IQ or high school accomplishment. Moreover, they rely on in-person assessments of physical appearance by individual interviewers. These may be influenced by other aspects of the interview experience. Finally, they frequently control for educational attainment and labor market variables which, themselves, could be the consequences of physical appearance. The apparent effects of "beauty" in Harper (2000) diminish or vanish in the presence of controls for undefined "academic ability" at age 11. Male earnings are generally insensitive to weight (Harper, 2000; Cawley, 2004; Norton and Han, 2008).

[115] "Fade-out" appears frequently elsewhere in the literature on human capital accumulation. Extensive evidence demonstrates that the positive effects of Head Start programs also eventually diminish or disappear (Currie and Thomas, 1995; Banerjee, et al., 2007; Anderson, 2008; Deming, 2009; Duncan and Magnuson, 2013; Bailey, et al., 2017). As in the case of alphabetism, available data do not readily identify the behavioral mechanisms through which Head Start programs achieve their initial effects or those that eventually erode them (Bailey, et al., 2017). The concept of "sustaining environments" was developed as a potential explanation for both in this context. Bailey, et al. (2017) provide a comprehensive discussion.

VI. The Interaction Between Surname Initial and Cognitive Ability

Section V estimates effects for alphabetic rank of surname initial that were common to all sample members. However, sections III.C and IV suggest that a characteristic that is not of primary salience, such as surname initial rank, may be less important for those who are distinguished with regard to more salient characteristics.

This section explores the effect of distinction with regard to more salient characteristics in greater detail. In the previous section, two personal characteristics, high school rank and IQ, had significant effects on all or almost all outcomes. These effects were plausible because more human capital should have contributed consistently to better outcomes. Moreover, both academic performance and cognitive ability were readily estimable, if not actually observable. Therefore, both were plausibly more salient individual characteristics than was alphabetic rank of surname initial.

Given the effects of surname initial rank on high school outcomes, high school rank may be structurally related to alphabetic rank of surname initial. In contrast, IQ is largely innate. Therefore, to a first approximation, surname initial rank is probably assigned randomly across IQ strata. This conceptual approximation is consistent with the empirical correlation between surname initial rank and IQ, -0.0067. To the extent that this approximation is appropriate, it should be possible to test unambiguously whether alphabetic rank of surname initial has more important effects for those who have intermediate cognitive ability than for those whose cognitive skills distinguish them.

Table 3.9 presents this test. It stratifies the sample into three strata, as in equation 2. The first consists of the 498 individuals with IQ scores more than one standard deviation below the sample average, between 61 and 86, inclusive. The third consists of the 536 individuals with IQ scores more than one standard deviation above the sample average, between 118 and 145, inclusive. The

TABLE 3.9: ALPHABETISM BY IQ STRATA

Explanatory variables	Alphabetical rank of initial			N	R^2
	Low IQ	Intermediate IQ	High IQ		
High school:					
Outstanding student	-0.000318	-0.000983	-0.00326	3,281	0.216
	(0.00138)	(0.000781)	(0.00214)		
Opinion on high school classes	-0.00243	-0.00293**	-0.00201	3,196	0.245
	(0.00311)	(0.00148)	(0.00251)		
Post-secondary educational attainment:					
Applied to college	0.00127	-0.00379***	-0.00307	3,281	0.172
	(0.00296)	(0.00122)	(0.00281)		
Withdrew from college	0.00223	0.00726***	0.00224	1,610	0.186
	(0.00842)	(0.00230)	(0.00270)		
Received post-high school degree	0.00299	-0.00420***	-0.00103	3,280	0.233
	(0.00292)	(0.00133)	(0.00263)		
Initial employment:					
Military service	-0.00166	0.00569***	0.00560*	3,281	0.038
	(0.00332)	(0.00184)	(0.00309)		
First employment - income score	0.00600	-0.00722**	-0.000855	3,220	0.171
	(0.00768)	(0.00339)	(0.00660)		
First employment - prestige score	0.382	-0.875*	-1.240	3,087	0.314
	(0.898)	(0.483)	(0.941)		
Employment in adulthood:					
1974 employment – earnings	0.000272	-0.00109	0.00352	2,694	0.079
	(0.00306)	(0.00178)	(0.00358)		
1974 employment - prestige score	0.415	0.0910	0.367	3,220	0.266
	(0.757)	(0.374)	(0.840)		
1992 employment – earnings	-0.00387	-0.00144	0.0117*	2,426	0.099
	(0.00611)	(0.00267)	(0.00652)		
1992 employment - prestige score	0.303	-0.0867	-1.044	2,863	0.209
	(0.886)	(0.440)	(0.802)		

Notes: N = sample size. Each regression includes full set of controls and high school fixed effects. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

intermediate stratum consists of the 2,247 individuals with IQ scores within one standard deviation of the sample average, between 87 and 117, inclusive.

