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#### ABSTRACT

# HOW LARGE CHANGES IN THE FUNCTIONING ECONOMY EFFECT CRIME RATES IN AMERICA: A NATIONAL EXAMINATION OF THE LESS CASH – LESS CRIME PARADIGM

By

# DONALD E HUNT

December, 2017

Committee Chair: Dr. Volkan Topalli

Major Department: Criminology and Criminal Justice

The amount of cash in circulation appears to be decreasing the world over. With advances in payments technology, society is trending toward cashlessness. While the benefits are numerous, one particular advantage is its reducing effect on crime. Scholars on a global level continue to show that cash and crime are linked. Decreasing cash decreases crime and the reverse. However, this concept went untested in the US until recently. Taking advantage of legislation mandating that states replace welfare benefits checks with reloadable debit cards, Wright et al. explored the idea that this change reduced the amount of circulating cash and, subsequently, decreased predatory crimes. In this study, I build on that research by testing the same phenomenon but at a national level. I then add to these results by testing the cash and crime relationship on the states receiving the most benefits, the most urban states, and those with the highest rates of predatory crime controlling for relevant economic and social factors shown to influence crime. Findings for each of these analyses provide modest support for the hypothesis that reducing cash reduces street crime. I further test the notion that of drugs could be acting as the mechanism driving the need to commit crime for cash, but the data contained too much missingness and did not allow for a robust analysis. However, the general pattern of significant

results imply that cash and street crime share a significant relationship. The results may also explain part of the American crime drop; not only by the decrease itself but perhaps also in the form of a crime shift. Policy implications advocate for continued advances in electronic payments, cooperation between government and private entities, and future explorations into new opportunities for crime in a digital age.

# HOW LARGE CHANGES IN THE FUNCTIONING ECONOMY EFFECT CRIME RATES IN AMERICA: A NATIONAL EXAMINATION OF THE LESS CASH – LESS CRIME PARADIGM.

# BY DONALD E. HUNT

A Final Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in the Andrew Young School of Policy Studies of Georgia State University

GEORGIA STATE UNIVERSITY 2017

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# ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Criminal Justice and Criminology in the Andrew Young School of Policy Studies of Georgia State University.

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Electronic Version Approved: Sally Wallace, Dean Andrew Young School of Policy Studies Georgia State University December 2017

# DEDICATION

I would like to dedicate this dissertation to my dad, Charles Frederick Hunt, whose dream for me was to achieve a doctorate and contribute to society through academia. I honor his memory now in the pages to follow.

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# CHAPTER I Introduction

This research explores the relationship between cash and street crime. Research indicates that cash can be a chief source of fuel for traditional street crime and its constituent offenses (robbery, burglary, theft, and auto theft) (Naylor, 2003, Youngs, Ioannou, & Eagles, 2014). What then would happen to the levels of these crimes with a reduction in the amount of circulating cash?

In the past, a key contributor to the amount of circulating cash in America has been welfare payments (Rhine & Greene, 2013). Before the mid-1990s, the government distributed assistance benefits at monthly intervals by paper check. While this antiquated system was costly, inefficient, and fraud-ridden, it also may have predisposed some of its recipients to crime victimization. Because recipients were typically unbanked, they were often required to cash their checks and carry it with them to pay bills and buy necessary items (Ford & Beverage, 2004; Katz, 1996; Rhine & Greene, 2013). This circumstance subsequently created a pool of potential victims for cash-oriented, or predatory, offenders.

Then, in the mid-1990s, Congress mandated the delivery of government benefits payments through an Electronic Benefits Transfer (EBT) system that replaced paper checks with reloadable debit cards (Pulliam, 1997). That shift saved millions in paper and ink costs, delivered funds more effectively, and simultaneously reduced welfare fraud (Pulliam, 1997). Moreover, this change lessened the need for beneficiaries to carry cash (Humphrey, Kim, & Vale, 2001) thereby reducing both the amount of cash in circulation and the size of the pool of potential victims of cash-driven crimes. Subsequently, it stands to reason that the switch to reloadable EBT cards might also have had a negative effect on the occurrence of crimes to obtain cash. With declining amounts of circulating cash brought about by EBT implementation, it is also plausible to assume this would also bring about a reduction in drug sales and possession resulting in fewer drug arrests. One possible motivation behind the need to commit crime to obtain cash is drugs. Since engaging in illicit drug activity requires cash (Inciardi, 1986, 2007; U.N., 2010; Walters, 2013), drugs could theoretically be acting as a mediator between cash and crime. Having less cash in circulation may negatively impact the drug market, which could have a negative effect on cash-driven street crimes.

To test these ideas, I first performed an analysis of the direct effect of reducing circulating cash through the EBT system on predatory crime (offenses driven by monetary gain). I based this part of the study on a previous study conducted in the state of Missouri where authors found that reducing the amount of circulating cash through EBT implementation brought about a 9.8% reduction in overall crime (see Tekin, Topalli, McClellan, Wright, 2014 and Wright, Tekin, Topalli, McClellan, Dickinson, & Rosenfeld, 2017). If the amount of circulating cash influences certain crimes, then a regression analysis using national data should produce similar results. This not only tests Wright et al.'s results and whether their findings were endemic to Missouri or protractible to the rest of the country, but also provides insight into the veracity of the cash and crime relationship in general. However, where the Missouri study stopped, I went on to more rigorously interrogate this relationship. It may not be enough to say that crime declines with a reduction in circulating cash. It is important to note that the predicted effects carry with them certain assumptions. First, street crime commonly concentrates in urban areas where populations are dense enough to support a thriving cash dependent market. Second, such crimes require infusion of cash that would logically tie to the distribution and expenditure of welfare benefits (most often manifested as cash). To address this, I include additional analyses

that focus on these characteristics. I performed additional analyses on the states receiving the most benefits in comparison to the states receiving the least, the states with the highest urban density in comparison to the most rural, and the states with the highest street crime rates in comparison to the lowest. Further, because some research suggests that street crime is a more urban phenomenon where welfare benefits are higher, adding these further analyses offers researchers a deeper understanding of the nature of cash as it influences offending behavior.

I then turn the focus of the study toward the determination of the effect of drugs as a potential mediator between cash and crime. It is possible that drug market patterns and cash flow patterns differ for endemic reasons from those that we would see at a national level. If people are motivated to acquire cash because they need an anonymous transnational medium to obtain illegal drugs, then we would expect to see that manifest itself in such a mediational analysis. Drug markets generally require cash. If cash is reduced then it could be that the drug markets are similarly affected and as a result, the crime to acquire the cash should also exhibit analogous effects. To make this determination, I utilized Sobol's test of significance by means of performing a path analysis.

Criminologists benefit from this research in two ways. Primarily, significant findings indicating that reducing cash reduces street crime would quantitatively strengthen research that has been, to this point, most often qualitative. On a larger scale, significant results might imply that some portion of the American crime decline could be due to a reduction in circulating cash brought about by advances in electronic payments technologies such as the EBT system. Since both the program's enactment and the crime rate reversal occurred in the mid-1990s, one could make the argument that the two share an important and, up to now, undiscovered correlation.

Moreover, if reducing cash also affects the drug market, drug policies would benefit from incorporating an element of digitizing payments.

## CHAPTER II Literature Review

# The Decline of Cash

With ever-advancing innovations in payments technologies, the global payments infrastructure continues to transform from cash-heavy to technology-driven (Kurzweil, 2004; Jorgenson, 2001). In particular, the financial industry has been moving ever closer to a completely digital transaction system (Erling, 2013). By all accounts, this trend will continue greatly reducing, or eliminating, the need for cash. As with any advancement, the emergence of a digital economy comes with benefits and challenges.

The advantages of an electronic financial system are numerous. Consumers enjoy the convenience of virtual transactions, the ease of tracking expenditures, and the overall speed of digital payments and purchases (Salamah, 2017). Governments, such as Africa institution the mobile payments application M-PESA system and Mexico implementing the conditional cash transfer (CCT) program, also benefit from the shift away from paper money. Through the emergence of the electronic infrastructure, the government delivers and receives funding more safely and efficiently, trimming operating costs in the process (Jarupunphol & Buathong, 2013; Ross-Roach, 2016). Additionally, the corporations developing the technologies facilitating the move toward a predominantly digital society benefit through increased profits, while businesses, in general, see increased returns through public spending on a global platform (Rogoff, 2015).

There are also disadvantages to a move toward a cashless society. The same technology that makes a virtual financial infrastructure advantageous also creates certain complications. Chiefly among these, the system itself is completely dependent on technology. That is, should the system fail (e.g. power failure, hacking, terrorist activity), the negative effects could be felt on a global basis, to include an economic crisis (Morley & Robins, 2002). Moreover, a cyber-

economy invites new opportunities for cyber-criminals. Money launderings, fraud, and illicit drug sales are among the more common methods of illegal exploitation of the virtual system (Alhogbani, 2014).

Despite these issues, the number of countries endorsing a cashless infrastructure increases each year. Sweden is considered one of the world leaders in the move toward a completely cashless country (Arvidsson, Hedman, & Segendorf, 2016). Cash transactions in that country currently make up only 3% of its total transactions, and the amount of krona (the national currency) in circulation has dropped from over 100 billion in 2009 to just over 80 billion in 2015 (Biswas, 2016; Henley, 2016). Best estimates project Sweden to be completely cashless by 2020 (Arvidsson, 2013). In Denmark, over 30% of the population transacts solely through mobile devices, and the Danish government has set a deadline for eliminating paper money by 2030 (Biswas, 2016). Similarly, banks in Norway no longer dispense cash (Mukhopadhyay, 2016).

The same pattern exists across Africa. Liquid cash in Somaliland is rapidly decreasing, and even street vendors accept mobile payments (Biswas, 2017). Cards are the primary mode of payment in this country where the average consumer makes 34 online transactions per month, the highest in the world (Biswas, 2017; Stremlau & Osman, 2015). Kenya also adopted and endorses the cell-phone based money transfer app *M-PESA*<sup>1</sup> for its citizens. The *M-PESA* design allows millions of Somalis with no access to a bank account but who possess a mobile phone to send and receive money and pay bills. Current estimates suggest that 15 million users subscribe to *M-PESA* (Vodaphone, 2017) and many Kenyans receive their salaries via this system (Biswas, 2017; Mbiti & Weil, 2013).

<sup>&</sup>lt;sup>1</sup> Pesa is the Swahili word for money.

Canada and the United States are likewise moving toward a cashless economy. Over 90% of Canadians opt for cashless transactions where the majority of payments occur through debit and credit cards (70%) and more than half of the public prefer online wallets to carrying cash (Biswas, 2017; Thomas, Jain, & Angus, 2013). In the United States, the leader in cashless technology innovation (Liu, Kauffman, & Ma, 2015), authorities estimate that consumers currently use cash for less than half of all transactions, and less than 40% of Americans carry cash on daily basis (Epstein, 2017; FRBSF, 2016; Rolfe, 2017). Further, greater than 75% of the population owns a cell phone and over half of them use it to make payments (Meola, 2016).

Current research indicates that new payments technologies emerge regularly, continuing the drive toward a cashless society (Taylor, 2016). Based on the increasing number of countries embracing payments technologies, the advantages seem to outweigh the drawbacks of a digital economy. One, yet unmentioned advantage of such a move, is that it appears to affect criminal behavior.

# What We Know about the Link between Cash and Crime

Research suggests that payments systems at large could be in some part responsible for worldwide reductions in crime and violence. Consider the Conditional Cash Transfer (CCT) Program; a system utilized in many third world countries. The CCT program offers monetary incentives to parents below the poverty line for their children's schooling and health checks (Fernald, Gertler, & Neufeld, 2008). Two countries, Uruguay and Brazil, instituted (revamped) the CCT program in 2008 with differing, and unintended, crime consequences (Borraz & Munyo, 2015; Chioda, De Mello, & Soares; 2016). One possible reason for these opposing responses may stem from the way these respective governments implemented the program. In Uruguay, the initial CCT enterprise failed to incentivize its citizens to participate. To increase involvement, the government not only doubled the amount of the incentive but also paid it in cash (Borraz & Munyo, 2015). The number of recipients increased by 15%. After the change, crime and violence in Uruguay increased (Borraz & Munyo, 2015). During the same year, however, the country of Brazil paid its CCT participants through an electronic bank deposit as opposed to cash payouts. After their program's implementation, crime significantly decreased (Borraz & Munyo, 2015). Because one main difference in the two programs was the type of incentive – cash payments versus electronic payments – an apparent link between cash and crime begins to appear. This correlation occurred in other countries as well.

In 2002, the Argentinian banking system nearly collapsed. Following a series of unfavorable events, thousands lost faith in the system and withdrew their funds from banks in cash (Boschi, 2005). During this time, the government offered its CCT incentives in cash as well. Meloni (2014) took this information and combined it with the known crime rates for burglary, larceny, aggravated assault, homicide, and overall crime. He then regressed these outcomes on the cash incentives and included relevant control variables both over time and lagged. The results indicated that the country's crime rates, especially for robbery and larceny, increased building on the premise that increasing the amount of circulating cash can contribute to a rising crime rate (Meloni, 2014). The Philippines and Mexico experienced similar drops post-CCT implementation (Brito, Corbacho, & Osorio, 2014; Crost, Felter, & Johnston, 2016). In the Philippines, Crost, Felter, and Johnston (2016) conducted a difference in differences analysis on the effect of program implementation on crime and violence. Their findings suggest that CCT program implementation may have contributed to a 2% drop in violent attacks with an underlying criminal motivation (Crost, Felter, & Johnston, 2016). Similarly, Brito, Corbacho, and Osorio (2014) conducted two-stage least squares regression analyses on the Mexican CCT

remittance program and found that every 1% increase correlated with a reduction in homicide by 0.05% and street robbery by 0.19% (Brito, Corbacho, & Osorio, 2014). Removing circulating cash through the CCT program in Africa may have also contributed to a marked reduction in crime factoring also into the decline of civil unrest (Garcia, Moore, & Moore, 2012; Standing, 2007). Using descriptive and multivariate regression analysis, both Garcia, Moore, and Moore (2012) and Standing, 2007) found that, among the various other benefits that implementing the CCT program brought with it, recipients felt safer, tended to migrate less, and were less targeted by the criminal element.

As time progresses, countries are recognizing that a cashless economy is an effective tool for reducing crime. For instance, DNB, the largest bank in Norway, proposed that the elimination of cash would reduce local black-market activity while at the same time serve to suppress money laundering on a global scale (Seth, 2017). In Sweden, the number of bank robberies dropped 85% from 110 in 2008 to 16 in 2011 as the nation continued its full-on initiative to eliminate cash from their economy (Biswas, 2017; Rogoff, 2016). Specific to the US, certain crime rates in the state of Missouri decreased by 9.8% after the government switched from paper checks to the electronic transfer of welfare disbursements (Wright et al., 2017).

But how does reducing the amount of cash in circulation bring about declines in crime rates? One explanation put forward has been the notion that cash fuels a certain lifestyle. Moreover, those engaging in that lifestyle tend to resort to crime to obtain the necessary cash to continue that type of living.

#### Street Life, Offenders, and Cash

To understand how cash affects crime, it is important to identify some of the motivations of offenders. Research suggests that a subsection of society engages in what scholars refer to as "street life" (Anderson, 1999, Hagan & McCarthy, 1991; Shover, 1996; Shover & Honaker, 1992; Jacobs & Wright, 1999). People involved in this lifestyle tend to reject the moral and social traditions of mainstream society opting instead to engage in oppositional behaviors and living life as one continuous "party" (Shover & Honaker, 1992). While adherents primarily focus on the acquisition and use of illicit drugs and alcohol, street life also includes other deviant activities such as skipping school, street gambling, and sexual promiscuity (Shover & Honaker, 1992). A common condition of engaging in many of these activities is that they often require cash. Further, because participants caught up in street life tend to spurn gainful employment, one practical way to obtain that cash is through predatory criminal behavior referred to as street crime (Jacobs, Topalli, & Wright, 2003; Lupton & Tulloch, 2002; Topalli & Wright, 2004, 2013; Tucker, Pollard, De La Haye, Kennedy, & Green, 2013).

#### Cash and its Importance to Street Life

The street lifestyle may at first appear to be a life of crime for crime's sake. Yet scholars point out that, in street culture, crime is a common and indispensable means of obtaining the cash necessary to purchase drugs, alcohol, and obtaining other black-market items underpinning this way of life (Naylor, 2004; Tucker et al., 2013; Topalli & Wright, 2004; Wright et al., 2017). Given the intensity with which adherents participate in street life, it is easy to understand why cash acts as the essential fuel that keeps the party going. It is important to note, however, that while cash is necessary for the purchase of goods in street markets, it has other advantages for street life participants.

