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An Exploratory Study of Macro-Social Correlates of Online Property Crime

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by

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ABSTRACT

Despite the recent decreasing trend of most traditional types of crime, online property crime (OPC), referring to crime committed online with a financial orientation such as online frauds, scams, and phishing, continues to increase. According to the Internet Crime Complaint Center, the number of reported complaints about OPC have increased by approximately sixteen fold from 16,838 cases in 2000 to 288,012 cases in 2015, and referred financial losses have also increased about sixty times from $17.8 million in 2001 to $1 billion in 2015. The increase in OPC might be directly related to advanced online accessibility due to the accelerated progress of information and communication technology (ICT). Since the progress of ICT continues forward and the advanced ICT infrastructure can affect our routine activities more significantly, issues regarding OPC may become more various and prevalent.

The present study aims to explore a macro-social criminogenic structure of OPC perpetration. Specifically, this study focused on exploring probable macro-social predictors of OPC rates and examining how effectively these possible macro-social predictors account for variance in OPC perpetration rates. In addition, this study explored possible predictors of macro-level online opportunity structure, which is expected to have a direct relationship with OPC rates. It also examined how much variance in online opportunity structure was explained by the included possible predictors. With these research purposes, the current study analyzed state-level data of the fifty states in the U.S. by applying a partial least square regression (PLSR) approach.

The results indicated that predictors related to macro-social economic conditions such as economic inequality, poverty, economic social support, and unemployment had a significant association with OPC. As expected, indicators in the domain of economic inequality predicted greater OPC rates and those in the domain of economic social support were related to lower OPC rates. However, poverty and unemployment predictors were negatively associated with OPC, which is the opposite direction of the relationships between these predictors and traditional street crime. In addition, indicators of online opportunity structure were found to have a significantly positive relationship to OPC as expected. The PLSR model for predicting OPC applied in the current study accounted for approximately 50% of variance in OPC rates across states.

For predictors of online opportunity structure, the results indicated that online opportunity was associated with state-level economic and socio-demographic characteristics. States with less poverty, more urban population, and more working age adults were more likely to report more online opportunities. The PLSR model for predicting online opportunity structure explained about 80% of variance in measured online opportunity. These results may imply that some types of macro-social conditions may have an indirect effect on OPC through online opportunity structure as well as their direct effects on OPC. Future study should pay more attention to examining structural relationships of macro-social contexts, online opportunity structure, and OPC to understand macro-level criminogenic mechanism of OPC.

CHAPTER ONE:

INTRODUCTION

Problem of Statement

In recent years, numerous studies have examined issues related to cybercrime. The rapidly expanding research interests in cybercrime appears to be related to its remarkable rise over the last two decades along with rapid development of Information and Communication Technology (ICT) and its influence on our routine practices. According to the Internet Crime Complaint Center, for instance, reported Internet crimes have increased by approximately sixteen fold from 2000 (16,838 cases) to 2015 (288,012 cases), and referred financial costs have rapidly increased by about sixty times from 2001 ($17.8 million) to 2015 ($1 billion) as well (see their annual reports).[1]

Not surprisingly, it was estimated that cybercrime victimization has gradually increased over time and its financial costs have surpassed that of traditional property crimes. Comparing financial losses from online fraud/theft (Javelin Strategy & Research, 2011) to those from traditional property crimes in the Uniform Crime Reports (UCR), Tcherni, Davies, Lopes, and Lizotte (2016) reported that the former ($54 billion in 2009) exceeded the latter (between $15.2 to $30.4 billion in 2009) substantially.

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[1] It should be noted that the rapid increases in both counts and financial losses of Internet crime might be driven by not only their actual increases but also peoples' increased awareness of the agency, the Internet Crime Complaint Center (IC3), where they can report their Internet crime victimization, given the newness of the agency. Regarding further discussions about limitations of IC3 data, see Chapter Four; Also, IC3 annual reports can be found at: http://www.ic3.gov/media/annualreports.aspx

Cybercrime research within a criminological perspective has primarily attempted to examine whether some traditional micro-social theories of crime (e.g., social learning, self-control, deterrence, and routine activities theories) are applicable to cybercrime perpetration and victimization. Specifically, social learning and self-control theories have been applied to analyses of some forms of online deviance such as violent behaviors (e.g., cyberbullying, online harassment, flaming, online shaming) and infringement of others' copyright (e.g., music, software, intellectual property piracy). Several of these studies have found that deviant peer relationships and low self-control were significant predictors for cyberbullying, computer hacking, and digital piracy (e.g., Barlett et al., 2014; Burruss, Bossler, & Holt, 2013; Higgins, 2004, 2006, 2007; Higgins, Fell, & Wilson, 2006, 2007; Higgins, Wolfe, & Ricketts, 2009; Hinduja & Patchin, 2013; Holt, Bossler, & May, 2012; Holt, Burruss, & Bossler, 2010; Kerstens & Jansen, 2016; Kim & Kim, 2015; Marcum, Higgins, Freiburger, & Ricketts, 2014; Moon, McCluskey, & McCluskey, 2010; Moon, McCluskey, McCluskey, & Lee, 2013; Morris & Higgins, 2010; Skinner & Fream, 1997).