Each row of table 3.9 presents the coefficients for surname initial alphabetic rank interacted with the dummy variable for each of these strata, from equation 2, for a single regression. They are generally consistent with the hypothesis that the ordering effects associated with surname initial rank are more important for individuals who are not distinguished in more salient dimensions.

The middle column of table 3.9 demonstrates that those with intermediate IQ scores were largely responsible for the sample-wide effects of surname initial alphabetic rank in tables 3.5, 3.6 and 3.7. The coefficients for alphabetic rank are significant at better than 1% in the regressions for whether the individual applied to college, whether the individual withdrew from college having enrolled, whether the individual earned a post-high school degree and whether the individual served in the military. They are significant at better than 5% in the regressions for the individuals' opinion regarding their high school classes and the income score of their first job, and at better than 10% for their first employment prestige score.

The coefficient for surname initial rank in the regression for income score for the first job is statistically significant in table 3.9 and larger in magnitude than its insignificant counterpart in table 3.7. The other six significant coefficients in table 3.9 are all larger in magnitude than the corresponding coefficients in tables 3.5, 3.6 and 3.7, and of at least the same statistical significance. The table 3.5 coefficient for surname initial rank in the regression for outstanding student recognition is the only effect that is significant for the entire sample but not for those of intermediate IQ in table 3.9.

In contrast, the first column of table 3.9 demonstrates that alphabetic rank of surname initial had no significant effects for those with low IQ scores. The coefficients are of smaller magnitude or opposite sign than the corresponding coefficients for those with intermediate IQ in all seven regressions in which the latter are statistically significant, and in three of the other five. This is consistent with the expectation that individuals with weak cognitive ability would receive distinctive recognition, perhaps in the form of supplemental instruction, regardless of their surname initial. This recognition would supersede any ordering effects associated with alphabetic rank.

Alphabetism was more important for those with strong cognitive ability than for those with weak, but much less so than for those with intermediate cognitive ability. The third column of table 3.9 demonstrates that the effects of alphabetic rank for these students were statistically insignificant in six of the seven regressions in which these effects were significant for those with intermediate cognitive ability. In five of these regressions, the coefficient for students with strong cognitive ability were of the same sign but smaller magnitude than the corresponding coefficient for students with intermediate cognitive ability.

In the regression for military service, the effects for both groups were significant and of equal magnitude. In the regression for the prestige score of the first job, the coefficient for those with strong cognitive ability was greater in magnitude than for those with intermediate cognitive ability, though statistically insignificant.

In addition, the coefficient for surname initial among those with strong cognitive ability indicates a significant positive effect on the natural log of earnings in 1992. This effect does not appear in the sample as a whole. It suggests, anomalously, that among those with high IQ scores, individuals with surname initials further from the beginning of the alphabet had higher earnings in that year.

These results are generally consistent with those summarized in section III.C. As there, the ordering effects of alphabetism are much stronger and more consistent among individuals who were not distinguished by more salient characteristics. A few of the estimated effects on individuals with strong cognitive skills are large and two are significant, but only one is both large and significant. None of the estimated effects on individuals with weak cognitive skills are large or significant. Surname initial rank has extensive effects only on those with intermediate cognitive skills.

VII. The Interaction Between Surname Initial, Cognitive Ability and Facial Appearance

Surname initial is probably assigned randomly across facial attractiveness scores for the same reasons that it would be randomly assigned across IQ scores. The empirical correlation between the two is -0.012, or essentially zero. The absence of significant facial attractiveness effects in tables 3.5 through 3.8 suggests that there may not be significant interactions between facial attractiveness and surname initial rank. None appear in regressions, analogous to those in table 3.9, that estimate

TABLE 3.10: SAMPLE SIZE BY IQ-ATTRACTIVENESS SUBSTRATA

	Low IQ Group	Intermediate IQ group	High IQ group	Total
Low attractiveness group	91 (2.77%)	337 (10.27%)	88 (2.68%)	516 (15.73%)
Intermediate attractiveness group	334 (10.18%)	1,533 (46.72%)	341 (10.39%)	2,208 (67.29%)
High attractiveness group	73 (2.23%)	377 (11.49%)	107 (3.26%)	557 (16.98%)
Total	498 (15.18%)	2,247 (68.49%)	536 (16.34%)	3,281 (100%)

interactions of rank with facial attractiveness strata in the presence of the continuous IQ measure.[116]

However, when the sample is stratified by both IQ and facial attractiveness, as in equation 3, the pattern of table 3.9 reemerges, reinforced. This stratification subdivides each of the IQ-defined strata of table 3.9 into three further substrata distinguished by the low, intermediate and high facial attractiveness scores.