Cash is one of the most liquid forms of transactions and, apart from modern cryptocurrencies, may be the only transactional medium capable of offering a high measure of anonymity allowing users to hide their activities from the authorities (Sander & Ta-Shma, 1999). Pursuits such as gambling, prostitution, drug dealing, and other forms of illicit trade require cash for precisely this reason (Anderson, 1999, Shover & Honaker, 1992; Tekin, et al., 2014). Cash is also liquid. It requires no conversion for use and reuse in any market; legal or illegal. This characteristic is especially advantageous for making ill-gotten gains appear to be legitimate. Cash is also prevalent in street culture as a symbol of status. It represents respect among active street life participants and a substantial portion of the decisions made in this environment revolve, directly or indirectly, around it and its acquisition (Anderson, 1999; Brezina et al., 2009; Jacobs & Wright, 1999; Stewart & Simons, 2006; Zelizer, 1989). For example, Zelizer (1997) notes that in street culture there is a palpable difference between "clean" and "dirty" money beyond financial utility. Obtaining cash through predatory means elevates a person to a higher cultural status in this environment (Jacobs & Wright, 1999; Zelizer, 1997).

Each of these characteristics makes cash well-matched for street life and the illicit gray and black-market transactions that it entails (Naylor, 2004; Schneider & Ernst, 2013). In street life, cash is valued as the primary medium to continue the party, a liquid and anonymous vehicle to obtain the goods common to the lifestyle, and a symbol of status and respect (Zelizer, 1997). However, its acquisition would hardly be possible without a pool of cash-carrying victims.

## **Decreasing Cash in the US through EBT Implementation**

Before the enactment of the EBT program, state governments disbursed welfare funds to their recipients via a monthly check. However, because these beneficiaries were receiving government assistance, they did not qualify for bank accounts (i.e., they were "unbanked" or "underbanked"; see FDIC, 2012; Ford & Beverage, 2004). This status generally forced beneficiaries to cash these checks to access their funds. Thus, they were left principally with only

cash to transact business, pay bills, or purchase necessities (Armey, Lipow, & Webb, 2012; Ford & Beverage, 2004; Rhine & Greene, 2014).

However, in the mid-1990s, Congress made a series of broadly sweeping policy changes. Recognizing that the current welfare structure was costly, inefficient, and open to fraud, legislators enacted the Omnibus Budget Reconciliation Act and the Omnibus Consolidated Rescissions and Appropriations Act. Proposed largely as a method to reduce government spending and streamline existing processes, Congress "strongly encouraged" each state to adopt a technology that disbursed assistance payments via the Electronic Benefits Transfer (EBT) system (Pulliam, 1997). Through this system, the government replaced monthly paper checks with reloadable payment cards (referred to as "EBT cards").

The advantages of this switch were numerous. Recipients now had a safer and more efficient manner of storing and accessing their funds. The EBT cards act as a *pseudo* bank account, which provided each cardholder with the beginnings of financial stability and creditworthiness. Moreover, the change made it extremely difficult to commit welfare check fraud (Cole, 2000). Finally, most relevant to this study, beneficiaries could now access only those funds that were necessary without having to resort to cashing their entire check and carrying that cash with them or storing it in their homes. Because the EBT system reduced the need to carry cash, it is logical to assume that it may have reduced some part of the amount of cash in circulation. Further, if EBT implementation reduced the amount of cash in circulation, it is also conceivable that the pool of cash-carrying potential victims also decreased, thereby providing fewer opportunities for street offenders to commit predatory crime.

#### **Predatory Crimes**

In as much as street life is different from traditional lifestyles, the crimes committed by street life participants also have unique qualities. Street offenders tend to engage in criminal behavior of a predatory nature born out of an environment that endorses such action. For example, Freeman (2000) demonstrated in a nationwide analysis of street crime that active engagement in street culture not only fosters the development of predatory crime but encourages its commission over legitimate means of attaining objectives, not the least of which are financial. Hallsworth (2013) published similar findings in his study of street life, writing that what differentiates street crime from others is that these offenses are cash-oriented, occur in an urban street environment, and tended to be violent. In addition, the results of several more studies show that more of these types of crimes exist in areas where welfare distribution and government assistance is higher (Linton, Jennings, Latkin, Kirk & Mehta, 2014; Martinez, 2014; Sampson, 2013; Willits, Broidy, & Denman, 2013). Each of these factors is important to the current research. These types of crimes are cash-oriented, born of desperation, and predatory in nature. They also occur in areas where street life is prominent, and welfare benefits meaningfully contribute to the local economy (Hannon & DeFronzo, 1998; Herbert, 1982; Krivo & Peterson, 1996; Lochner, 2004; McBride-Murry, Berkel, Gaylord-Harden, Copeland-Linder, & Nation, 2011). By reducing the amount of cash those welfare recipients need to carry, this might also decrease the occurrence of predatory offenses by reducing the pool of potential victims.

Recall that prior to the advent of the EBT system, beneficiaries tended to cash their paper checks due to their unbanked status. This created a pool of potential cash carrying victims at a specific time and place), a fact known to would-be predatory offenders (Foley, 2011; Hastings & Washington, 2010; Ray et al., 2013; USDA, 2016; Vanroose & D'Espallier, 2013). As a case in

point, Foley (2011) studied 12 metropolitan cities over the course of the welfare payment cycle and observed a significant increase in crime around the same time beneficiaries received their welfare checks. The most sizeable increase in cash-oriented crimes occurred at the beginning of each month when the government distributed most of these payments suggesting that the offenders likely knew when and where to commit their offenses (Foley, 2011).

Additionally, predatory crimes stand out from others because unlying motivations such as desperation, determination, fear, and greed are at play with the added pressure of doing so to maintain the "party lifestyle" (Shover & Honaker, 1994; Topalli & Wright, 2013). These pressures may become manifest in the form of offenses with violent undertones, for example, carjacking, robbery, and assault (Jacobs & Wright, 1999; Rosenfeld & Messner, 2013). Jacobs and Wright's interviews with active armed robbers in St. Louis, Missouri exemplifies this point. The authors observed that the endorsement of criminal behavior and mounting pressure to fund the street lifestyle drove the need to obtain quick cash (which was subsequently exhausted in short order). However, what is it about this lifestyle that causes such pressure to drive someone to commit such behavior? One possible explanation is the desperate need for drugs.

#### **Drugs and Street life**

One possible reason why street life participants engage in such predatory crime is to obtain the cash necessary to purchase the illicit drugs they desperately need. Allowing for this, one can reasonably assume that without drugs the relationship between cash and crime might be weaker than originally hypothesized. Illicit drugs, therefore, could be mediating the effect of that relationship. Scholars rooted in this field consistently find that illicit drug use is a staple of street culture and that cash is critical to maintaining access to it (Boardman et al., 2001; Collison, 1996; Inciardi, 1979; McAra & McVie, 2005; Tucker et al., 2013; Vigil, 2010). For those

actively involved in street life, one way to obtain cash is through predatory crime (Freeman, 2000; Hallsworth, 2013; Wright et al., 2017). Therefore, the cash-rich environments created by the welfare system before the implementation of the EBT program could support such criminality. Not surprisingly, these same locales also foster robust drug markets (MacDonald & Marsh, 2002). If one assumes that the reason behind the desperate need for cash is drugs and that the benefits distribution system before the change to electronic funding was a substantial source of the cash needed to purchase those drugs, then it is plausible to accept that EBT implementation reduced the pool of cash-carrying potential victims. That being the case, EBT implementation should also have a detrimental effect on the drugs market. In other words, if drugs mediate the relationship between cash and crime, then reducing cash should also reduce the drug market in some way.

To determine if drugs are truly acting as the mechanism for committing crime to obtain cash, I consider a model referenced by Wright et al. (2014) and found in Wright & Decker, (1997); the Etiological Cycle of Street Crime (Figure 1). This model represents a good demonstration of inductive theory development and is notable for using individual-level interview-based qualitative data on street offender decision-making to explain larger patterns of crime. Additionally, the base assumptions of the theory are in line with other structural explanations of crime; that there is a strong association between criminality and larger structural background factors. Scholars note that such antecedent conditions may include, for example, impoverished conditions, adherence to a street culture, unemployment, and a lack of formal education (Altindag, 2012; Anderson, 1999; Hannon & DeFronzo, 1998; Hjalmarsson & Lochner, 2012; Lochner, 2004, 2011; McBride, Berkel, Gaylord-Harden, Copeland-Linder, & Nation, 2011; Mesters, van der Geest, & Bijleveld, 2016; Shover, 1996; Shover & Honaker,

1992; Topalli & Wright, 2013) Wright and his colleagues (2017) further argue, however, that these factors do not cause crime *per se*; rather they place a certain subset of individuals at risk for participation in street life which sets the stage for predatory criminality later. A deeper look at the cycle provides more insight as to how cash drives crime in the street setting.



Figure 1: Etiological Cycle of Street Crime

The cycle follows this basic pattern: After prolonged exposure and assimilation to street life, individuals enter the pursuit of illicit action and conspicuous consumption; often through partying and drug use. Eventually, the cash fueling these behaviors depletes resulting in a real sense of financial desperation. At this point, participants turn to predatory crime to replenish their cash stores. With cash replaced, the pursuit of illicit action and conspicuous behavior begins anew, and the cycle repeats. As offenders move through the cycle and their involvement in serious crime goes on unabated, their prospects for breaking the pattern and participating in conventional society (e.g., gainful employment, pursuing an education) diminish apace. The only constant that remains is the pursuit of illicit action and the seeking out of cash through street crime to keep the party going.

Two elements of the cycle lend themselves well to the current analysis. First, cash underpins nearly every stage of the cycle. Second, according to research, a good portion of the illicit action in street life is rooted in the conspicuous consumption of illegally obtained drugs (Boardman et al., 2001; Collison, 1996; Inciardi, 1979; McAra & McVie, 2005; Tucker et al., 2013; Vigil, 2010). It is plausible, then, to assume that drugs are driving the need for cash in the first place opening the door to the possibility that reducing the amount of available cash in circulation could diminish an offender's ability to obtain the cash necessary to maintain the conspicuous consumption phase of the cycle.

#### **Testing these Relationships**

One method to test the effect of reducing cash on street crime is to view EBT implementation as the treatment in a natural experiment and apply appropriate analytic techniques. Because different states introduced the program at varying times, and data exist both before and after EBT implementation, performing a panel data analysis will demonstrate the effect of reducing cash on predatory street crime. Moreover, the additional analysis of the cash and crime relationship in urban areas where benefits and street crime levels are high offers deeper insight into the true effects in a variety of environments. Testing drugs as a mediator between cash and crime also requires performing a path analysis in the style of Baron and Kenney's (1986) original framework utilizing additional drug arrest data. The next section explains these processes in detail.

# CHAPTER III Method

## **Strategic Overview**

To test the direct effects of reducing cash on street crime and additionally drugs as a mediator between them, I performed the analysis in two stages. In the first stage, I conducted a national examination based loosely on Wright et al.'s (2017) Missouri study utilizing the stateby-state variation in EBT implementation to produce estimates of reducing cash on street crime(s). However, where the author's focused their attention on the effect of reducing cash on crime in general, I went deeper and tested this effect under various conditions. I analyzed and compared this effect in both high and low benefits receiving states, urban and rural states, and states with the highest and lowest levels of street crime. Moreover, in the second phase of the overall analysis, I went even further and performed a path analysis in which I consider the notion that drugs may be acting as mechanism through which the need for cash influences crime.

#### Data

The data for these analyses are a collection of publicly available, official government statistics consisting of street crimes, EBT implementation dates, and demographic information such as population, poverty level, unemployment rates, high school education, and imprisonment rates. These data originate from the FBI's Uniform Crime Report (UCR), the Bureau of Justice Statistics (BJS), the US Census Bureau, and the United States Department of Agriculture (USDA) spanning five years before and after EBT implementation for each state individually and as a group. The first states began implementation in 1989, and every state was operating on the system by the end of 2004. The states that began implementing the program earlier took longer to completely onboard the program (likely due to the infrastructure at the time). However, as more states initiated the program, the total time it took to switch completely from paper

checks to electronic disbursement decreased. For instance, Maryland was the first to start the changeover. The process began in 1989 and did not finish until the middle part of 1993. Texas began implementing the system in mid-1994 and completed the process by the end of 1995. Later, states like Louisiana, Connecticut, and Alabama implemented the system completely in one year, 1997. Thus, at a national level, the entire country began implementation in 1989 and completely changed over to the electronic system by 2004. But because the first state to implement the EBT system was Maryland, and a trend prior to this initiative is necessary to perform difference in differences analysis, I added in five years of previous data to Maryland's data set. California was the last state to completely implement the EBT system in 2004. The analysis also requires data for five years post implementation completion. Therefore, I added in those data to California's dataset. I treated the remaining states in the same way. When adding in data 5 years before and after implementation for each state to establish the trends necessary for the analysis, the final dataset captured statistics from 1984 to 2009.

#### **Uniform Crime Report**

The FBI is responsible for compiling the UCR and describes it as "a nationwide, cooperative statistical effort of nearly 18,000 cities, university and college, county, state, tribal, and other law enforcement agencies voluntarily reporting data on crimes brought to their attention."<sup>2</sup> The Bureau organizes each agency's monthly records and makes them publicly available through their official website. The UCR is divided into Part I and Part II crimes. In general, the FBI differentiates Part I from Part II crimes by the seriousness of the offenses. Part I crimes include the offenses of homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson. Part II crimes include simple assault, forgery and

<sup>&</sup>lt;sup>2</sup> http://www.fbi.gov/about-us/cjis/ucr.

fraud, vandalism, prostitution, drug violations, and other less serious crimes. The current study utilizes the Part I crimes of robbery, burglary, larceny, and auto theft in addition to the Part II offense of drug violations.

Admittedly, the UCR contains some degree of error due to monthly reporting delays, or outright missingness from individual contributing agencies. However, researchers have shown these factors to be stable throughout each reporting state (Maltz & Targonski, 2002; Marcotte & Markowitz, 2011). Because the analyses performed in the current study include data from all or multiple states, this spread the missingness across the groups, which arguably evens out much of the bias by and large. Moreover, I aggregated monthly data to a year-end total to perform the analysis. According to Lynch and Addington (1996), while there may be a lag in the reporting of monthly data, the vast majority of agencies report their full annual data by the conclusion of each year. Because I am using year-end data in the analysis, the missingness in any of the months during the year are likely rendered immaterial by the end of the year and should not significantly bias the results.

Moreover, I am employing a fixed effects regression model for the subsequent analyses. This technique is particularly useful when there is a concern that omitted factors might correlate with key predictors at the group level; in this case, state-level data. Fundamentally, this type of regression takes into consideration the effect and correlation of the independent variable(s) *within* each unit of measure on the dependent variable over time. By doing so, this method takes into account the variation for each independent variable inside each state on multiple occasions considerably reducing the effect of omitted variable bias (see Cameron & Trivedi, 2010 and Gardiner, Luo, & Roman, 2009). This technique is explained in more detail later in this section.

Even with these techniques in place, there still remains a central weakness with utilizing UCR data. That is, it only contains those crimes reported to the police rather than those that occurred. For instance, someone who has suffered a robbery as a result of drug rip-off might not report the robbery to the police for fear of revealing their involvement in illicit activity. The commission of the crime actually took place but the *reporting* of it did not (Skogan, 1977). Others might simply not report the crime because of the inconvenience. In either case, scholars refer to this issue as the "dark figure of crime" and can prove to be problematic when interpreting results based on this type of data (Biderman & Reiss, 1967; Coleman & Moynihan, 1996; MacDonald, 2002). Unfortunately, there is no method that effectively accounts for this when using this data of data and interpretation of results stemming from this issue should be tempered with this knowledge. This includes the results to follow in the current study.

#### Measures

#### **Dependent Variables**

Gathering the crime variables necessary to perform the analysis was relatively straightforward. The dependent variables collected for this part of the analysis include robbery, burglary, theft, and auto theft. Together, these crimes make up the aggregated *street crime* variable, which is the sum total of these crimes for each specific year in each individual state. To estimate drugs as a mediator between cash and crime, I utilized the Part II crime of drug violation. For each of the outcome variables, I utilized crime rates weighted per 100,000 residents, rather than by individual count to bring each state onto the same metric.