Table 3.10 reports the numbers of individuals within each of the nine substrata. The four substrata with either high or low scores for both facial attractiveness and IQ together comprise 10.9% of the sample. The four substrata with intermediate scores for one and high or low scores for the other comprise 42.3% of the sample. The substratum with intermediate scores for both IQ and facial attractiveness includes 46.7% of the sample.[117]

Table 3.11 presents results for the regressions of table 3.5 with this expanded specification. It reports only the coefficients for alphabetic rank of surname initial within each substratum of the IQ-

[116] As with IQ, the analysis here stratifies individuals into those with attractiveness scores more than one standard deviation below or above the sample average and those with scores within one standard deviation of that average. The range of scores for each stratum is, respectively, from the minimum of -4.011 to less than -1.24, from 1.37 to the maximum of 4.14 and between -1.24 and less than 1.37.
[117] Stratifications that narrow the definition of "undistinguished" to less than one standard deviation from the sample average place more of the sample in the extreme categories. However, they yield less distinctive results. Empirically, it seems that "within one standard deviation of the sample average" is an appropriate implementation of "undistinguished". However, it is possible that some of the differences in statistical significance apparent in the following tables are the consequences of different subsample sizes, rather than differences in behavioral responses.

TABLE 3.11: ALPHABETISM IN HIGH SCHOOL BY IQ-ATTRACTIVENESS SUBSTRATA

Explanatory variables	Outstanding student	Opinion on high school classes
Alphabetical rank of surname initial:		
Low IQ group:		
Low attractiveness group	0.00336	0.00458
	(0.00292)	(0.00907)
Intermediate attractiveness group	-0.00130	-0.00312
	(0.00170)	(0.00376)
High attractiveness group	0.000769	-0.00535
	(0.00246)	(0.00808)
Intermediate IQ group:		
Low attractiveness group	0.000335	-0.000378
	(0.00171)	(0.00357)
Intermediate attractiveness group	-0.00233**	-0.00457***
	(0.00103)	(0.00170)
High attractiveness group	0.00325	0.000905
	(0.00224)	(0.00329)
High IQ group:		
Low attractiveness group	-0.00380	-0.00194
	(0.00497)	(0.00643)
Intermediate attractiveness group	-0.00376	0.000773
	(0.00292)	(0.00327)
High attractiveness group	-0.000992	0.00464
	(0.00456)	(0.00587)
Observations	3,281	3,196
R^2	0.224	0.252

Notes: Includes full set of controls and high school fixed effects. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

by-facial attractiveness stratification, $\beta_{ir,\alpha}$. These coefficients confirm that alphabetic rank of surname initial was important only for those who were not distinguished in terms of cognitive ability or facial attractiveness.[118] Significant effects occur only for those who were of intermediate IQ and intermediate facial attractiveness, in substratum ($M_I M_R$). In magnitude, these effects are approximately double those for the entire sample in table 3.5 and larger than the effects in table 3.9.

Table 3.12 presents the same elaboration on the regressions of table 3.6. Once again, the

[118] Variations in alphabetic effects across substrata defined in part by facial attractiveness indicate that the absence of significant linear effects of facial attractiveness in the regressions of tables 3.5 through 3.9 arises because its true effects are non-linear.

TABLE 3.12: POST-SECONDARY EDUCATIONAL ATTAINMENT BY IQ-ATTRACTIVENESS SUBSTRATA

Explanatory variables	Applied to college	Withdrew from college	Received post-high school degree
Alphabetical rank of surname initial:			
Low IQ group:			
Low attractiveness group	0.0144**	-0.0392**	0.00275
	(0.00680)	(0.0159)	(0.00836)
Intermediate attractiveness group	-0.000963	0.00918	0.00303
	(0.00357)	(0.0101)	(0.00369)
High attractiveness group	-7.69e-05	-0.0157*	0.00536
	(0.00877)	(0.00907)	(0.00815)
Intermediate IQ group:			
Low attractiveness group	-0.00441	0.00240	0.00128
	(0.00342)	(0.00579)	(0.00334)
Intermediate attractiveness group	-0.00335*	0.00917***	-0.00591***
	(0.00174)	(0.00275)	(0.00169)
High attractiveness group	-0.00435	-0.000513	-0.00309
	(0.00327)	(0.00490)	(0.00319)
High IQ group:			
Low attractiveness group	-0.0126*	-0.00355	-0.00607
	(0.00738)	(0.00593)	(0.00668)
Intermediate attractiveness group	-0.00267	0.00473	-0.00318
	(0.00361)	(0.00308)	(0.00301)
High attractiveness group	-0.00104	0.00108	0.00839
	(0.00526)	(0.00553)	(0.00609)
Observations	3,281	1,610	3,280
R^2	0.178	0.214	0.239

Note. – Includes full set of controls and high school fixed effects. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

effects of surname initial rank in all three regressions are significant for those with intermediate IQ scores and intermediate facial attractiveness. The signs are identical to those estimated for the entire sample in table 3.6.

The coefficient measuring the effect of surname initial rank for those with intermediate IQ scores and intermediate facial attractiveness on the probability of applying to college is slightly larger in magnitude than the coefficient for the entire sample in table 3.6, but slightly smaller than that for all with intermediate IQ scores in table 3.9. However, the coefficient magnitudes for this substratum with regard to the probabilities of withdrawing having enrolled and of receiving a college degree are

TABLE 3.13: INITIAL EMPLOYMENT BY IQ-ATTRACTIVENESS SUBSTRATA

Explanatory variables	Military service	First employment	
		Income score	Prestige score
Alphabetical rank of surname initial:			
Low IQ group:			
Low attractiveness group	-0.00729	-0.0109	-0.0387
	(0.00866)	(0.0205)	(2.365)
Intermediate attractiveness group	-0.000708	0.0119	1.225
	(0.00412)	(0.00842)	(1.055)
High attractiveness group	-0.00350	-0.000379	-1.613
	(0.00948)	(0.0187)	(2.136)
Intermediate IQ group:			
Low attractiveness group	0.00324	-0.00783	-0.364
	(0.00455)	(0.00859)	(1.143)
Intermediate attractiveness group	0.00618***	-0.0114***	-1.386**
	(0.00211)	(0.00420)	(0.569)
High attractiveness group	0.00653	0.0110	0.739
	(0.00441)	(0.00865)	(1.254)
High IQ group:			
Low attractiveness group	0.000646	0.00369	-2.043
	(0.00689)	(0.0166)	(2.747)
Intermediate attractiveness group	0.00753*	-0.00216	-1.475
	(0.00409)	(0.00733)	(1.159)
High attractiveness group	0.00195	0.00144	-0.427
	(0.00651)	(0.0158)	(2.149)
Observations	3,281	3,086	3,087
R^2	0.045	0.221	0.318

Notes: Income score is in natural log. Includes full set of controls and high school fixed effects. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

much larger than in table 3.6 and markedly larger than in table 3.9.

These regressions also display incidental significance for three of the other 24 surname initial rank coefficients. The inconsistency of these effects across these regressions, compounded by inconsistency across the other tables in this section, suggests that they were probably not substantive.

Table 3.13 expands the regressions of table 3.7 with the interactions between IQ score, facial attractiveness score and surname initial rank. Here, surname initial rank is associated with only one significant coefficient in substrata other than that with intermediate IQ and intermediate facial attractiveness scores.

TABLE 3.14: EMPLOYMENT IN ADULTHOOD BY IQ-ATTRACTIVENESS SUBSRATA

Explanatory variables	Employment in 1974		Employment in 1992	
	Earnings	Prestige score	Earnings	Prestige score
Alphabetical rank of surname initial:				
Low IQ group:				
Low attractiveness group	0.0102	-0.477	-0.00502	-0.318
	(0.00791)	(1.709)	(0.0152)	(2.671)
Intermediate attractiveness group	-0.00379	0.884	-0.00946	0.848
	(0.00362)	(0.826)	(0.00707)	(1.059)
High attractiveness group	0.00949	-0.313	0.0185	-1.632
	(0.0111)	(2.043)	(0.0132)	(2.152)
Intermediate IQ group:				
Low attractiveness group	0.00162	0.944	-0.0125**	-0.772
	(0.00445)	(0.918)	(0.00576)	(1.104)
Intermediate attractiveness group	-0.00385**	-0.303	0.00101	-0.0834
	(0.00174)	(0.425)	(0.00345)	(0.502)
High attractiveness group	0.00586	0.767	-0.00437	0.375
	(0.00637)	(0.898)	(0.00752)	(1.251)
High IQ group:				
Low attractiveness group	0.0169	2.837	0.0354	-0.987
	(0.0142)	(2.277)	(0.0254)	(1.938)
Intermediate attractiveness group	8.20e-05	0.113	0.00259	-0.544
	(0.00383)	(1.053)	(0.00648)	(0.958)
High attractiveness group	0.00647	-1.020	0.0290	-2.474
	(0.00723)	(1.668)	(0.0224)	(1.876)
Observations	2,694	3,220	2,426	2,863
R^2	0.09	0.272	0.114	0.213