#### Street Crime

According to Hallsworth (2013), what differentiates street crime from others is that these offenses are predatory (cash-oriented) in nature and occur in the street environment. Moreover,

they tend to occur in urban-dense areas and may concentrate where poverty, unemployment, and welfare assistance abound (Hannon & DeFronzo, 1998; Herbert, 1982; Krivo & Peterson, 1996; Lochner, 2004; McBride-Murry, Berkel, Gaylord-Harden, Copeland-Linder, & Nation, 2011). Scholarly research indicates that the crimes of robbery, burglary, theft, and motor vehicle theft fall into this category (Baumer, Horney, Felson, & Lauritsen, 2003; Cherbonneau & Jacobs, 2015; Jacobs & Cherbonneau, 2014; Harris & Clarke, 1991; Jacobs & Wright, 1999; Jacobs, Topalli, and Wright, 2003; Roberts & Block, 2013; Sampson, 1987; Topalli, Wright, and Fornango, 2002). The remaining UCR Part I offenses of criminal homicide, forcible rape, aggravated as assault, and arson do not necessarily have at their core a motivation toward acquiring immediate cash. Consequently, I did not include these offenses in the current analysis because they did not fit the definition of a street crime for purposes of this evaluation. The *street crime* variable, therefore, is a consolidation of each of the crimes of robbery, burglary, theft, and motor vehicle theft reported to the FBI by each state for each year in the study timeframe.

#### **Robbery**

The FBI defines robbery as the taking or attempted taking of anything of value from the control of a person by force or threat of force or violence and/or by inducing fear in the victim (FBI, 2010). One of the most common forms of obtaining cash through crime (Miller, 1998), robbery falls squarely into the category of a predatory offense. By its nature robbery implies that it might often be driven by monetary gain, and street life participants have been known to commit this act as a common method of immediately acquiring cash (Baumer, Horney, Felson, & Lauritsen, 2003; Bennett & Wright, 1984; Sampson, 1987; Silverman, 2004; Topalli, Wright, and Fornango, 2002; Wright & Decker, 1994). While a robbery can occur for reasons other than the acquisition of cash, the research indicates that monetary gain is one prevailing reason for its

occurrence (Jacobs & Wright, 1999, Wright & Decker, 1994; Wright, Brookman, & Bennet, 2006). As such, this offense fit squarely into the definition of a street crime and, as such, I included robbery as an outcome variable in this study.

## **Burglary**

Burglary is "the unlawful entry of a structure to commit a felony or theft" (FBI, 2010). The notion that someone would enter a dwelling with the intention of removing something from it certainly indicates that burglary has predatory motivations. However, burglary can be far more than simply illegally entering a structure and removing something). There is a particular subset of burglars who subscribe to street culture and commit this crime with a sense of urgency originating from a desperate need for cash (Bennett & Wright, 1984; Blumstein, 1995; Chang, 2011; Cromwell, Olson, & D'Aunn, 1991; Wilkinson, Kawachi, & Kennedy, 1998; Wright & Decker, 1994). Qualitative interviews with active burglars show that these offenders not only know when and where to commit their crimes, but also what they expect to take away to include cash or items easily converted to cash (Bennett & Wright, 1984, Maguire & Bennett, 1982; Wright & Decker, 1994). Not all burglaries occur strictly for cash. However, because burglary can happen as a result of street life involvement and a specific, targeted need for cash, I included burglary as an outcome variable.

# Theft

Theft is the most frequently occurring of all the Part I offenses (FBI, 2010). Defined as the unlawful taking, carrying, leading or riding away of property from the possession or constructive possession of another (FBI, 2010), theft takes place for a variety of reasons including the conversion of stolen items into cash (Silverman, 2004). It can also occur simply through the unlawful taking of cash directly (Silverman, 2004; Sutton, 1999). However, I

recognize that not all offenders perpetrate theft as a means of obtaining cash. Scholarly work indicates that a considerable portion of reported theft centers around shoplifting (see Bamfield, 2012) and this particular motivation does not fit within the boundaries of street crime. However, while this offense does not necessarily happen for the sole purpose of acquiring cash, it would be remiss not to consider that the theft statistics contained in the UCR may be, in some part, predatory. With the lessening of available cash due to benefits transfer technology, thefts with the intention converting stolen goods to cash, or the straight-out theft of cash itself, should decrease. I therefore also included theft in the models tested in this study.

## Auto Theft

The FBI categorizes the theft or attempted theft of a motor vehicle as motor vehicle theft in the UCR (FBI, 2010). There are many reasons for its occurrence. Motor vehicle theft can be a method of exacting revenge, retaliation, expressing dominance, joy-riding, and robbery, (see e.g., Cherbonneau & Jacobs, 2015; Jacobs & Cherbonneau, 2014; Jacobs & Wright, 1999; Jacobs, Topalli, and Wright, 2003). Research in this area connects these behaviors and motivations with offenders who actively participate in street culture (Jacobs & Wright, 1999; Jacobs, Topalli, & Wright, 2003; Wright, Topalli, & Jacques, 2014). Scholars have also considered the act of auto theft as a means to attaining cash through either the conversion of stolen goods to usable funds through chop shops and underground cash-only markets or resale of the vehicle itself (Harris & Clarke, 1991; Roberts & Block, 2013). In either case, the expectation is that some part of the motor vehicle theft rate in each state contains motivations towards obtaining cash. It should, therefore, decrease as a function of less cash in circulation and fewer cash-rich buyers. Consequently, I included auto theft as an outcome variable in the subsequent models.

#### **Drug Violations**

To test the hypothesis that drugs may act as a possible mechanism for cash-driven crime, UCR Part II drug arrest data were collected from the official BJS website. Stated previously, if the EBT system is responsible for lesser amounts of circulating cash, then fewer potential victims are carrying it. As a result, there could be less street crime to obtain the cash necessary for the purchase of illicit drugs.

The underlying premise for using this particular drug arrest variable is as follows. Having less cash in circulation should adversely affect the drug market. This could occur both in the decreasing amount of cash necessary to purchase drugs in the black market and through the diminishing number of buyers who can obtain said cash through predatory means. Assuming this to be the case, there is the possibility that there could be fewer arrests of people either selling or possessing drugs after EBT implementation. While it is also likely that the war on drugs simultaneously affected the drug arrest rate, the argument still stands that some portion of any effect found in this study may contain elements of the reduction of circulating cash in each state post-EBT implementation. Since the data published by BJS specifically contain arrest information for individuals either in possession of or selling illicit drugs encompassing both sides of the drug market in one statistic, I argue that the drug violation arrests contained in the UCR can feasibly represent the drug market. Because Part II crimes are only available through the BJS arrest data tool at the agency level year over year, the individual figures were collected and aggregated to the state level. This variable served as the dependent variable for the first part of the mediator analysis (path a) and the independent variable in the second part of the mediator analysis (path b).
## **Independent Variables**

# EBT

Directly measuring the amount of cash in circulation in any area is problematic. The Federal Reserve produces estimates at the national level relating to the number of purchases made by each payment medium (e.g., cash, check, credit card) and, as expected, cash purchases have been gradually declining over time. Unfortunately, disaggregating these data to any individual state is not possible because they do not accurately describe the amount of cash in circulation and, moreover, the government and private investors hold a significant amount of cash outside the US. Research establishes, however, that a key source of circulating cash in America is welfare payments (Ford & Beverage, 2004; Rhine & Greene, 2012). Further, the US Department of Agriculture (USDA) produces comprehensive and measurable statistics on welfare disbursement for each state encompassing the time frame of this study. In lieu of a direct measure of circulating cash, one can look to circumstances and characteristics of the economy that could serve as a substitution. One such proxy is the implementation of the EBT system. Though not a direct measure of the exact reduction in the amount of circulating cash, it is logical to assume that its implementation removed some portion of cash from locales where benefits distributions are most common. It is, in fact, the geographical and time-related variation of EBT implementation that I capitalize on to perform the analysis. Thus, I utilized EBT implementation as the key predictor in this study.

The US Department of Agriculture houses and publishes official benefits statistics, including state implementation dates, on their public website. Because EBT implementation in most states took place at various times at various intervals, no single point of commencement or completion was common to each jurisdiction. For example, the state of Ohio took the longest to

board all its recipients onto the platform. The process took seven years. Further, to establish a trend and perform the analysis (see Cameron & Trivedi, 2010), I added in the relevant data for five years before and after the implementation process making the total time span of necessary data in Ohio consisted of 17 years. Pennsylvania implemented the EBT system in just under a year. With five years before and after implementation added in, the total time span for Pennsylvania was 11 years. This six-year implementation variance is problematic for properly evaluating a difference in differences analysis since each state in the model must contain the same number of variables in the same number of observed years. To address this issue, I expanded the before and after years in Pennsylvania equally on each side of implementation to reach 17 years and align its data with the state of Ohio. I employed the same technique for each of the remaining states to form a complete dataset.

In essence, this variable acts as an indicator of whether or not a state received the treatment. In a general sense, a variable such as EBT implementation would be coded dichotomously where if a particular state had boarded its recipients onto the EBT platform that state would receive a "1" and if not, a "0". However, because each state completed the implementation process in varying time intervals (between one and seven years), simply coding each state in a specific year as either 1 or 0, implemented or not implemented, was not appropriate. Instead, I coded EBT implementation a fraction for each observation ranging from 0.00 to 1.00 representing the proportion of completion over the course of the total implementation years. In this way, a coding of zero (0) in a specific year indicates that a state had not yet begun implementation. Fractional coding of the EBT variable (e.g., .33, .50, .75) indicated that implementation had commenced in a particular year for that state. A coding of one (1) designated that the state had fully implemented the system. For example, if a particular state

began boarding its recipients in September 2000 and finished in December 2001, implementation took a total of 15 months. I would code the EBT variable for the year 1999 as a "0" because implementation had not yet begun. The EBT variable in the year 2000 would be coded as "0.20" because three of the 15 months it took to implement the system (3/15=0.20) took place in that year. Moreover, because the state completed EBT implementation by the end of 2001, I would code the EBT variable as a "1" for that year. <sup>3</sup>

#### **Percent Male**

Males commit the majority of the reported crimes in the US (Carrabine, Iganski, & Lee, 2004). Estimates in 2011 showed that nearly three-quarters of the persons arrested in 2011 were men (FBI, 2011). Research further indicates that individuals engaging in hard-core street life also tend to be male (Hallsworth, 2013, Anderson, 1999). Because being male is a consistent predictor of crime (particularly violent crime) and participation in street culture, I controlled for this characteristic by including a percent male variable in the model. I collected the data for this variable from official US Census Bureau, Bureau of Labor Statistics, and individual state publications for each year and weighted it by state population. This variable indicates and controls for the percentage of males in a particular state in each specific year of the analysis.

#### **Percent Black**

Official government statistics show that a substantial portion of arrests in the US are of black individuals (FBI, 2016). Between 1988 and 2002, the same basic years the majority of the states implemented the EBT program, law enforcement arrested blacks at a higher rate than any other ethnicity. This is particularly evident in the crimes of homicide and robbery (FBI, 2016).

<sup>&</sup>lt;sup>3</sup> I acknowledge that this type of coding might be problematic, yet, I also coded the EBT variable as a one as soon as the implementation started and also as a zero until implementation was completed. Results varied little in either case and were robust to further alternative coding.

Because the data utilized in the current research consist of official government records, I collected and controlled for the percentage of black for each state and year in the model to avoid confounding the findings.

## **Population**

Gathered from official US Census Bureau figures and coupled with individual state data reported to the BJS and FBI, I included the population of each state in the analysis. Different states are more populous than others and have higher or lower "raw" crime numbers per se (FBI, 2014). For instance, in 2014, the state of New York had 27,241 robberies where the state of Indiana had 7,114. Moreover, each state's population grows at a different rate. While this variable allows for the establishment of each state's particular crime rate(s) placing them on the same metric, it also stands alone as its own influence on the results of the analyses. By controlling for each state's population and rate of growth in the analytical models, the results are more precise. I collected this variable as a continuous count of the residents in each state and year and included it in the overall dataset.

## **Poverty**

The government designed the welfare system to assist those living below the poverty level with, among other things, the supplemental nutrition assistance program (SNAP) (USDA, 2016). Unfortunately, poverty is also a factor that scholars link to criminal behavior (Brown & Males, 2011; Bursik & Grasmick, 1993; Hannon & DeFronzo, 1998; McBride-Murry et al. 2011; Muggah, 2012; Small & Newman, 2001). A significant part of the foundation of this study is contingent upon the assumption that EBT system, the primary SNAP benefits disbursement tool, reduces the amount of circulating cash. If true, then impoverished conditions could potentially confuse the results. I therefore added poverty into the regression equation as a means of

controlling its influence on the outcome. The data for this variable came from the U.S. Census Bureau yearly figures and recorded as the percentage of residents in a specific state living below the poverty line.

### Unemployment

Unemployment shares a relationship with poverty and, likewise has been shown to influence criminal behavior (Altindag, 2012; Corcoran & Hill, 1980; Heller, 2014; Hooghe, Vanhoutte, Hardyns, & Bircan, 2010; Lochner, 2004; McBride et al., 2011; Phillips & Land, 2012; Raphael & Winter-Ebmer, 2001). Furthermore, a considerable portion of the unemployed rely on government assistance to survive, particularly during the time frame when the nation was implementing the EBT system (McDonald, 1996; Van Berkel, 2010). Because the focus of this study centers on EBT implementation reducing circulating cash and the crime associated with it, and that unemployment correlates with criminal behavior, I created an unemployment variable and included it in the final analysis to reduce bias in the model. I collected the data to create this variable from the official yearly statistics published by the US Census Bureau and entered into the dataset as a rate per 100,000 residents.

### **High School Education**

In addition to poverty and joblessness, research establishes that a lack of education is also a substantial contributor to the crime equation (Altindag, 2012; Hannon & DeFronzo, 1998; Hjalmarsson & Lochner, 2012; Lochner, 2004, 2011; McBride, Berkel, Gaylord-Harden, Copeland-Linder, & Nation, 2011; Mesters, van der Geest, & Bijleveld, 2016). In short, there is a negative correlation between completing high school and criminal behavior where persons with a high school education tend to commit less crime and the reverse (Hannon & DeFronzo, 1998; Van Berkel, 2010). Collected from the US Census Bureau, the US Bureau of Labor Statistics, and the US Department of Education as a percentage of a state's population with a high school diploma, I created and included this variable in the subsequent analyses to avoid confounding the final results.

### **Imprisonment Rate**

There is some basis for the notion that incarceration may reduce the crime rate, most plausibly through incapacitation (Blumstein & Rosenfeld, 2008; Levitt, 2004; Lynch & Sabol, 2004; Rosenfeld & Messner, 2009; Spellman, 2006). Evidence produced from a variety of studies consistently reveals a negative relationship between incarceration and crime (for a full review see Liedka, Piehl, & Useem, 2006). Liedka and colleagues' (2006) research covering three decades of data – including the period for the current study - indicates not only that as the prison population rises crime rates decrease, but also that even in areas with lower levels of incarceration its effect on the crime rate has been grossly underestimated. More specific to the current research, Lynch and Sabol (2004) conducted research using BJS data and observed that nationwide increases in the incarceration rate shared a negative relationship with crime rates particularly in disadvantaged neighborhoods, the same areas where government assistance is higher.

Due to these correlations, I created and included an imprisonment variable in the regression equations as a control variable. The variable consists of data collected from the BJS' National Prisoner Statistics (NPS) Historical Corrections website. I incorporated this variable into the dataset as a rate for each state encompassing those under the jurisdiction of both federal and state correctional authorities. I recognize that private prisons do not necessarily report or make available their data. As a consequence, the true incarceration rates could be less than the official figures utilized. Even if this is the case, I argue that it would only bias the results in the

opposite direction of the analysis. The effect of EBT implementation on crime, therefore, would be under-estimated.

# Trend

Data comprised of repeated measures over time (panel data) carry with them an inherent trend. If the outcome of interest, in this case crime, is growing over time, subsequent regression analyses must account for this growth. This is commonly referred to as the *trend* and is critical to difference in differences modeling (Cameron & Trivedi, 2010). Adding a trend variable to this analysis helps control for any exogenous increases in crime unexplained by the variables already included in the model. Creating a trend variable consists simply of recording a progressive numeric value for each consecutive year in the data set. For instance, if the data for a particular analysis began in the year 2000 and ended in 2004, the trend variable would equal "1" for the year 2000. A "2" would be recorded for the trend variable in the year 2001 and would increase until ending with the value of "5" in 2004.

### **Method of Analysis**

## Difference in Differences Analysis

Criminologists infrequently have access to true experimental data relying more on socalled "natural" or quasi-experiments (Lum & Yang, 2005; Weisburd & Braga, 2006). Most often in these designs, the administration of the treatment was not random, and the researcher did not control how that treatment was assigned. This is the case with EBT implementation. Each state initiated the system according to their own agenda in their own time. Moreover, these states did not publish the reasoning behind their implementation strategies, so it is impossible to know how authorities decided when are where to begin. In circumstances such as this, basic regression techniques are not always useful, and researchers must look to alternative methods. Difference in differences (DD) analysis is especially advantageous for such situations (Abadie, 2005; Alison, 2006; Cameron & Trivedi, 2010). Employing this method produces the appropriate counterfactual estimate used to calculate the average treatment effect on the treated entities (commonly referred to as the ATT) of an event regardless of non-random treatment selection (Roberts, 2015). This makes DD strategies appropriate for the analyses in the current study. Moreover, the DD method is designed for aggregate, pooled cross-sectional or longitudinal data to observe trends in the outcome variable (in this case crime rates) for two groups before and after the intervention (in this case EBT implementation).

There are essentially three DD methods. The simplest involves conducting a comparison of the trends of the outcome variable for both the control and treatment groups before and after an event. The outcome estimates of the treatment group before and after the intervention is subtracted from the outcome estimate of the control group's before and after estimates. The two differences are then subtracted from each other yielding the difference in the differences estimate or the ATT (Card & Krueger, 1994). The drawback of this particular method of DD estimation is that it only accounts for variation in the outcome variable with no consideration given to the input of other factors, observed or unobserved. This was problematic for the current study because I suspected unobserved and unquantifiable influences, such as adherence to street culture, might the results of the final analysis. Moreover, for this type of DD analysis to yield a proper ATT estimate, a definitive point of treatment for both groups needs to exist. Because EBT implementation in most states took longer than one year, no common intervention point for each jurisdiction existed. This, this particular type of DD analysis was not appropriate to conduct the analyses in the current study.

Researchers can also estimate the ATT using ordinary least squares (OLS) regression by including a specific interaction term. Creating this interaction term consists of multiplying a dichotomous variable whether the group received the treatment, (1=yes/0=no) by a dichotomous variable indicating if the specific observation occurred before or after the treatment (1=yes/0=no). Formally, the equation is such that:

 $Y_{it} = \beta_0 + \beta_1 * [Time] + \beta_2 * [Treatment] + \beta_3 * [Time * Treatment] + \beta_4 * [Covariates] + \varepsilon_{it}$ where  $y_{it}$  is the outcome variable of interest for the individual unit at a particular point in time. The symbol  $\beta$  represents the regression coefficient for each of the independent variables. The *Treat*<sub>it</sub> variable represents whether or not the individual value was recorded for the treatment or control group while *Post*<sub>it</sub> indicates whether or not the individual value occurred pre-event or post event. The term  $\varepsilon_{it}$  represents the residual error in the equation.

In principle, this model would produce the ATT estimate through the interaction term coefficient ( $\beta_3$ ). However, one of the weaknesses of OLS regression is that it is open to omitted (unobserved) variable bias. While this type of model would estimate of the effect of reducing cash through EBT implementation on crime, it would not for exogenous, unobservable influences such as sentiment, religious beliefs, culture, or adherence to a particular way of life. The model would, therefore, produce inaccurate results by way of omitted variable bias.

Fixed effects regression analysis, however, is a DD design particularly suited to account for omitted variable bias (Cameron & Trivedi, 2010). This method is one of the most tested and preferred designs for the analysis of panel data where repeated observations occur over time, as is the case with the data utilized in the current study (see Alison, 2004). Because I suspect the presence and influence of unobservable factors in the analyses performed in this current research, such as adherence to street life, and I am utilizing panel data, I utilize a fixed effects (FE) regression design to produce the ATT of reducing cash on street crime.

# Fixed Effects Regression

The identifying assumption of fixed effects regression analysis is that unobserved variables affect both the left and right side of the equation are time-invariant and can therefore be removed by differencing them out of the equation over repeated observations (Alison, 2006). It does this by considering only the variation *within* the individual units of observation (in this case the states) over time, not between them. When subtracting each state's yearly observations from their mean before and after implementation, and then regressing the outcome differences on the predictor differences, FE eliminates the source of omitted variable bias; that is, unobservable cross-state differences in crime (Cameron & Trivedi, 2010; Gardiner, Luo, & Roman, 2009). By doing so, the coefficient estimates cannot be biased because the omitted time-invariant influences (e.g., culture, religion, etc.) are held *fixed*.

For example, the state of Ohio had different rates of crime over a 17-year period surrounding EBT implementation. Comparing the variables particular to Ohio to their 17-year means produces the within-state variation and accounts for the time-invariant unobserved variables. The crime outcome differences are then regressed on the predictor differences resulting in the effect estimate in that state. The same is done for every other state included in the model until the analysis estimates the final ATT coefficient on the main predictor variable, EBT implementation. Employing this design fundamentally eliminates a key source of omitted variable bias, the unobserved differences across-states, by removing contamination from confounding units of observation (other states) and additional unobserved factors that might otherwise produce biased estimates (Alison, 2006). Moreover, FE regressions can provide

estimates of count-based differences of either Poisson or negative binomial distributions (Alison, 2006, Cameron & Trivedi, 2010). But because Poisson regression forces the mean and the variance to equal estimates – when in the data used for the current study they are not – the appropriate routine for this analysis is the negative binomial distribution.

Given the above, I chose to perform a FE negative binomial, difference in differences regression analysis to produce the ATT of implementing the EBT system on various forms of street crime. The final model equation is such that:  $Crime_{sy} = f(\alpha EBT_{sy} + \beta_s + Trend_{sy} + \varepsilon_{sy})$ . Crime<sub>sy</sub> is the specific street crime rate for state s in the calendar year y. The EBT<sub>sy</sub> variable is the treatment which equals zero if state s did not have the EBT system in effect in the calendar year y, a fraction if implementation was in progress and a one if the system was completely in effect. The coefficient  $\beta_s$  is the state fixed effects vector accounting for any cross-state permanent differences that may affect crime. I also incorporate a state-specific yearly time trend variable, Trend<sub>sy</sub>, that accounts for possible non-random variation in the program implementation that might be correlated with unobserved factors that vary by state and year, and that might also affect crime including population.<sup>4</sup> Last,  $\varepsilon_{sy}$  is the idiosyncratic error left over in the equation. To ensure that this error is unbiased and uncorrelated within the states, I clustered the standard errors at the state level for each year encompassed in the model. This left the remaining coefficient of interest, a. Controlling and accounting for each of the other model factors, this coefficient is what measures the effect reducing cash through EBT implementation had on crime. This coefficient indicates the percent change in the outcome variable given the other factors in the model.

<sup>&</sup>lt;sup>4</sup> The regression is weight by annual state population.

Note that fixed effects regression has a counterpart, random effects regression. Both techniques are appropriate for panel data analysis, but FE analysis allows the free association between the error and predictor terms where random effects regression does not. To determine the correct design, I employed a Housman specification test of endogeneity that analyzes the correlation between the predictor variables and the error term. This procedure tests the null hypothesis that the coefficients of the random effects model are equal to its fixed effects counterpart (Alison, 2006). If the test produces a significant p-value, the null hypothesis is rejected and indicates that the researcher should utilize a fixed effects model (Alison, 2006). All of the models in the current study returned a statistically significant Hausman test p-value indicating that fixed effects analyses were appropriate.

#### Stage 1: Less Cash, Less Crime Analysis

Stated earlier, the first part of the analyses conducted in this study begins as a national examination loosely based on the original Missouri study conducted by Wright et al. evaluating the effect of EBT implementation on crime. In doing so, I perform an analysis on the entire nation to produce the overall effect of reducing cash on street crime. The FE analysis to follow capitalizes on the fact that there is variation in the time frame in which the individual states implemented EBT. Not all states initiated the system in the same year. This inconsistency is what forms the treatment and control states and allows for the estimation of the ATT on the country as a whole.

However, EBT benefits are not distributed evenly across the country. Some states receive more SNAP benefits than others. If EBT implementation reduces circulating cash and that reduction negatively affects street crime, then the effects should be greater in the states receiving more of the benefits than others. While Wright et al. (2017) focused on one specific state where

benefits are fairly localized, the current analysis encompasses not only the states receiving average benefits, but also the high and low extremes. Adding this more focused analysis to the original analysis format provides a more in-depth understanding of how reducing cash affects crime by exploring whether states receiving greater amounts of government benefits - in dollars issued per the USDA (2016) – might be different from those receiving fewer. Utilizing data from the USDA was the most appropriate measure because, first, they are responsible for the national distribution of EBT benefits through the SNAP program, and second, the EBT systems is the primary independent variable of interest. Thus, I performed FE regression analysis on both the top ten<sup>5</sup> and bottom ten<sup>6</sup> states receiving benefits and compared the results side by side.

Some studies suggest that street crime is generally considered an urban event (Herbert, 1982; Krivo & Peterson, 1996). However, the analysis of the top and bottom states receiving benefits consists principally of more rural states as defined by the US Census Bureau urban density statistics (US Census Bureau, 2000). To strengthen the case that cash connects to street crime, I performed an analysis of the top ten urban states and the ten most rural states in the country. An analysis of this nature would test whether the cash and street crime connection holds true on a more granular level. While it is true that street crime does not necessarily have to be an urban event, enough research exists to justify that a significant portion of this type of offending occurs in this environment (Anderson, 1999; Shover & Honaker, 1992). If the less cash, less crime hypothesis holds true, and assuming this is a model that best fits in the analysis of street offending, there should be a greater effect in the more urban<sup>7</sup> states compared to the more rural<sup>8</sup>

<sup>&</sup>lt;sup>5</sup> Texas, California, New York, Florida, Illinois, Pennsylvania, Ohio, Michigan, Georgia, and Tennessee.

<sup>&</sup>lt;sup>6</sup> District of Columbia, Rhode Island, Montana, Delaware, South Dakota, Alaska, New Hampshire, Vermont, North Dakota, and Wyoming.

<sup>&</sup>lt;sup>7</sup> District of Columbia, California, New Jersey, Hawaii, Nevada, Massachusetts, Rhode Island, Florida, Arizona, and Utah.

<sup>&</sup>lt;sup>8</sup> Vermont, Maine, West Virginia, Mississippi, South Dakota, Arkansas, Montana, Alabama, Kentucky, and North Dakota.

states. Thus, an exploration of the effects of EBT implementation in both urban and rural areas yields a more complete understanding as to how it affects street crime in these environments. In testing this notion, I conducted the same regressions as previous and made side-by-side comparisons of these two groups.

Finally, if reducing circulating cash also reduces street crime, then it should also be the case that states with different levels of street crime will be affected differently as a result of EBT implementation. In the last part of the stage one analyses, I test for differences between the states with the highest levels of street crime<sup>9</sup> in comparison to the states with the lowest levels<sup>10</sup> of street crime. Performing an analysis of this nature could point out the types of crimes most affected by a reduction in circulating cash in areas with specific levels of EBT implementation offending levels. A design of this nature allows for a sharper focus on the cash and crime connection in areas of varying crime levels. Again, I conducted regression analyses and compared top street crime states against bottom street crime states side by side.

The results of each of these analyses subsequently open the door for the second stage of this study's analytical strategy: That is, a test of whether drugs have a mediating effect between cash and street crime.

### Stage 2: Path Analysis of Drugs as a Mediator

The next stage of the overall analysis was to determine whether drugs could be acting as one possible underlying mechanism for the commission of crime to obtain the necessary cash for

<sup>&</sup>lt;sup>9</sup> District of Columbia, Florida, Arizona, New Mexico, Texas, Maryland, Hawaii, South Carolina, Louisiana, and Oregon.

<sup>&</sup>lt;sup>10</sup> New Hampshire, North Dakota, Virginia, South Dakota, Maine, Vermont, West Virginia, Iowa, Kentucky, and Wisconsin.

their purchase. The method used to evaluate this hypothesis was a path analysis utilizing Sobol's test of significance (STS).<sup>11</sup> Figure 2 illustrates this strategy.



Figure 2: Sobel's Test of Drugs as a Mediator

Formally, Sobel's test of mediation is a path analysis formulated such that:

$$Z = \frac{a * b}{\sqrt{\{[b^2 * SEa^2(a)] + [a^2 * SEb^2(b)]\}}}$$

where *a* represents the standardized beta coefficient value of EBT implementation regressed on drug arrests holding fixed each of the control variables, *b* represents the standard beta coefficient value for drug arrests regressed on crime holding fixed each of the control variables, and *SE* represents the standard errors of the individual regressions. The symbol *c* represents the direct effect coefficient of crime regressed on cash (EBT implementation) holding fixed each of the control variables. Converting the Z score to a p-value determines the strength of drugs as a mediator. A significant p-value indicates that drugs are, in fact, the mechanism between cash and crime.

<sup>&</sup>lt;sup>11</sup> See Baron, R. M. & Kenny, D.A. (1986) for a full explanation of tests of mediation.

# CHAPTER IV Results

# **National Analysis**

# **Descriptive Results**

Evaluating the effect of reducing the amount of circulating cash on street crime begins with describing the data. Table 1 depicts the summary statistics for the national analysis and displays each variable's mean, standard deviation, and range for each state encompassing the five years before and after complete EBT implementation. Thus, the total end-to-end time frame for the entire study spans from 1984 and 2009. <sup>12</sup> At the national level, the mean rates of street crime, robbery, burglary, larceny, and auto theft were 4142.59, 143.68, 851.30, 2727.67, and 420.08, respectively. The nation's mean percent black population was 10.83% and gender distribution was approximately even (males = 49.63%). The mean high school education percentage was 71.48% over the course of the study, and the mean rate of persons living in poverty was 12.74% nationally. The country's mean unemployment rate was 5.23 with a national imprisonment rate of 367.67. Finally, the nation's mean population was 5,405,138.50.

Statistic	Mean	St. Dev.	Min	Max
Street Crime rate	4142.59	1278.53	1786	10751
Robbery rate	143.68	141.63	6	1266
Burglary rate	851.3	328.24	308	2171
Larceny rate	2727.67	749.69	1336	5834
Auto theft rate	420.08	252.79	75	1840
Percent black	10.83	11.62	0.3	65.8
Percent male	49.63	14.73	46	48.2
Percent high school education	71.48	9.08	47.56	95.1
Percent below poverty	12.74	3.39	5.6	23.9
Unemployment rate	5.23	1.52	2.2	13.1
Imprisonment rate	367.67	205.84	59	1712
Population	5405138.5	6125711.64	453588	37683933

Table 1: US Overall Descriptive Statistics, 1984-2009

<sup>&</sup>lt;sup>12</sup> Because the last state converted to the EBT system on 2005, data were collected until 2009 to allow for analysis five years before and after throughout the study.

The last variable in the model was EBT implementation, which served as a proxy for the reduction of circulating cash. Each state executed EBT rollout in various years across the study and took varying lengths of time to completely onboard each of their respective recipients. Figure 3 depicts in gray the years each state began and completed the switch to the EBT system. Maryland was the first to initiate the switch from paper checks to the electronic benefits system in 1989; even before Congress made it mandatory. The remaining states followed accordingly with California the last to fully convert in 2004. This state-by-state implementation variation in the time line what I capitalize upon to perform the FE difference in differences regressions to follow and produce the ATT.

State	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Maryland																	
New Mexico																	
Minnesota									1								
Ohio																	
New Jersev																	
Texas																	
South Carolina						_											
Wyoming																	
Utah																	
North Dakota																	
South Dakota																	
Kansas																	
Illinois																	
Louisiana																	
Colorado																	
Connecticutt																	
Alabama																	
Massachusetts																	
Missouri																	
Oklahoma																	
Georgia																	
Arkansas																	
Idaho																	
Oregon																	
Florida																	
Pennsylvania																	
Alaska																	
Hawaii																	
North Carolina																	
District of Columbia																	
Rhode Island																	
Vermont																	
Arizona																	
New Hampshire																	
Tennessee																	
New York																	
Washington																	
Kentucky																	
Wisconsin																	
Michigan																	
Indiana																	
Nevada																	
Virginia																	
Montana																	
Nebraska																	
Mississippi																	
California																	
West Virginia																	
Maine																	
Delaware																	
lowa																	

Figure 3: State by State EBT Implementation Timeline.

## **Regression Results**

The regression results displayed in Table 2 are a representation of the effect of reducing circulating cash on street crime nationwide. Included in the model are the estimate (regression coefficient), the standard error, and the R-squared value, in addition to the model diagnostic value represented by the F statistic and its significance with standard asterisk notation. The first EBT column depicts the direct effect of implementation alone on the outcome variables of overall street crime, robbery, burglary, larceny, and auto theft. The second EBT column includes the control variables. The third EBT column incorporates not only the control variables but also a linear trend variable. As noted earlier, the trend variable controls some of the omitted timeinvariant bias that the model might otherwise contain when performing FE regression techniques. Moreover, it yields the most conservative estimate when accounting for the omitted variable bias. Although adding the trend variable reduces the effect size and sometimes causes it to become non-significant due to its accounting for endogeneity in the model, this estimate is the most appropriate as it includes as many of the factors that could influence a change in crime as a result of reducing cash in circulation. As such, the interpretations of the results that follow refer to the full model with control and linear trend variables included. Finally, for ease of reading, in this particular column, I bolded the regression coefficient estimates that were significant as noted by the p-value asterisks super scripted above them.