Notes: Earnings are in natural logs. Includes full set of controls and high school fixed effects. Standard errors are clustered by high school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Within this substratum, the coefficients for surname initial rank in the regressions for military service and the prestige score for first employment are significant, of the same sign and larger in magnitude than the corresponding coefficients for the entire sample in table 3.7 and for those with intermediate IQs in table 3.9. The significant coefficient for surname initial rank among those with intermediate IQ and intermediate facial attractiveness scores in the first employment income score regression is much larger than the insignificant coefficient for the entire sample in table 3.7 or the significant coefficient for those with intermediate IQs in table 3.9.

Finally, table 3.14 presents the elaboration of table 3.8. Within the substratum of intermediate

IQ and intermediate facial attractiveness, the association of surname initial rank with earnings in 1974 is negative and significant. It is much larger in magnitude than the insignificant effects of surname initial for the entire sample, in table 3.8, and for all of those with intermediate IQ, in table 3.9.

Within this substratum, surname initial rank is also associated negatively, though insignificantly, with occupational prestige in 1974 and 1992. The first of these effects presents a contrast to the estimated effects of surname initial rank in the sample as a whole and among all of those with intermediate IQs. In tables 3.8 and 3.10, the estimated effect of surname initial rank on occupational prestige in 1974 is insignificant but positive. The estimated effects of surname initial rank on occupational prestige in 1992 are negative but insignificant for the entire sample and for all of those with intermediate IQ, as well as in table 3.14.

In sum, tables 3.11 through 3.14 indicate that the effects of alphabetism are consistently weak or non-existent for those who are distinguished by either high or low cognitive ability or by high or low facial attractiveness. A few of the 96 coefficients for these substrata are statistically significant or of large magnitude. However, the absence of any pattern suggests that these results are spurious.

In contrast, the effects of alphabetism are pervasive for those of both intermediate cognitive ability and intermediate facial attractiveness. Within this substratum, these effects are statistically significant for nine of the 12 outcomes under examination, including the seven outcomes for which significant effects appeared for the entire sample in tables 3.5 through 3.8 and the seven for which significant effects appeared for those of intermediate cognitive ability in table 3.9. Most are larger in magnitude than the effects for the entire sample or for all those with intermediate cognitive ability.

In addition, in table 3.14, surname initial rank had a significant negative effect on earnings in 1974 for those with both intermediate cognitive ability and intermediate facial appearance in table 3.14. The effects for the entire sample in table 3.8 and for all those with intermediate cognitive ability in table 3.9 are negative, but estimated with little precision. This suggests that the appearance of "fadeout" in the sample as a whole may be somewhat misleading. The effects of surname initial may have persisted for those who were most likely to have been affected.

VIII. Conclusion

The analyses presented here demonstrate that outcomes regarding investments in human capital and the returns to those investments, from late adolescence through middle age, are consistently affected by individual characteristics measured as of high school graduation. All 12 outcomes examined here, measuring educational experiences, educational success and educational attainment, as well as incomes and occupational prestige, are significantly and positively affected by improved high school performance, as measured by higher rank in graduating class. Respondents' assessments of friends aspirations to attend college are also significantly associated with more positive outcomes for all 12.

Holding constant high school rank and friends' ambitions regarding college, greater cognitive ability and parental support are nearly as influential. IQ score has significantly positive effects for nine of the 12 outcomes, and for all seven that measure labor market outcomes. Parental encouragement for college attendance has significantly positive effects for 10 of the 12.

At the same time, appearance measures appear to be unimportant with regard to investments in human capital and the subsequent returns. Both the facial attractiveness and body mass ratings have statistically significant effects for only one of the 12 outcomes.

However, the characteristic of interest here, alphabetic rank of surname initial, has significant and substantial negative effects on outcomes in high school, educational attainment and first labor market experiences. Those with higher-ranked initials are less likely to be recognized as outstanding students in high school, less likely to have favorable opinions of their high school experience, less likely to apply to college while in high school, less likely to remain in college if admitted and less likely to earn a college degree. They are also more likely to have military experience and to have first jobs with lower occupational prestige scores.