This phase of the analysis indicates that EBT implementation was responsible for a 1.3% nationwide reduction in street crime. Each of the other crime outcomes also significantly declined. Nationally, the reduction of cash through the electronic payments system had the greatest effect on burglary (4.4%) while larceny was the least affected (1.6%). Robbery and auto

theft also declined by 3.1% and 3.5%, respectively, as a result of the switch from paper checks to the EBT system.

Offense		EBT	EBT	EBT
Street Crime	Estimate	-0.099***	-0.084***	-0.013*
	S.E.	0.003	0.004	0.005
	R-squared	0.562	0.617	0.709
	F statistic	1047.73***	162.86***	218.76***
Robbery	Estimate	-0.100***	-0.065***	-0.031***
	S.E.	0.005	0.007	0.001
	R-squared	0.308	0.400	0.414
	F statistic	363.45***	67.28***	63.56***
Burglary	Estimate	-0.133***	-0.105***	-0.044***
	S.E.	0.004	0.005	0.007
	R-squared	0.550	0.660	0.700
	F statistic	1001.79***	191.83***	214.21***
Larceny	Estimate	-0.088***	-0.080***	-0.016**
	S.E.	0.003	0.004	0.005
	R-squared	0.490	0.540	0.648
	F statistic	790.63***	118.37***	164.98***
Auto Theft	Estimate	-0.093***	-0.086***	-0.035**
	S.E.	0.006	0.008	0.012
	R-squared	0.180	0.250	0.330
	F statistic	240.92***	43.61***	44.18***
Direct Effects		Yes	Yes	Yes
Controls		No	Yes	Yes
Linear Trends		No	No	Yes

Table 2: EBT Effects on US Street Crime(s) Nationally, 1984-2009

These outcomes, however, are contingent upon the assumption that each state's pretreatment outcome trends were moving in parallel. By including a linear trend variable in the model, I loosely controlled for unobserved variables (e.g. state specific policies or characteristics) that move linearly over time. Strictly speaking, incorporating a trend variable into the model relaxes the parallel trends assumption and the results could be considered valid with the inclusion of this variable alone. Yet, I went further in testing the parallel trends assumption by conducting an event study analysis.

At its core, an event study analysis allows the treatment – in this case EBT implementation – to affect the outcome variable in the pre-treatment years as a type of placebo test, removing any pre-existing differences between the treatment and control groups. But EBT implementation took some states longer to complete than others. While defining the exact pretreatment, and post treatment years for this test in all 50 states was straightforward, the treatment needed to be one definitive unit - for purposes of this study, within one calendar year. For example, the state of Utah began EBT implementation in October of calendar year 1995 and completed the process in April 1996. While they did complete the process in less than one year, the process spanned two calendar years. Thus, I could not determine one calendar year in which the treatment occurred and consequently, the pretreatment trend years are ambiguous. Because I am utilizing end of calendar year data, selecting the state of Utah would have unnecessarily biased the results of the event study. In contrast, the state of Rhode Island implemented and completed the process entirely in the calendar year1998 allowing for a definitive treatment point and a "clean" pre-treatment trend. Of all 50 states and the District of Columbia, 16 of them<sup>13</sup> began and completed<sup>14</sup> EBT implementation within one calendar year (see Figure 3). Although it would have been helpful to have included every state in the event history analyses, the data at hand prohibit a full test of the parallel trends assumption but I argue that a sample of nearly half could act as a proxy for the country in general.

The first part of the event history analysis consists of creating dummy variables for the five years prior (P1, P2, P3, P4, and P5) and post EBT implementation (D1, D2, D3, D4, and D5). I then performed individual analyses regressing each of the outcome crimes onto the

<sup>&</sup>lt;sup>13</sup> Alabama, Alaska, Connecticut, Delaware, District of Columbia, Hawaii, Iowa, Kentucky, Louisiana, Maine, Massachusetts, Mississippi, Montana, Nebraska, Rhode Island, and Vermont.

<sup>&</sup>lt;sup>14</sup> Some states included in the event study took slightly over one year but not so much as to detract from the results.

dichotomous EBT implementation variable while including the newly created dummy variables. The p-values of the P1 through P5 variable in the results act as an indicator of whether the pretreatment trends were parallel. If these p-values turned out to be statistically significant, the parallel assumption fails indicating that some exogenous variable was driving the reductions found in the nationwide examination. Nevertheless, the results of the event study indicated that the parallel trends assumption held for each of the crimes under analysis (see Tables 3, 4, 5, 6, and 7).

Street Crime	Coef	SE	Sig.	95% Con	f. Interval
EBT	-0.063	0.042	0.136	-0.146	0.020
P5	0.048	0.042	0.253	-0.035	0.131
P4	0.033	0.042	0.434	-0.050	0.116
P3	0.021	0.042	0.621	-0.062	0.104
P2	0.010	0.042	0.805	-0.072	0.093
P1	(Omitted)				
D1	0.048	0.042	0.253	-0.035	0.131
D2	0.031	0.042	0.459	-0.051	0.114
D3	0.017	0.042	0.696	-0.066	0.099
D4	0.012	0.042	0.773	-0.071	0.095
D5	(Omitted)				
Constant	3.608	0.030	0.000	3.550	3.667
Observations	230				
Clusters	18				

Table 3: Event Study Results for Street Crime Analysis 1984-2009

Robbery	Coef	SE	Sig.	95% Cont	f. Interval
EBT	-0.037	0.136	0.788	-0.303	0.230
P5	0.033	0.136	0.810	-0.234	0.299
P4	0.029	0.136	0.833	-0.238	0.295
P3	0.023	0.136	0.865	-0.243	0.290
P2	0.016	0.136	0.906	-0.250	0.283
P1	(Omitted)				
D1	0.018	0.136	0.896	-0.249	0.284
D2	-0.011	0.136	0.934	-0.278	0.255
D3	-0.001	0.136	0.992	-0.268	0.265
D4	-0.010	0.136	0.939	-0.277	0.256
D5	(Omitted)				
Constant	1.885	0.096	0.000	1.697	2.074
Observations	230				
Clusters	18				

Table 4: Event Study Results for Robbery Analysis, 1984-2009

 Table 5: Event Study Results for Burglary Analysis, 1984-2009

Burglary	Coef	SE	Sig.	95% Cont	f. Interval
EBT	-0.064	0.050	0.203	-0.162	0.035
P5	0.081	0.050	0.107	-0.018	0.179
P4	0.057	0.050	0.260	-0.042	0.155
P3	0.034	0.050	0.500	-0.065	0.132
P2	0.016	0.050	0.755	-0.083	0.114
P1	(Omitted)				
D1	0.043	0.050	0.387	-0.055	0.142
D2	0.026	0.050	0.603	-0.072	0.125
D3	0.012	0.050	0.808	-0.086	0.111
D4	0.005	0.050	0.924	-0.094	0.103
D5	(Omitted)				
Constant	2.855	0.036	0.000	2.786	2.925
Observations	230				
Clusters	18				

Theft	Coef	SE	Sig.	95% Con	f. Interval
EBT	-0.067	0.034	0.048*	-0.133	-0.001
P5	0.035	0.034	0.304	-0.032	0.101
P4	0.023	0.034	0.496	-0.043	0.089
P3	0.015	0.034	0.653	-0.051	0.082
P2	0.008	0.034	0.817	-0.059	0.074
P1	(Omitted)				
D1	0.055	0.034	0.105	-0.012	0.121
D2	0.038	0.034	0.258	-0.028	0.105
D3	0.022	0.034	0.512	-0.044	0.089
D4	0.019	0.034	0.581	-0.048	0.085
D5	(Omitted)				
Constant	3.416	0.024	0.000	3.369	3.463
Observations	230				
Clusters	18				

Table 6: Event Study Results for Theft Analysis, 1984-2009

Table 7: Event Study Results for Auto Theft Analysis, 1984-2009

Auto Theft	Coef	SE	Sig.	% Conf. Inter	val
EBT	-0.048	0.080	0.550	-0.205	0.109
P5	0.033	0.080	0.680	-0.124	0.190
P4	0.031	0.080	0.700	-0.126	0.188
P3	0.021	0.080	0.790	-0.136	0.178
P2	0.003	0.080	0.970	-0.154	0.160
P1	(Omitted)				
D1	0.030	0.080	0.708	-0.127	0.187
D2	0.009	0.080	0.909	-0.148	0.166
D3	-0.005	0.080	0.948	-0.162	0.152
D4	0.006	0.080	0.939	-0.151	0.163
D5	(Omitted)				
Constant	2.498	0.057	0.000	2.387	2.609
Observations	230				
Clusters	18				

## **Benefits Comparison Analysis**

If switching from paper checks to the EBT system reduces the amount of circulating cash and subsequently decreases street crime, then its effect should be larger in the states receiving the most benefits and lower in the states receiving the least amount of benefits. The government distributes SNAP benefits through the EBT program which make up a large portion of the total welfare disbursements transferred to recipients through the system. The USDA publishes state by state annual reports on SNAP distribution and lists the number of total benefits dollars distributed to each state. From these reports, I determined the top ten states with the most and least amounts of SNAP benefits distribution by total benefits dollars<sup>15</sup> in each state. Texas, California, New York, Florida, Illinois, Pennsylvania, Ohio, Michigan, Georgia, and Tennessee were consistently the top ten states receiving the most benefits while the District of Columbia, Rhode Island, Montana, Delaware, South Dakota, Alaska, New Hampshire, Vermont, North Dakota, and Wyoming made up the bottom ten states.<sup>16</sup> Again, I included the five years before each states implementation for trending purposes. These data spanned from 1989 to 2009. With the data in place, I ran both descriptive and FE DD analyses on the top ten states receiving SNAP benefits and then on the ten states receiving the least amount of SNAP benefits and compared the results side by side.

<sup>&</sup>lt;sup>15</sup> The USDA lists not only each state's disbursements in total dollars, but also by number of households and number of individuals within each state. While I used total dollars to rank each state top to bottom, had I used either of the other two metrics the list ranking for the top and bottom ten states would have remained the same.

<sup>&</sup>lt;sup>16</sup> The order of these states did not appreciably change year over year during the time frame in this study.

		Top SNA	P States			Botton Sl	NAP States	5
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Street Crime rate	4342.34	(1220)	2149	<i>7983</i>	3745.33	(1729.42)	1785	10751
Robbery rate	210.51	(80.38)	112	597	137.42	(271.56)	6	1266
Burglary rate	919.19	(345.10)	336	2171	653.88	(331.50)	308	2074
Larceny rate	2700.55	(725.88)	1506	4574	2585.92	(867.58)	1336	5834
Auto theft rate	512.19	(164.10)	129	944	368.24	(398.73)	95	1840
Percent black	14.25	(5.49)	5.80	29.80	9.24	(18.03)	0.30	65.80
Percent male	48.74	(0.55)	47.69	50.50	49.36	(1.41)	46.00	53.00
Percent high school education	66.33	(7.78)	50.40	79.97	74.88	(7.82)	58.90	<i>89.92</i>
Percent below poverty	13.58	(2.22)	9.50	19.60	11.78	(3.04)	5.60	21.90
Unemployment rate	5.70	(1.43)	3.30	12.10	5.02	(1.72)	2.50	9.30
Imprisonment rate	408.87	(116.65)	187	754	384.06	(358.67)	63	1712
Population	14,711,104	(8,028,854)	4,953,000	37,683,933	759,356	(220,339)	453,588	1,314,895

Table 8: Descriptive Results for Top and Bottom SNAP States, 1989 - 2009

Table 8 illustrates the descriptive results of each predictor or control variable in the model. With the exception of high school education, and percent male, the mean values for each variable in the top SNAP states were higher than those of the bottom SNAP receiving states. This indicated that the states receiving the most benefits not only had higher rates of predatory crime(s) but also had higher levels of the known predictors of these crimes. Taken together, it seemed probable that the effect of EBT implementation on street crimes would be greater in the areas where SNAP was most prominent. And, in fact, the results that follow confirmed this assumption (see Table 9).

The results displayed in Table 9 demonstrate that this model, as with the previous models, had a significant F statistic values (p < .001) verifying the validity of the variables included in the regressions to predict the outcome. The regression results in this analysis demonstrate significant reductions in every street crime in the ten states receiving the most benefits.<sup>17</sup> In comparison to the 1.3% decrease in the national model, overall street crime dropped 3.2%, nearly three times as much. The results of robbery were similar. Where EBT implementation reduced robbery across the country by 3.1%, robbery decreased by 9.5% in the

<sup>&</sup>lt;sup>17</sup> A variance inflation factor analysis indicated multicollinearity between the imprisonment rate and the percentage of black individuals in this sample. As a result, the imprisonment rate was dropped from the equation.

top SNAP states. A similar pattern continued burglary (4.4% compared to 7.0%), larceny (1.6% compared to 3.9%), and auto theft (3.5% compared to 5.0%) indicating the effect of reducing circulating cash on street crime both individually and in the aggregate, was stronger in the states receiving the most benefits as opposed to the US as a whole. Moreover, compared to the states receiving the least amount of SNAP benefits, the reduction of circulating cash through the EBT system did not significantly affect any of the crime outcomes. While the R-squared values on the bottom ten SNAP states in both robbery and auto theft were less that .50, indicating that less than half of the variance in the outcomes were explained by the models utilized, the fact that each of the values in every other crime outcome were well above .70 demonstrates that the overall model fit is generally robust.

However, one could argue that most of the states in this analysis are rural and street crime typically occurs in urban environments (Hallsworth, 2013; Hannon & DeFronzo, 1998; Linton et al., 2014; Martinez, 2014; Sampson, 2013; Silverman, 2004; Willits, Broidy, & Denman, 2013). Consequently, it could be that the results of this part of the analysis contain some manner of selection bias. Thus, I continued to interrogate the cash and crime relationship through a comparison of the country's most urban and rural states.

		Тор	10 SNAP S	States	Botton	n 10 SNAP	States
		EBT	EBT	EBT	EBT	EBT	EBT
Street Crime	Estimate	-0.128***	-0.103***	032*	-0.116***	-0.066***	0.002
	S.E.	0.007	0.011	0.015	0.007	0.011	0.012
	R-squared	0.663	0.754	0.787	0.640	0.735	0.819
	F statistic	313.45***	58.16***	70.42***	282.14***	60.52***	86.39***
Robbery	Estimate	-0.186***	-0.157***	-0.095***	-0.047***	-0.056*	-0.014
	S.E.	0.011	0.017	0.024	0.014	0.024	0.029
	R-squared	0.649	0.731	0.752	0.069	0.165	0.201
	F statistic	294.49***	51.68***	50.74***	11.76***	4.31***	4.23***
Burglary	Estimate	-0.168***	-0.121***	-0.070***	-0.149***	·0.0627***	-0.011
	S.E.	0.010	0.014	0.020	0.012	0.015	0.018
	R-squared	0.662	0.770	0.788	0.509	0.740	0.775
	F statistic	312.55***	63.73***	62.33***	165.03***	62.32***	57.71***
Larceny	Estimate	-0.101***	-0.080***	-0.039**	-0.119***	-0.063***	-0.007
	S.E.	0.007	0.010	0.014	0.008	0.012	0.013
	R-squared	0.589	0.704	0.732	0.609	0.724	0.798
	F statistic	227.50***	45.27***	45.88***	247.40***	57.34***	66.48***
Auto Theft	Estimate	-0.191***	-0.189***	-0.050*	-0.083***	-0.044*	-0.010
	S.E.	0.013	0.021	0.027	0.012	0.019	0.023
	R-squared	0.569	0.658	0.743	0.233	0.448	0.470
	F statistic	210.24***	36.61***	48.45***	48.17***	15.45***	14.88***
Direct Effects		Yes	Yes	Yes	Yes	Yes	Yes
Controls		No	Yes	Yes	No	Yes	Yes
Linear Trends		No	No	Yes	No	No	Yes

Table 9: Fixed Effects Results for Top and Bottom SNAP states, 1989 - 2009

# **Urban and Rural Comparison**

If it is true that street crime is a marker of urban density, then it should be that EBT implementation will have a greater effect in the most urban states in comparison to their rural counterparts. Consequently, I conducted regression analyses on the ten most urban (District of Columbia, California, New Jersey, Hawaii, Nevada, Massachusetts, Rhode Island, Florida, Arizona, Utah) and the ten most rural (Vermont, Maine, West Virginia, Mississippi, South Dakota, Arkansas, Montana, Alabama, Kentucky, North Dakota) states by urban percentage of the population according to the US Census Bureau at the time of EBT implementation. Tables 10 and 11 list the comparative results.

		Top Urban	States			Top Rural S	States	
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Street Crime rate	4945.81	1723.73	2479.604	10751.08	3359.59	837.37	1895	5319
Robbery rate	237.40	247.54	44	1266	58.13	48.75	6	186
Burglary rate	966.00	362.84	448	2171	685.55	258.55	309	1292
Larceny rate	3045.39	1066.67	1524	5834	2194.46	496.84	1336	3834
Auto theft rate	697.18	339.02	238	1840	205.01	83.63	75	489
Percent black	11.82	16.84	0.7	65.8	9.14	12.11	0.30	37.00
Percent male	49.17	1.47	46	55.46	51.57	33.12	47.74	482.00
Percent high school education	70.24	10.00	47.56	95.1	74.24	9.27	55.50	89.92
Percent below poverty	12.21	3.10	7.8	21.9	14.89	3.24	8.70	23.00
Unemployment rate	5.56	1.83	2.4	13.1	5.09	1.51	2.50	10.70
Imprisonment rate	438.16	347.86	121	1712	324.34	168.48	63.00	749.00
Population	7648567.44	10092574.52	519000	37683933	1973521.64	1329045.95	562758	4599030

Table 10: Descriptive Results for Urban and Rural States, 1989 - 2009

Unsurprisingly, the mean crime outcomes in Table 10 were higher in the urban states. The imprisonment rate in urban areas was also notably higher as was the percentage of black residents, as prior research would suggest (Fischer, 2003; Percival, 2010).<sup>18</sup> Scholarly literature additionally suggests that rural states should have higher basic education levels (Ladson-Billings, 2006) and was also the case in this study as the high school education percentage in the rural states was greater than the urban states. As expected, the mean population in the urban states was nearly four times higher (7,648567.44) than in the rural states (1,973,521.64); by definition, this should be the case. The percentage of males, however was just slightly higher in the rural states (51.57%) as opposed to the urban states (49.17%). The descriptive results of the remaining variables were approximately the same for both groups.

<sup>&</sup>lt;sup>18</sup> Once again diagnostics tests on the data prior to the analysis revealed significant multicollinearity between the imprisonment rate and percentage of black residents in the urban states. To address this, I removed imprisonment rate from the model in this phase of the research which eliminated this issue.

		Тој	p Urban Sta	ates	Тор	Rural Stat	tes
Offense		EBT	EBT	EBT	EBT	EBT	EBT
Street Crime	Estimate	-0.143***	-0.129***	0.010	0.0716***	·0.0372***	0.005
	S.E.	0.008	0.010	0.015	0.006	0.010	0.012
	R-squared	0.667	0.736	0.831	0.462	0.550	0.627
	F statistic	319.10	61.06***	93.74***	137.04***	23.19***	28.19***
Robbery	Estimate	-0.143***	-0.112***	-0.084***	-0.023	0.010	-0.005
	S.E.	0.011	0.014	0.023	0.012	0.018	0.022
	R-squared	0.511	0.643	0.652	0.023	0.223	0.230
	F statistic	165.96***	39.31***	31.46***	3.76*	5.46***	5.02***
Burglary	Estimate	-0.193***	-0.174***	-0.062**	-0.076***	-0.042**	-0.021
	S.E.	0.011	0.013	0.019	0.008	0.013	0.015
	R-squared	0.665	0.771	0.831	0.364	0.466	0.487
	F statistic	315.80***	73.48***	82.22***	91.14***	16.61***	15.90***
Larceny	Estimate	-0.138***	-0.119***	-0.010	0.069***	-0.044***	0.005
	S.E.	0.008	0.010	0.013	0.007	0.012	0.013
	R-squared	0.665	0.725	0.841	0.364	0.441	0.569
	F statistic	315.19***	57.49***	88.66***	90.83***	15.01***	22.18***
Auto Theft	Estimate	-0.085***	-0.094***	-0.025	-0.067***	-0.025	-0.011
	S.E.	0.017	0.023	0.037	0.010	0.014	0.017
	R-squared	0.134	0.274	0.337	0.226	0.484	0.492
	F statistic	24.65***	8.25***	8.54***	46.50***	17.85***	16.22***
Direct Effects		Yes	Yes	Yes	Yes	Yes	Yes
Controls		No	Yes	Yes	No	Yes	Yes
Linear Trends		No	No	Yes	No	No	Yes

Table 11: Fixed Effects Results for Urban and Rural States, 1989 - 2009

Table 11 illustrates the regression analyses results. If, as some scholars propose, street life and street crime are an urban phenomenon (Hallsworth, 2013; Vigil, 2010) and dependent on cash (Jacobs & Wright, 1999; Wright et al., 2017), then reducing the amount of cash in circulation should have a stronger effect on crime in urban states in comparison to their rural equivalents. The findings depicted in Table 11 partially support this supposition. The model diagnostics, again, indicated the model fit was satisfactory with all F-statistics being statistically significant. Primarily, decreasing the amount of circulating cash significantly reduced robbery and burglary in the most urban states yet these effects were not strong enough to make the aggregated street crime variable significantly reduced. The model demonstrated that the EBT shift was responsible for a decline in robbery of 8.4% and burglary dropped by 6.2% adding further support to the notion that reducing cash in a specific environment, such as urban areas where street life is endorsed, can lower the amount of predatory crime associated with it. Moreover, as with the lowest SNAP recipient states, the EBT shift did not affect any of the crime outcomes in the rural states thus adding further strength to the notion.

# Street crime: High and Low-Level analysis

The last test was to examine how EBT implementation affected the states with the most street crime<sup>19</sup> as opposed to the states with the least amounts.<sup>20</sup> By dividing the groups in this way, I expected the distribution of the significant effects to be spread evenly across them rather than more present in one over the other. Conducting this type of comparison shed light on the offenses most affected by the reduction of cash in high street crime states in comparison to low street crime states. Table 12 depicts the descriptive results of this analysis.

	Top 10 Street Crime States				Bottom 10 Street Crime States			
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Street Crime rate	5756.74	1248.57	3815	10751	2760.75	469.56	1785	4225
Robbery rate	256.79	242.72	68	1266	130.55	69.56	34	410
Burglary rate	1204.82	324.71	615	2171	540.89	136.50	308	1087
Larceny rate	3625.25	637.68	2504	5834	1996.46	344.86	1336	2920
Auto theft rate	669.98	325.42	319	1840	177.63	63.50	75	432
Percent black	18.22	18.06	1.5	65.8	4.16	5.67	0.3	20.88
Percent male	48.91	0.96	46	51.15	49.26	0.54	47.74	51.34
Percent high school education	63.72	6.94	48	86.79	78.21	6.23	62.3	<i>89.92</i>
Percent below poverty	15.12	3.85	7.9	23.9	11.75	3.23	5.6	19.9
Unemployment rate	5.81	1.41	2.4	9.4	4.50	1.40	2.2	8.7
Imprisonment rate	517.58	338.38	147	1712	258.88	114.91	63	513
Population	5955489	6072132	519000	22928508	2578490	2167777	562758	8023953

Table 12: Descriptive Results for Top and Bottom Street Crime States, 1985 - 2008

<sup>&</sup>lt;sup>19</sup> The District of Columbia, Florida, Arizona, New Mexico, Texas, Maryland, Hawaii, South Carolina, Louisiana, and Oregon.

<sup>&</sup>lt;sup>20</sup> New Hampshire, North Dakota, Virginia, South Dakota, Maine, Vermont, West Virginia, Iowa, Kentucky, and Wisconsin.

The means, standard deviations, minimum and maximum crime outcomes were, not unexpectedly, all higher in the top street crime states. The top states were also higher in terms of race, poverty, unemployment, imprisonment, and overall population. The bottom street crime states had a higher percentage of the population with a high school education while the percentage of male residents in each group was relatively equal.

		Top S	Street Crime	States	Bottom Street Crime States			
Offense		EBT	EBT	EBT	EBT	EBT	EBT	
Street Crime	Estimate	-0.100***	-0.048***	-0.022	-0.081***	-0.034***	0.025	
	S.E.	0.007366	0.010	0.014	0.007	0.010	0.010	
	R-squared	0.53608	0.714	0.724	0.487	0.619	0.744	
	F statistic	183.73***	47.46	44.11***	150.91***	30.86***	48.77***	
Robbery	Estimate	-0.121***	-0.044*	-0.009	0.002	0.057**	0.041*	
	S.E.	0.013	0.019	0.025	0.011	0.018	0.022	
	R-squared	0.362	0.519	0.532	0.000	0.212	0.220	
	F statistic	90.15***	20.48***	19.10***	0.027	5.11***	4.74***	
Burglary	Estimate	-0.173***	-0.109***	-0.056***	-0.087***	-0.036**	-0.001	
	S.E.	0.009	0.012	0.014	0.009	0.013	0.015	
	R-squared	0.690	0.826	0.855	0.377	0.564	0.608	
	F statistic	353.75***	90.16***	98.98***	96.044***	24.59***	26.00***	
Larceny	Estimate	-0.089***	-0.051***	-0.002	-0.082***	-0.037**	0.014	
	S.E.	0.008	0.011	0.014	0.007	0.011	0.011	
	R-squared	0.441	0.626	0.685	0.457	0.565	0.698	
	F statistic	125.23***	31.74***	36.56***	133.83***	24.67***	38.81***	
Auto Theft	Estimate	-0.032*	0.071***	<i>0.049*</i>	-0.081***	-0.008	0.027	
	S.E.	0.014	0.019	0.026	0.011	0.016	0.018	
	R-squared	0.032	0.389	0.396	0.250	0.519	0.554	
	F statistic	5.26*	12.07***	10.98***	53.08***	20.52***	20.88***	
Direct Effects		Yes	Yes	Yes	Yes	Yes	Yes	
Controls		No	Yes	Yes	No	Yes	Yes	
Linear Trends		No	No	Yes	No	No	Yes	

Table 13: Fixed Effects Results for Top and Bottom Street Crime States, 1985 - 2008

I next performed the FE regression analyses on both groups and displayed the results in Table 13. Side by side comparisons partially confirmed that EBT implementation affected individual street crimes differently in areas with varying levels of criminal behavior. In the states with the highest levels of street crime, reducing cash effected burglary and auto theft. Burglary decreased by 5.6%; however, auto theft increased by 4.9%. In the states with the least amount of street crime, robbery increased by 4.1% after EBT implementation. The switch to electronic payments had no significant effect in either group on overall street crime or larceny.

# Path Analysis: Drugs as a Mediator

While the findings in the stage one analyses demonstrated that reducing the amount of circulating cash significantly affects different street crimes under various conditions, the second stage analysis testing drugs as the mechanism for predatory criminal behavior was inconclusive. Although several data sets exist both restricted and unrestricted, no one collection lent itself easily to the analysis at hand. The primary issues with most data (i.e. ADAM, TEDS) centered around either time frames that did not coincide with that used in the first stage of the current research, figures that weakly represented the drug market, or data that I could not adequately define as belonging to a specific location. Because of these issues and the fact that I utilized UCR Part I statistics in the first stages of this analysis, I chose the UCR Part II crime of drug violation arrests as a proxy for the drug market. As stated earlier, these violations encompass both sides of the drug market, sale and possession. It could be, then, that these data represent in some manner the effect of reduction cash on the drug market and subsequently on the crimes committed to obtain them. Unfortunately, once collected, these data were also unsuitable for analysis.

The root cause was the amount of missingness in the available drug data. Previously discussed, one of the principal concerns with using UCR Part I statistics was inconsistent reporting which lead to some measure of missingness (Lynch & Jarvis, 2008). Regrettably, this issue in the UCR Part II data was more extreme, especially concerning the drug violations data.

This caused two insurmountable problems prohibiting the analysis and production of meaningful results.

First, UCR reporting is voluntary (Lynch & Jarvis, 2008; FBI, 2004). Reporting data to the FBI often requires that agencies absorb the costs of employing a person to collate and transmit monthly figures. A large portion of police agencies in the US are rural and tend to have limited staff and constrained budgets (Carson, 2014). As such, they regularly direct available resources toward equipment, maintenance, competitive salaries, and other demands necessary to sustain a working police department rather than on voluntary tasks (Lynch & Jarvis, 2008; Maltz, 1999). If an agency chooses to report their statistics, they tend to report the more serious Part I offenses with less time spent on reporting minor offenses resulting in a large amount of missingness in the Part II data figures (Maltz, 1999). In fact, after inspecting every individual US agency's contribution to their respective state's yearly drug arrest numbers,<sup>21</sup> the amount of missingness was higher than the accepted 20% rule recommended by Lynch and Jarvis (2008) when utilizing UCR crime data and Alison (1994) for analysis of datasets in general. Figure 5 portrays an example of this missingness in West Virginia that typifies the entire US dataset.

<sup>&</sup>lt;sup>21</sup> Over 20,000 individual agencies are listed in the BJS data analysis tool.



Figure 4: Missingness in West Virginia, 1984-2009

Because West Virginia has over 400 agencies, Figure 4 contains only a representative 10% sample for ease of interpretation. The columns represent each year in the study and every row represents an individual agency. Highlighted in red (darker cells) are the cells with missing data which also contain a "-1" indicating that a particular agency did not report drug data to the FBI in a specific year. The white, or non-highlighted cells, indicate that an agency in a specific year reported their figures and contain the actual number of drug arrests for an agency in that year. A visual inspection provides the reader with an immediate sense of the overall missingness problem. The red (darker) cells on the graphic indicate missingness as opposed to the white (nonhighlighted) cells where the data exists. Clearly, the cells with missing data outnumber those with usable information.

The conventional method to deal with such missingness in an analysis is to perform multiple imputation techniques that take into consideration each of the other observations in the dataset and produce estimates for the missing data (Alison, 1994). Had the missingness in this study been observed at the state level, imputation would have been straightforward because the rest of the variables in the dataset contained enough information about the states to have replaced the missing drug arrest data. However, because each state's data is comprised of the statistics from every individual agency within that state, it would mean gathering an inordinate amount of data for each of the individual jurisdiction with missingness to impute and complete the dataset. Since there are over 20,000 reporting agencies (Lynch & Jarvis, 2008) and the dataset for this study spans over 20 years, this issue was simply too large to effectively overcome.

The second obstacle to overcome with using the UCR Part II drug arrest data was that, on its face, there appears to be an uptrend over time (see Figure 5). But this trend could be falsely inflated. Because Part II crimes are less serious, they tended to be less reported or not reported at all (Lynch & Addington, 2007; Maltz, 1999). But over time, government officials turned their attention toward a mounting drug problem and larger numbers of agencies began to report this and other Part II crimes to the FBI (Lynch & Addington, 2007; Lynch & Jarvis, 2008). As an example, the Reagan and Bush administrations pushed a nationwide agenda to end drug abuse with the so-called "war on drugs" campaign (Gerber & Jensen, 2014). Their influence potentially increased the number of drug offenses being reported. The increase in the number of drug offenses reporting Part II drug crimes created a numerical uptrend in the number of drug offenses reported year over year by each state. This uptrend, however, is possibly exaggerated.



Figure 5: National Drug Arrest Rate, 1984 – 2009

Because the FBI aggregates individual agency data to the state level and publishes it as such, it would appear that the number of reported drug arrests increased over time. Yet upon a closer inspection of the data at the agency level, it was not necessarily the number of arrests that increased for a particular state, but more likely the growing number of individual agencies within that state *reporting* the drug arrests to the FBI that increased. Figure 6 illustrates this point. The cells on the left-hand side of the table in Figure 6 show that many individual agencies did not start reporting drug arrests until after 1999 (these are represented by the dark, red cells). Past this date, agencies began to increasingly report their drug arrests giving the appearance of an upward
trend in the number of arrests when in actuality the increase was in the number of agencies within a state reporting the offense (represented by the white cells). Drug arrests were undoubtedly taking place all along prior to 1999, but the agencies themselves were simply not reporting them to the FBI. Numerically this created an upward trend represented by the inset in Figure 6. The x-axis of the inset shows the progressive years of the analysis time frame. The y-axis reflects the number of drug arrests reported. The first several years shows that the reported drug arrests were equal to zero, thus a flat, horizontal line along the x-axis. As more agencies began reporting drug arrests, the trend line along the x-axis began to rise creating a (likely) false uptrend. While it could be that the upward trend in reported drug arrests accurately reflects the number of drug arrests being made, considering that each of the Part I crimes since the mid-1990s have been steadily decreasing over the same time period, the increase in drug arrests is suspect at best. Moreover, statistical findings that include Part II crime drug arrests reported to the FBI could likewise be suspect.