These effects would be consistent with the experience of alphabetic orderings, both in assigning opportunities and in conditioning individuals to be receptive to opportunities. Those whose surname initials are ranked further from the beginning of the alphabet are presumably offered fewer opportunities in any alphabetic-based ordering. They are consequently less prepared to take advantage of those opportunities that are offered.[119]

These effects also appear to be dependent on experiences of distinction in other domains. They are inconsequential for those who are distinctive, either through especially low or especially high scores, in cognitive ability. Moreover, within those of intermediate cognitive ability, these effects appear to afflict only those of intermediate facial attractiveness. For these men, who otherwise attract the least attention, the further disregard associated with later surname placement in the alphabet is especially harmful and may persist into adulthood.

119 Erwin and Calev (1984, 223) suggest similar mechanisms for the effects of given name stereotypes.

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Appendix

A. Welfare Disbursements

Certain parts of the population exhibit cycles in their monthly behavior that could be correlated with criminal activities, due to uneven access to resources over the course of a month.

Welfare payments are paid out on a monthly basis, with the disbursement schedule typically falling on the earlier days of the month.[120] These payments mitigate the liquidity constraints of their recipients and enable some to purchase behavior-altering substances the consumption of which might be a crime on its own, or whose use is positively correlated with the commission of other types of crimes. Several works have connected increased drug consumption (typically measured by the recorded numbers of overdose hospitalizations and drug-related deaths) to the arrival of welfare checks (Riddell and Riddell, 2006; Dobkin and Puller, 2007; Cotti et al., 2016; Hsu, 2017).[121] Furthermore, welfare recipients are more vulnerable to substance abuse than the general population, further increasing the discussed risk (Grant and Dawson, 1996; Pollack and Reuter, 2006).

In addition, welfare payments may reduce certain types of crimes in the period shortly after their disbursement, or alternatively, increase the number of crimes on the days after which the payments have been exhausted. Shapiro (2005) finds that the caloric intake of SNAP recipients declines over a month, behavior that is consistent with quasi-hyperbolic discounting. This suggests that welfare recipients exhaust their resources relatively quickly, leaving them to depend on other

[120] The three largest welfare programs in terms of benefit outlays are: the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and Supplemental Security Income (SSI). SSI payments are made on the first day of the month, unless the disbursement date falls on the weekend or a holiday, in which case the payment is made on the first business day prior. TANF distributions depend on the state, with most states paying out in the first few days of the month (Hsu, 2017). SNAP benefits are also state-dependent with disbursement typically taking place early in the month; SNAP payments tend to be more staggered and tend to span more days of the month (Cotti et al., 2016).

[121] Cotti et al. (2016), in contrast to the listed works, find a decrease in alcohol related fatalities on the weekdays of SNAP disbursements and no effect if SNAP distributions fall on the weekend.

FIGURE 1.4: WELFARE DISBURSEMENT SCHEDULE

Form EBT-52A
Rev. 1/2/13

Human Resources Administration
Department of Social Services
Family Independence Administration

EBT Pick-up Schedule
January – June 2013

Note: As of August 29th, 2012, any reference to the Food Stamp Program shall mean the Supplemental Nutrition Assistance Program (SNAP), and any reference to Food Stamps shall mean SNAP benefits.

Toe Digit	January CA & SNAP		February CA & SNAP		March CA & SNAP		April CA & SNAP		May CA & SNAP		June CA & SNAP	
	1A	1B	2A	2B	3A	3B	4A	4B	5A	5B	6A	6B
0	1/2	1/16	2/1	2/16	3/1	3/16	4/1	4/16	5/1	5/16	6/1	6/17
1	1/3	1/17	2/2	2/19	3/2	3/18	4/2	4/17	5/2	5/17	6/3	6/18
2	1/4	1/18	2/4	2/20	3/4	3/19	4/3	4/18	5/3	5/20	6/4	6/19
3	1/7	1/19	2/5	2/21	3/5	3/20	4/4	4/19	5/6	5/21	6/5	6/20
4	1/8	1/22	2/6	2/22	3/6	3/21	4/5	4/22	5/7	5/22	6/6	6/21
5	1/9	1/23	2/7	2/23	3/7	3/22	4/8	4/23	5/8	5/23	6/7	6/22
6	1/10	1/24	2/8	2/25	3/8	3/25	4/9	4/24	5/9	5/24	6/10	6/24
7	1/11	1/25	2/11	2/26	3/11	3/26	4/10	4/25	5/10	5/25	6/11	6/25
8	1/12	1/28	2/12	2/27	3/12	3/27	4/11	4/26	5/11	5/28	6/12	6/26
9	1/14	1/29	2/13	2/28	3/13	3/28	4/13	4/29	5/13	5/29	6/13	6/27

Note: Toe digit is the last digit of your case number.

means to obtain resources. These alternative means could be criminal in nature. Foley (2011) finds that financially motivated crimes increase over the course of a month in jurisdictions where SNAP benefits are distributed early in the month.[122,123]

In New York City, welfare recipients have access to the following major assistance programs: Supplemental Nutritional Assistance Program (SNAP), Supplemental Security Income (SSI), Family Assistance (FA), and Safety Net Assistance (SNA). FA is New York's analogue to the Temporary

[122] Foley (2011) does not find a similar effect for other crimes that are not financially motivated. This gives credence to the influence of welfare timing rather than police deployment changes or differential incentives to report crimes on different dates. Furthermore, he finds that the staggering of SNAP payments smooths crime rates, presumably due to improved consumption smoothing for payment recipients, which lowers the marginal utility of consumption towards the end of the month. Carr and Packham (2017) find similar results where the staggering of SNAP payments reduced overall theft by 20% and grocery store theft by 28%.
[123] In addition to the aforementioned literature, several other works have found support for intra-month systematic variations when considering non-criminal outcomes such as consumption, mortality, and various economic activities driven by earlier-in-the-month receipts of various payments (Phillips et al., 1999; Stephens, 2003; Evans and Moore, 2009, 2012; Andersson et al., 2015).

Assistance for Needy Families (TANF) program. SNA is a New York City-specific welfare program provided for those who are not eligible for other social assistance programs, and can be thought of as an extension to FA once FA benefits run out (NYC Human Resources Administration). Taken together, FA and SNA are referred to as Cash Assistance (CA).

In 2013, New York City's average monthly benefits per individual receiving assistance were \$155, \$562, \$460 (in 2013 dollars) for SNAP, SSI, and CA respectively, with program participation rates of 22%, 5.1%, 4.3% (Report # Q03, NYC Human Resources Administration and SSI Annual Statistical Report 2013, Social Security Administration).

With regard to the schedule of the programs' payments, SNAP benefits are staggered during the first ten banking days of the month, SSI is disbursed on the first business day of the month, and CA is disbursed bimonthly (starting at the beginning of the first and second halves of a month). There were no changes to this schedule during the years covered in this paper (Office & Evaluations, NYC Department of Social Services).[124]

Figure 1.4 shows an example of New York City's EBT (Electronic Benefit Transfers) form which announces the dates during which SNAP and CA benefits will be available. This regime is characterized by a staggered payment schedule in which SNAP benefits are distributed in line with schedule A (the first 10 banking days of the month, as indicated by the letter "A" in Figure 1.4), and CA benefits according to both schedules A and B. This suggests that the "first-of-the-month" effect should not be as strong, as welfare payments are still available later in month. Nonetheless, a larger proportion of welfare resources are distributed in the earlier part of the month as only parts of CA are distributed during the second half (schedule B in Figure 1.4).

[124] A special thanks to Kinsey Dinan, Deputy Commissioner – Officer of Evaluations & Research, for clarifying the municipal government's procedures and providing *EBT-52* and *EBT-52A* forms outlining the welfare schedule for the years 2003–2016.

B. MO Rev Stat § 301.227.9

"Notwithstanding subsection 4 of this section or any other provision of the law to the contrary, if a motor vehicle is inoperable and is at least ten model years old, or the parts are from a motor vehicle that is inoperable and is at least ten model years old, a scrap metal operator may purchase or acquire such motor vehicle or parts without receiving the original certificate of title, salvage certificate of title, or junking certificate from the seller of the vehicle or parts, provided the scrap metal operator verifies with the department of revenue, via the department's online record access, that the motor vehicle is not subject to any recorded security interest or lien and the scrap metal operator complies with the requirements of this subsection. In lieu of forwarding certificates of titles for such motor vehicles as required by subsection 5 of this section, the scrap metal operator shall forward a copy of the seller's state identification along with a bill of sale to the department of revenue. The bill of sale form shall be designed by the director and such form shall include, but not be limited to, a certification that the motor vehicle is at least ten model years old, is inoperable, is not subject to any recorded security interest or lien, and a certification by the seller that the seller has the legal authority to sell or otherwise transfer the seller's interest in the motor vehicle or parts. Upon receipt of the information required by this subsection, the department of revenue shall cancel any certificate of title and registration for the motor vehicle. If the motor vehicle is inoperable and at least twenty model years old, then the scrap metal operator shall not be required to verify with the department of revenue whether the motor vehicle is subject to any recorded security interests or liens. As used in this subsection, the term "inoperable" means a motor vehicle that is in a rusted, wrecked, discarded, worn out, extensively damaged, dismantled, and mechanically inoperative condition and the vehicle's highest and best use is for scrap purposes. The director of the department of revenue is directed to promulgate rules and regulations to implement and administer the provisions of this section, including but not limited to, the development of a uniform bill of sale. Any rule or portion of a rule, as that term is defined in section 536.010 that is created under the authority delegated in this section shall become effective only if it complies with and is subject to all of the provisions of chapter 536, and, if applicable, section 536.028. This section and chapter 536 are nonseverable and if any of the powers vested with the general assembly pursuant to chapter 536, to review, to delay the effective date, or to disapprove and annul a rule are subsequently held unconstitutional, then the grant of rulemaking authority and any rule proposed or adopted after August 28, 2012, shall be invalid and void."