Figure 6: False Uptrend in West Virginia, 1984 - 2009

Data issues notwithstanding, I nonetheless performed the path analysis with the available data as is and, as expected, observed null findings. Taken at face value, the results indicate that drug arrests were not affected by the reduction of cash through EBT implementation. That being the case, they also cannot be confirmed to act as a mediator between cash and crime based solely on the mathematical formula behind Sobel's test. I did not, however, stop the inquiry there.

One possible alternative method of accounting for the missing data was to take the most populous cities in each state and examine the amount of collective missingness reported. In examining the missingness in each state, it appeared larger cities were more likely to report Part II crimes consistently over time with minimal amounts of missingness than smaller agencies. Larger cities are also more urbanized. From the results of the stage one analyses, the reduction of cash had a greater effect in the more urban states, so it was plausible that these results could be transferred to urban cities within the states. If there was consistent reporting in these cities, the sum total of these cities' data could conceivably act as a proxy for the state in which they reside.

I examined the data from the five largest city agencies in each state (see Figure 7) and observed generally consistent reporting. I then aggregated their individual reported drug arrest totals and found the missingness issue persisted and I could not consider them a proxy for the entire state. Moreover, the uptrend still existed and, while I performed the first part of the analysis (path b in Figure 2) the results were non-significant. Although null findings generally indicate no association between the outcome variables and their predictors, under the current circumstances the more correct interpretation was that I did not have contradictory evidence concerning drugs as a mediator. The data was simply not robust enough. Given these data, and the non-significant findings associated with them, it was difficult to draw any conclusions on whether drugs act as a mechanism for predatory street crimes.

Alabama   Birmingham   356   326   375   413   875   294   254   1341   160   1589   1677   1660   738   280   2979   2533   2917   2109   164   158   1670   1680   177   160   2738   280   2979   2533   2917   213   2917   213   2917   213   2917   213   2917   213   213   2917   140   1   237   1   1   1   1   1   1   1   1   1   1   1   1   1 <th>9   1996   2136     -1   -1     1088   1570     7   1670   1625     826   704     476   556     38   47     96   61     -1   59     14   28     6731   6945     9   2165     258   670     7073   6823     9   2165     8800   -1     670   772     1241   1188     800   -1</th> <th>2735   2597     -1   -1     1314   1352     1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6559   1989     774   605     1250   1352</th>	9   1996   2136     -1   -1     1088   1570     7   1670   1625     826   704     476   556     38   47     96   61     -1   59     14   28     6731   6945     9   2165     258   670     7073   6823     9   2165     8800   -1     670   772     1241   1188     800   -1	2735   2597     -1   -1     1314   1352     1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6559   1989     774   605     1250   1352
Alabama   Montgomery   377   360   30   41   236   253   350   138   101   226   261   319   290   639   475   90   357   41   41   -1   -1   -1   1     Alabama   Muntswile   444   324   302   182   246   275   1   41   333   558   435   480   704   869   106   677   648   680   102   637   41   41   773   772     Alabama   Mobile   772   12   133   250   271   1   103   55   14   56   358   430   430   430   431   474   482   633   666   661   434     Alaska   Anchorage   773   12   214   12   273   255   31   47   42   43   430   430   430   430   430   430   430   433	-1 -1 1088 1570 1670 1625 826 704 476 556 38 47 96 61 -1 59 14 28 6731 6945 47073 6823 9 2165 2258 670 772 2165 2258 670 772 11188 800 -1 601 470	-1   -1     1314   1352     1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alabama   Huntsville   444   324   302   182   246   275   1   -1   33   558   435   480   704   890   106   677   634   804   638   480   772   772     Alabama   Tuscalossa   268   222   4   133   236   277   1   71   725   133   137   772   772     Alabama   Tuscalossa   268   222   4   133   26   277   1   235   261   78   13   137   482   633   646   641     Alabama   Anchorage   275   1   243   21   21   23   24   1	1088   1570     7   1670   1625     826   704   476     476   556   38   47     95   61   -1   59     14   28   6731   6945     4   7073   6823   9     9   2165   2258   670   772     1241   1188   800   -1   601   470	1314   1352     1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     1250   1352
Alabama   Mobile   752   846   732   107   120   267   1   701   635   688   951   742   947   1123   145   41   973   1333   157   1493   1707   1433   177   1493   1707   1433   1277   1493   1707   1493   1207   1433   157   1493   1707   1493   1207   1433   157   1493   1207   1433   127   1493   1207   1433   127   1493   1207   1203   125   21   121   212   213   35   12   14   140   12   273   255   362   617   1787   1 <th< td=""><td>7   1670   1625     826   704     476   556     96   61     -1   59     14   28     6731   6945     4703   6823     9   165     205   2258     6707   772     1241   1188     800   -1     601   470</td><td>1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     1250   1352</td></th<>	7   1670   1625     826   704     476   556     96   61     -1   59     14   28     6731   6945     4703   6823     9   165     205   2258     6707   772     1241   1188     800   -1     601   470	1665   1724     659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     1250   1352
Alabama   Tuscalossa   268   222   1   13   26   297   1   1   213   211   251   271   213   251   271   213   213   251   271   213   251   271   213   213   271   213   251   271   273   255   61   787   1   987   686   607   486   596   609   506   496     Alaska   Juneau   41   48   40   42   1   72   24   27   18   4   35   1   4   3   4   72   24   51   29   1   4   35   4   47   211   41   4   41	826   704     476   556     38   47     96   61     -1   59     14   28     1   6731     9216   2258     6707   772     1241   1188     800   -1     601   470	659   585     578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alaska Anchorage 275 -1 243 251 271 241 -1 212 273 255 362 661 787 -1 987 686 607 486 596 699 506 496   Alaska Juneau -1 48 1 149 29 51 29 13 4 35 12 -1 -1 -1 -1 -1 -1 -1 -1 -1 51 33 32   Alaska Fairbanks 38 44 0 42 1 -1 -1 -1 -1 -1 -1 -1 -1 54 33 32   Alaska Wasilla -1	476   556     38   47     96   61     -1   59     14   28     1   6731     96   623     973   6823     9165   2258     670   772     1241   1188     800   -1     601   470	578   700     30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alaska   Juneau   -1   48   -1   19   29   51   29   13   4   35   12   -1	38   47     96   61     -1   59     14   28     1   6731     4   7073     2165   2258     670   772     1241   1188     800   -1     601   470	30   26     70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alaska Fairbanks 38 34 40 42 -1 72 24 72 18 24 53 -1 47 231 123 161 105 62 53 49 30 43   Alaska Wasilia -1	96   61     -1   59     14   28     1   6731   6945     4   7073   6823     9   2165   2258     670   772     1241   1188     800   -1     601   470	70   129     45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alaska   Wasilla   -1	-1   59     14   28     1   6731   6945     4   7073   6823     9   2165   2258     670   772     1241   1188     800   -1     601   470	45   37     30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Alaska Sitka 1 -1	14   28     1   6731   6945     4   7073   6823     9   2165   2258     6   670   772     1241   1188   800   -1     601   470	30   25     6371   6547     6550   7421     1995   1989     774   605     1250   1352
Arizona   Phoenix   352   3482   3740   4356   4701   4984   4624   4604   5036   5092   5133   5821   5747   7078   7529   7052   5836   5506   5689   6238   7064   6683     Arizona   Tuscon   394   991   713   3126   322   -1   2525   2533   3196   975   4339   5032   4438   4303   511   5694   6173   6247   6408   606   758   744   649   639   950   1007   1458   1240   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   1240   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438   124   1400   1438	1   6731   6945     4   7073   6823     9   2165   2258     670   772     1241   1188     800   -1     601   470	6371   6547     6550   7421     1995   1989     774   605     1250   1352
Arizona   Tuscon   394   997   1713   3126   3222   1   2525   2593   3166   3576   4339   5021   4633   4303   5111   5646   6173   6247   6408   6806   7588   7844     Arizona   Mesa   394   485   380   322   366   516   469   950   1070   1488   1240   1348   1264   1341   1264   1655   2171   2388   1399     Arizona   Chandler   153   157   109   240   139   390   121   288   322   305   322   695   653   664   786   781   734   691   638   640   640   640   640   640   640   640   640   640   641   641   641   641   641   641   641   641   641   641   641   641   641   641   641   641   641   641<	4   7073   6823     9   2165   2258     670   772     1241   1188     800   -1     601   470	6550   7421     1995   1989     774   605     1250   1352
Arizona   Mesa   391   485   380   362   360   636   516   449   639   950   1007   148   120   1400   143   124   1264   1265   117   238   1995     Arizona   Chandler   153   157   109   240   193   300   281   284   322   305   322   699   653   64   786   781   691   693   684   604   Arizona   Constraints   127   1288   1291   241   305   221   305   322   699   653   64   786   781   691   693   684   604   780   781   780   801   802   321   305   321   61   350   716   787   780   808   808   814   814   814   814   814   814   814   814   814   814   814   814   814   814   814	2165   2258     670   772     1241   1188     800   -1     601   470	1995 1989 774 605 1250 1352
Arizona   Chandler   153   157   109   240   193   390   128   392   321   305   322   699   653   664   766   781   734   691   693   684   604     Arizona   Scotsdale   152   107   167   74   21   190   224   346   342   420   455   1   1   58   714   746   691   693   684   604     Arizona   Scotsdale   152   107   167   74   21   190   224   346   342   455   1   1   58   714   746   706   795   800   841     Arianas   Little Rock   225   341   370   400   449   1   724   744   810   1123   1220   1488   169   132   1220   1488   169   132   1220   1488   169   132   1220   1488	670 772 1241 1188 800 -1 601 470	774 605 1250 1352
Arizona   Scotsdale   152   107   167   174   241   261   197   222   190   264   346   420   455   -1   -158   714   784   706   795   800   841     Arkansas   Little Rock   225   341   370   400   449   -1   784   740   123   120   1488   169   1365   121   832   781   494   544   706   799   837	1241 1188 800 -1 601 470	1250 1352
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	601 470	759 662
Arkansas   Fayetteville   58   69   71   56   210   283   345   187   227   356   340   403   432   427   472   479   464   453   419   544   372   428		379 310
Arkansas Springdale 80 83 81 137 125 119 126 85 78 108 115 181 193 183 185 317 310 192 134 136 293 445	-1 -1	-1 169
Arkansas Jonesboro 42 34 38 50 36 39 60 62 103 122 167 315 347 259 365 355 388 -1 -1 -1 170 356	427 403	529 520
Arkansas North Little Rock 172 95 113 137 95 284 357 459 684 504 377 586 482 470 468 339 274 736 775 765 652 590	612 627	571 468
California Los Angeles 23151 41082 29481 34959 31552 47827 36338 23730 24762 24065 27626 26590 29451 32968 33682 27741 20048 18415 19691 23764 27676 2851	2 30494 27660 2	24171 16518
California San Diego 5713 6515 7505 14127 17136 20152 16463 14630 14811 13497 15545 15449 12269 12649 12572 12817 12986 12541 12875 13796 15472 14634	6 12467 10483	9661 9968
California San Jose 3697 4946 9169 7816 8552 9757 8360 7209 8670 7577 8541 8529 9537 10133 8344 7953 7574 6960 6723 6755 -1 6666	6 6527 6593	6213 5414
California San Francisco 3233 4341 5364 5810 11439 13473 9698 9342 9538 9245 9622 8745 10160 9737 11253 11023 10119 8397 9300 7681 7573 7589	7807 8522	9825 8995
California Fresno 1098 1538 2328 2196 3416 4430 4712 3795 3322 3882 4858 4464 3785 4252 4444 4416 4093 4164 4013 4564 5547 5567	7 6315 6514	5012 4308
Colorado Denver 2907 3284 3461 3205 3854 3577 2831 2629 3262 4284 5057 5290 6146 6347 6865 6581 6181 5862 5574 5129 4272 4578	8 2742 1453	1918 1571
Colorado Springs 566 423 416 419 553 555 534 647 729 984 1739 1244 -1 1290 2216 1859 2344 1743 1528 1797 1759 1718	3 1547 1736	1372 1038
Colorado Aurora 725 745 -1 544 649 628 519 529 764 972 1208 -1 -1 1289 -1 1482 1353 860 787 911 960 1045	5 1394 1483	1450 1417
Colorado Fort Collins 118 121 109 76 211 122 112 107 -1 -1 -1 269 301 291 210 254 403 315 367 422 400 274	274 293	298 293
Colorado Lakewood 296 289 254 235 294 257 210 195 238 335 394 566 433 190 199 355 507 582 751 779 884 841	922 995	918 710
Connecticut Bridgeport 1147 1308 1259 1860 1822 1651 2050 1318 1788 2042 2134 1985 1739 1761 1503 1552 1779 1690 1297 1379 1077 907	960 1170	1154 1033
Connecticut New Haven 739 613 696 1127 2717 2764 -1 1904 1864 2346 2635 2677 2436 2526 2236 1948 1801 1438 1261 -1 -1 -1	-1 -1	1342 1352
Connecticut Stamford 284 401 -1 892 1118 701 844 618 679 526 387 546 552 503 334 395 401 392 455 564 459 251	512 550	501 426
Connecticut Hartford 2669 2593 1378 2049 3580 688 3383 -1 2583 3430 3669 3872 -1 3896 4151 3357 2792 3464 3329 2743 3182 3163	3 3277 3066	3478 3022
Connecticut Waterbury 298 352 319 664 996 1385 1528 1006 709 785 1048 1267 1296 1007 1308 1301 978 1152 1106 1085 1102 940	1137 1010	940 835
Delaware Wilmington 635 619 605 -1 592 989 1009 1212 -1 -1 -1 -1 -1 -1 963 924 1014 957 1083 1217 772 1092	2 1108 1054	1205 1218
Delaware Dover 28 30 46 58 132 179 154 204 157 163 238 194 212 205 231 230 316 188 138 293 327 353	387 389	388 341
Delaware Newark 71 75 60 68 72 87 44 59 -1 -1 -1 -1 49 44 64 66 70 85 88 122 116 144	135 126	159 133
Delaware Middletown 4 2 1 3 7 4 11 15 24 -1 16 -1 2 1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	59 79
Delaware Milford 18 9 7 15 9 28 22 29 -1 -1 -1 -1 47 76 44 60 49 25 27 62 71 96	95 93	74 141
Florida Metro-Dade 3672 3303 3773 3517 -1 -1 4471 -1 4329 4287 4852 4069 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	-1 -1
Florida Miami 2928 3225 6483 6388 -1 -1 7555 -1 6442 6981 7487 4998 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	-1 -1
Florida Tampa 2623 2477 2872 3542 -1 -1 2485 -1 2603 2737 3546 6134 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	-1 -1
Florida Orlando -1 915 926 1295 -1 -1 1701 -1 1320 1817 2453 2504 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	-1 -1
Florida St. Petersburg 702 942 1153 1608 -1 -1 1299 -1 1410 1686 2103 2078 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1	-1 -1	-1 -1
Georgia atlanta 3617 3197 3934 -1 6901 9929 10142 10354 8680 7982 7047 8945 10982 13019 10902 10519 10135 9592 8819 8121 10147 1281	2 12584 7540	8302 8275
Georgia warner robbins 67 96 112 202 274 332 239 146 196 149 121 144 260 331 305 286 266 279 292 305 318 331	344 359	386 413
Georgia savannah 425 479 421 639 931 1048 789 529 592 637 524 410 456 458 460 470 475 484 797 1007 1217 1427	7 1637 1845	1555 1304
Georgia athens 34 35 52 7 34 59 60 61 331 168 5 214 422 619 335 448 469 491 464 501 474 634	664 718	630 550
Georgia macon 351 425 428 435 442 636 830 1023 965 670 543 557 552 483 481 478 552 588 716 772 923 501	628 847	901 680

Figure 7: Sample of Missingness on the Top 5 Cities in Ten US States, 1984 – 2009

## CHAPTER V Discussion

# **Review of Results**

## Cash and Crime

The findings in this research indicate that reductions in the amount of circulating cash tends to effect predatory street crime. At the national level, implementation of the EBT system significantly reduced not only street crime in the aggregate, but also each of its constituent parts; robbery, burglary, larceny, and auto theft. These results are consistent with Wright et al.'s earlier findings in that, first, cash is a substantial motivator of predatory street crime and, second, interrupting the flow of cash reduces the occurrence of street crime. But where previous research stops, I pressed the cash and crime relationship further by testing and comparing the relationship in the highest and lowest states receiving SNAP benefits, the most urban and rural states, and the states with the highest and lowest levels of overall street crime. These analyses provided a more robust understanding of the effect than a simple national overall analysis.

As stated earlier, in addition to street crime in general being decreased nationwide, if the introduction of EBT in fact reduced predatory street crime, it should also be the case that the states receiving the highest levels of benefits see the strongest drops. This is because the states receiving the most benefits were likely the states with the highest amounts of circulating cash prior to the EBT switch. The findings from this study support this hypothesis. All five of the predatory crimes dropped significantly. By comparison, the states receiving the lowest amount of SNAP benefits had no significant decreases. These results are important because they support the idea that the systematic removal of circulating cash through payments technology can lead to a reduction of predatory offending.

I also conducted a further analysis comparing the reduction of street crime in urban and rural areas. This was necessary because the argument could be made that many of the states in the SNAP analysis are rural and street crime is typically an urban phenomenon and the results of the previous analysis could contain some measure of selection bias. Street crime is a consistent facet of urban environments (Hannon & DeFronzo, 1998; Krivo & Peterson, 1996; Lochner, 2004; McBride-Murry et al., 2011) and these crimes are often predatory (Freeman, 2000; Hallsworth, 2013) so a decrease in circulating cash should result in a higher reduction in predatory offenses in the more metropolitan areas. To address this supposition, I compared the EBT implementation effect in the most urban states to its effect in the most rural states. Again, as expected, the findings revealed that the reduction of cash had a stronger impact in urban dense areas where two of the five outcome variables saw significant reductions where none of these crimes in the rural areas were significantly affected. The most urban states had significant reductions in robbery and burglary while EBT implementation had no significant effect on any of the crime outcomes in the most rural states. These results augment the notion that cash plays a significant role in street crime.

As a final test of the link between circulating cash and street crime, I investigated this relationship in the states with the nation's highest and lowest levels of overall street crime. If cash and street crime are linked in a linear fashion, it should be the case that states with the highest levels of street crime react differently to the reduction of circulation cash than the states with the lowest levels. The significant findings were, in fact, spread between groups indicating that cash may possibly drive street offending differently in areas with varying levels of overall street crime; at least in the cases of robbery and auto theft. These results shed additional light on the relationship at a more granular level. In contrast to the each of the findings in the previous

two analyses where only one group experienced significant reductions in street crime(s), the results of this inquiry illustrated that cash affects crime differently where overall street crime is varied. In the states with the highest levels of overall street crime, burglary decreased by 5.6%; post EBT implementation. However, auto theft increased by 4.9%. By comparison, in the states with the lowest levels of overall street crime, the only significant change resulting from EBT implementation brought about a 4.1% increase in robbery. This is the only analysis in which crime went up. While a number of assumptions could be made about this particular result, all that can be accurately stated about this finding is that it might provide insight as to how cash motivates some forms of crime in areas where overall street crime is varied.

This study shows a distinct relationship between cash and street crime overall. Reducing the amount of circulating cash brought about significant changes in the levels of street crime. There is evidence that certain crime rates fell more in urban areas. The same areas where street life adherence was strongest. This is in line with the expectations set forth by scholars in previous studies (Hallsworth, 2013; Anderson, 1999). But the link was particularly strong in areas where poverty and government assistance are prevalent (highest SNAP receiving states) where all street crime rates fell after implementation. This was consistent with what would be expected based on the previous literature because it lowered cash in high cash areas (Brown & Males, 2011; Hannon & DeFronzo, 1998; McBride-Murry et al., 2011; Muggah, 2012; Small & Newman, 2001). The effect of reducing cash on predatory offending was stronger in, and unique to, those states receiving the highest amount of government assistance (SNAP) due to an impoverished status. Prior to the EBT switch, SNAP benefits were disbursed in paper check form that recipients customariliy cashed. The areas with the highest number of SNAP beneficiaries naturally created a more cash-rish environment than those states receiving the least amount of

SNAP disbursements. After the conversion to the EBT system, the subsequent reductions in the number of people carrying cash were, naturally, greater in the states receiving the highest anmounts of SNAP benefits. With the removal of so many recipients carrying cash, there were immensely fewer potential victims of predatory crimes. Unsurprisingly, the significant reductions in predatory crimes were greater in comparison to the lowest SNAP receiving states.

Additionally, the results in this study offer a unique, quantitative insight into the effect that cash has on street offending. Up to now, the research regarding street offending has been largely qualitative (Anderson, 1999; Bennett & Wright, 1984; Brezina, Tekin, & Topalli, 2009; Cherbonneau & Jacobs, 2015; Jacobs & Cherbonneau, 2014; Jacobs & Wright, 1999; Jacobs, Topalli, & Wright, 2003; Jacobs, Topalli & Wright, 2000; Maguire & Bennett, 1982; Miller, 1998; Shover & Honaker, 1992; Topalli & Wright, 2004; Topalli & Wright, 2013; Topalli, Wright, & Fornango, 2002; Vigil, 2010; Wright & Decker, 1994; Wright & Decker, 1997; Wright, Brookman, & Bennett, 2005; Wright, Topalli, & Jacques, 2014). And of the quantitative studies (Hallsworth, 2013; Krivo & Peterson, 1996; Silverman, 2004; Stewart & Simons, 2006; Wright et al., 2017), only one has analyzed the influence cash has on street offending (Wright et al., 2017). The research performed in the current study probed deeper into the understanding of the specific environments in which street crime was prevalent. By doing so, a more developed quantitative picture emerged into the nature of predatory street offending and the environments in which it thrives. Cash-rich environments, such as those created prior to the advent of the EBT system, serve as prime areas for predatory offending; the same types of crimes commonly associated with street life. This finding supports the suggestions made in much of the previous qualitative research (Brezina, Tekin, & Topalli, 2009; Jacobs, 2000; Jacobs & Wright, 1999; Jacobs, Topalli, & Wright, 2000; Miller, 1998; Naylor, 2003, 2004; Topalli &

Wright, 2013; Topalli, Wright, & Fornango, 2002; Wright & Decker, 1997; Wright Brookman, & Bennet, 2005). Moreover, crime rates appear to be more affected in urban, impoverished, high benefits-receiving areas where street culture thrives, again aligning with extant qualitative research (Muggah, 2012; Small & Newman, 2001; Topalli & Wright, 2004; Wright, Topalli, & Jacques, 2014).

Finally, the findings revealed a previously unknown and interesting characteristic about the relationship between cash and predatory crime specific to the top and bottom street crime states analysis. In the states where street crime was the highest, post EBT implementation, the rate of burglary dropped but the rate of auto theft increased. In the states where street crime was lowest, the rate of robbery increased. These results revealed that predatory crime may occur differently in areas with varying levels of street crime. Unfortunately, without stronger data, this interpretation is all that can be said without speculation. It is likely that there is more at work below the surface of these results; however, an in-depth understanding of this phenomenon fleshing out the reasons behind this finding might require further research from a qualitative perspective.

#### Drugs as a Mediator

Turning now to the second stage of the analysis, while the direct effect findings were significant and shed important additional light on the cash and crime connection, unfortunately, the available data did not allow for a definitive investigation of drugs as the mediating mechanism. The amount of missingness in the data was too much to overcome. With more robust data, the notion that drugs act as the mechanism driving the need to commit crime to acquire cash might be tested more thoroughly. However, that notwithstanding, among street life participants cash has its own attractions with the potential for direct effects on criminality

independent of its role in the acquisition of drugs (Hallsworth, 2013). Nonetheless, to determine a mediator there first must be a significant relationship between the outcome and its predictor, and the examination results show a firm statistical association between cash and crime. These findings could serve as a foundation upon for a future mediation analysis should better data become available in the future.

#### Limitations

Recall that the logic behind the study was that cash fuels street crime and that drugs may mediate that relationship. While the research conducted offers insight into the cash and crime connection, no new information arose regarding the role of drugs driving this relationship. However, the findings in both stages of this research should be considered within the boundaries of the data used to derive them. The data serving as the foundation for these analyses were the crimes reported to the FBI made available through the UCR. Mentioned earlier, researchers have expressed two chief concerns over the use of these data. First, the UCR captures only the number of crimes reported as opposed to the actual number of crimes that occurred in a certain jurisdiction (Lynch & Addington, 2006; Maltz & Targonski, 2002). For instance, some crimes, such as being robbed for illicit drug proceeds, go unreported because doing so would place the person reporting it at risk of arrest for their involvement in such illicit activity in the first place. In fact, this "dark figure" of crime is the issue criminologists most often contend with when conducting (street) crime research (Biderman & Reiss, 1967; Coleman & Moynihan, 1996; Jacobs, 2000; MacDonald, 2002; Topalli, Wright, & Fornango, 2002). The current research was subject to the same limitation. In essence, this research captured the effect of reducing cash on reported street crime and the results, therefore, may contain some element of bias because unreported crimes were missing from the final data set.

There was also the issue of inconsistent reporting issues with the Part I offense data. Studies show that some agencies may skip one or several months' reporting throughout the year choosing rather to transmit all their figures at year end (Akiyama & Rosenthal, 1990; Lynch & Addington, 2006; Skogan, 1974). This issue is a broad and long running issue, and overcoming it is beyond the scope of this study. Still, to address it, I used year-end data which minimized this problem. I acknowledge that this method might not account for erroneous reporting year over year but the chance of multiple errors over multiple was small. Yet, the necessity for more robust data in this area is apparent. Even without the reporting missingness problems, there is still the issue of the "dark figure" of crime. When using data such as those found in the UCR Part I and II crimes, researchers are only able to base findings on what was reported which may or may not be different in relation to the true number of crimes that occurred. One important step toward even more robust analyses would be for studies encompassing and anticipating crimes where dark figure missingness may be problematic, to incorporate qualitative data specific to both the crime and the reporting of that crime.

## Implications

#### Crime and Enforcement

The findings in this study demonstrate that reducing the amount of circulating cash may be a useful tool to lessen the occurrence predatory offending. It appears that the ever-evolving developments in payments technologies, such as those like the EBT system, could increasingly deny street offenders the opportunity to commit predatory crimes simply because they lower the amount of available cash necessary to continue such behaviour. Although it is unlikely that US society will eliminate cash soon, in the interim law enforcement would be well-served directing street crime reduction efforts toward urban impoverished areas where cash remains a predominant transactional medium. Combining innovations that promote a more digital economy with concentrated policing efforts has the potential to drive crime even further below their current rates. Members of law enforcement might also consider adding into their training programs, information about not only how cash drives certain street crimes, but about the such crimes that may emerge as a result of the increasing shortage of cash carrying potential victims.

While interrupting the flow of cash appears to lower the rate of street crime, data from the FBI indicates that financial fraud is on the rise (Choo, 2011; FBI IC3, 2016). Moving forward in time, cash as a transactional medium displays all the signs of a continued decline (FRBSF, 2015). Payments systems such as the EBT system will continue to evolve, incorporating new technologies and capabilities. While it is evident that cash is in decline, other forms of money are already poised to take its place (Kelly, 2014). Cutting-edge innovations are ushering in a new economy and with it new forms of crime (Choo, 2011; Shrier, Canale, & Pentland, 2016). At the same time, mobile and other internet-based payment systems will begin to exert their own influences on crime. Changing money means changing crime, making it likely that new types of offenders will also emerge in the age of digital payments (FBI IC3, 2016).

Modernizations in digital payments bring with them new opportunities for crime and new types of offenders to commit them. Given that offenders commit their crimes within the parameters of what they have to work with (see Cornish & Clarke, 2014), this could be extended to the idea that *the form of crime you get is related to the form of currency you use*. Crime itself could be adapting to and exploiting advanced technologies as it moves into the future, perhaps a shift in what would normally be considered traditional crime. Take, for example, the American crime decline, which has been taking place for over three decades. At about the same time American crime rates began to drop, technological advances in the electronic payments were

increasing at an unprecedented rate (Shrier, Canale, & Pentland, 2016), the same technology that created the EBT system removing cash from circulation (Rhine & Greene, 2013). Given that the EBT program and other alternative payments solutions came on line at approximately the same time crime rates began to descend, it is not unreasonable to speculate that these systems might have been responsible for at least some portion of the drop. This is not to say, however, that crime was dying out over this period. Rather, it could be that it was simply changing form given the new opportunities with which offenders were presented; perhaps to a form that until recently, the FBI had not captured. As the nation moves closer to a cashless society, law enforcement will need to respond in new innovative ways to effectively reduce these opportunities.

## **Policy**

Although the government implemented the EBT system for the purposes of increasing efficiency, saving operating costs, and reducing fraud, the program also affected street crime by fundamentally reducing the amount of circulating cash. Further advances in this type of technology, therefore, could conceivably reduce crime as a resource for obtaining cash and lessen participation in the criminal economy. The findings in this study imply that continued advances in payments technology could be central to lowering street crime rates even further. Each year the industry develops ever changing technologies further digitizing payments. In that respect, officials might advocate for policies that encourage and reward the trend toward even more widespread electronic payment alternatives, especially where they are seen to provide a net benefit to society in the form of crime and harm reduction. Incorporating strategies that reduce the amount of cash in circulation even further could be beneficial in future approaches to crime prevention.

Given that the form of crime you get connects to the form of currency you use, future policy and crime prevention strategies must also account for these technologies in both the short and long term. While completely eliminating cash from American society is unlikely, law makers and government officials may possibly consider partnering with corporate leaders in the electronic transactions and banking industries to construct innovative strategies to address the changing face of crime in the digital space. If governments, either individually or collectively, work toward garnering the cooperation and guidance from entities such as VISA, MasterCard, electronic transaction processors, local banks, and alternative payments companies (i.e. PayPal, Apple Pay, Venmo). In this way, officials could create stronger prevention strategies to effectively deal with the crimes which exploit advances in virtual payments technologies. Moreover, this type of partnership could produce new data upon which build stronger crime prevention policies as society approaches a cashless, online state.

#### Future Research

When Congress enacted the change to the EBT program, the design was not intended to directly or indirectly reduce street crime. Yet, the analyses performed in this research demonstrated a significant relationship between EBT implementation and a decline in predatory crimes; the effect varying by location, urban density, benefit recipients, and existing levels of street crime. The implementation of EBT most likely had its effect on these outcomes via its ability to remove cash from those areas where predatory crime is prevalent. These effects were ancillary and unintended though highly beneficial outcomes of the legislation mandating the switch from paper checks to electronic disbursement.

Scholars interested in further developing the currency and crime relationship might consider the correlations between electronic transaction innovations and subsequent reductions in

crime outcomes. Such inquiries might include how these innovations have affected the type of crimes street offenders commit, crimes that have emerged in response to alternative payments solutions, and how the criminal justice system has adapted to these changes. For instance, as cash continues its decline, monetary instruments are not only changing to adapt to new technologies, but are also becoming more virtual. This change brings with it a multitude of issues such as jurisdictional authority (currently cyber space remains open and unregulated) and emerging crime trends. With this comes the need for new types of data from sources outside traditional law enforcement; quantitative and qualitative. The government and academics should consider working with banks, technology companies, and other private agencies to construct rich, longitudinal data sets more suited for both the continued analysis of predatory crimes and the new types of crimes to come in the emerging era of advanced payments technologies.

## Conclusion

The effect of EBT implementation on predatory crime is only a small part of the overall story. Payment systems at large could be, in part, responsible for the decline in certain street crimes not only in this study, but in the continued research occurring around the world in this area. Yet surprisingly the amount of research focused on the influence of cash and payments technology as they relate to crime pales in comparison to the larger body of work related to other types of crime motivations. There is a profound global change happening with cash, currencies, and payments that could well exert its influence on the way crime is and will be conducted moving forward. Changes in economic technologies will likely spawn changes in crime, the enforcement of crime, crime research, and crime policy. How this trend toward a cashless economy will affect crime in the future is an important question for scholars to begin considering.

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# VITA

Donald Hunt was born in Providence, Rhode Island. He performed undergraduate work in mathematics at Iona College in New Rochelle, New York and completed his B.S. in Criminal Justice at Georgia State University where he subsequently went on to complete his M.S in Criminal Justice and Criminology. After completing his master's thesis entitled The Influence of an Audience on Victim Precipitated Homicide, he continued his graduate education at Georgia State University in the Department of Criminal Justice and Criminology's doctoral program. This dissertation completes his final work in the program, and he will graduate with a Ph.D. in Criminal Justice and Criminology in December 2017.

The main focus of Don's research is centered on the quantitative analysis of the impact of technological advances on current and emerging crime trends. His work has been published in such journals as Homicide Studies, Criminal Justice Review, and the Encyclopedia of Criminology and Criminal Justice. During his doctoral program, he taught various undergraduate courses at Georgia State University, including Statistics in Criminal Justice, Corporate Crime and Security, and Innovations in Law Enforcement. He also was invited to speak to both professional and academic audiences on the topics of financial crime, cash and crime, the funding of organized crime, and cybercrime.

He is a member of numerous professional associations, including the American Society of Criminology, the Royal Statistical Society, and the American Statistics Association. Most recently, Don was awarded the prestigious Bureau of Justice Statistics Graduate Fellowship for his doctoral work.