C. Definitions of Select FBI Crimes:

Motor Vehicle Theft - The theft of a motor vehicle. A motor vehicle is defined for UCR purposes as a self-propelled vehicle that runs on land surface and not on rails and which fits one of the following property descriptions:

- Automobiles - sedans, coupes, station wagons, convertibles, taxicabs, or other similar motor vehicles which serve the primary purpose of transporting people.
- Buses - motor vehicles which are specifically designed (but not necessarily used) to transport groups of people on a commercial basis.
- Recreational Vehicles - motor vehicles which are specifically designed (but not necessarily used) to transport people and also provide them temporary lodging for recreational purposes.
- Trucks - motor vehicles which are specifically designed (but not necessarily used) to transport cargo on a commercial basis.

- Other Motor Vehicles - any other motor vehicles, e.g., motorcycles, motor scooters, trail bikes, mopeds, snowmobiles, golf carts, whose primary purpose is to transport people.
- Classify all cases where automobiles are taken by persons not having lawful access as motor vehicle theft even if the vehicles are later abandoned. Include joyriding.
- Do not include the taking of a vehicle for temporary use when prior authority has been granted or can be assumed, such as in family situations; or unauthorized use by chauffeurs and others having lawful access to the vehicle. Other Group A offenses may, however, have occurred in these situations. For example, if a chauffeur steals a car entrusted to his care, an embezzlement should be reported.

Larceny/Theft Offenses - The unlawful taking, carrying, leading, or riding away of property from the possession, or constructive possession, of another person. Larceny and theft mean the same thing in UCR. Motor vehicle theft is not included and is counted separately because of the great volume of such thefts. Local offense classifications such as grand theft, petty larceny, felony larceny, or misdemeanor larceny have no bearing on the fact that each distinct operation of larceny is reported as one offense for UCR purposes. Also, all larceny offenses are reported regardless of the value of the property stolen. Do not classify embezzlement; fraudulent conversion of entrusted property; conversion of goods lawfully possessed by bailees; counterfeiting; obtaining money by false pretenses; larceny by check, larceny by bailee; and check fraud as larceny offenses. Each of the aforementioned crimes falls within other offense categories.

Pocket-picking - The theft of articles from another person's physical possession by stealth where the victim usually does not become immediately aware of the theft.

Purse-snatching - The grabbing or snatching of a purse, handbag, etc., from the physical possession of another person.

Shoplifting - The theft, by someone other than an employee of the victim, of goods or merchandise exposed for sale.

Theft From Building - A theft from within a building which is either open to the general public or where the offender has legal access.

Theft From Coin-Operated Machine or Device - A theft from a machine or device which is operated or activated by the use of coins.

Theft From Motor Vehicle - The theft of articles from a motor vehicle, whether locked or unlocked.

Theft of Motor Vehicle Parts or Accessories - The theft of any part or accessory attached to the interior or exterior of a motor vehicle in a manner which would make the item an attachment of the vehicle or necessary for its operation.

All Other Larceny - All thefts which do not fit any of the definitions of the specific subcategories of larceny/theft listed above. This offense includes thefts from fenced enclosures. Thefts of bicycles, boats, bulldozers, airplanes, animals, lawn mowers, lawn furniture, hand tools, and farmland construction equipment are also included where no breaking or entering of a structure is involved. Additionally, the illegal entry of a tent, tent trailer, or travel trailer used for recreational purposes, followed by a theft or attempted theft, should be counted as "all other larceny." Yet another example is the taking of gasoline from a self-service gas station and leaving without paying.