Within deterrence and routine activities perspectives, empirical studies have examined effects of situational deterrent/opportunity factors on both cybercrime perpetration and victimization. For some computer-oriented deviant behaviors (e.g., unauthorized access to computer/network system, password hacking), recent studies reported that technology-oriented deterrence (e.g., warning signs on the screen) decreases duration of trespassing on computer system (Maimon, Alper, Sobesto, & Cukier, 2014; Wilson, Maimon, Sobesto, & Cukier, 2015). With regard to cybercrime victimization, studies based on the routine activities perspective have found effects for online-oriented risk/protective factors such as time spent online, types of online activity, and the use of anti-virus/hacking programs (Bossler & Holt, 2009, 2010; Choi, 2008; Holt & Bossler, 2013; Holt & Turner, 2012; Leukfeldt, 2014; Leukfeldt & Yar, 2016; Ngo & Paternoster, 2011; Pratt, Holtfreter, & Reisig, 2010; Reyns, 2013; Van Wilsem, 2013). Furthermore, evidence of an effect for offline-oriented risk factors related to temporal availability (e.g., official business hours) and geographical feasibility (e.g., proximity to a target computer) was also reported (Maimon, Kamerdze, Cukier, & Sobesto, 2013; Maimon, Wilson, Ren, & Berenblum, 2015).

In spite of these contributions from prior studies, cybercrime research is still deficient in the one key aspect: Macro-level variations in cybercrime perpetration. Only a few studies have sought to address whether structural characteristics affect the macro-level distributions of cybercrime perpetration (e.g., Kigerl, 2012). Seemingly, structural contexts have rarely been considered in cybercrime research as it is broadly believed that online space where cybercrime is embedded lacks physical spatiality. That is, cyberspace has been considered an 'anti-spatial' space (Mitchell, 1995, p.8) in which physical constraints on interactions between individuals disappear and incidents occurring in the anti-spatial space tend to be less dependent on geographical patterns and rules embedded in physical proximity or separation (Yar, 2005). According to this point of view, macro-social contexts are merely associated with a prevalence of cybercrime due to the distinct spatial dimension of cyberspace.

Nonetheless, a macro-level approach to cybercrime is still required because online settings are, to a certain degree, structured by contexts such as political, economic, and cultural institutions varying across geographical boundaries (Castells, 2001; Dodge & Kitchin, 2001). Warning against simply accepting the concept of cyberspace as a completely separated place with 'placelessness' detached from the real world, Dodge and Kitchin (2001, pp. 15-17) argued that cyberspace was interdependent with face-to-face structural contexts rather than independent of them. In other words, cyberspace reflects local and geographical characteristics and processes because it is, at least partially, embedded in features of the real world. For example, many online sites and applications (e.g., Craiglist, Uber, Yelp etc.) target local communities providing local residents with information and services related to interests in their communities. Discussing the applicability of routine activities theory to cybercrime, Yar (2005) pointed out that structural characteristics might have an effect on cybercrime due to spatial convergence between virtual and non-virtual environments. He pointed out that potential offenders and victims of cybercrime might be disproportionately distributed by the same structural characteristics that affect traditional crime. This occurs because cyberspace is rooted in the real world and Internet access is associated with socio-demographic variations such as gender, age, race/ethnicity, income, and education attainment.

Some descriptive statistics and research findings from multivariate analyses support this speculation. For instance, it has been found that some probable online opportunity factors for cybercrime such as unequal accessibility to the Internet and ICT devices, and distinct patterns of using the Internet (e.g., types of location using Internet, types of online activity etc.) varied across geographical differences (Castells, 2001; DiMaggio, Hargittai, Celeste, & Shafer, 2004; For the findings of multivariate analyses, see also Hargittai & Hinnant, 2008; Mossberger, Tolbert, & Gilbert, 2006; Ren, Kwan, & Schwanen, 2013). These differences in online settings embedded in diverse structural conditions justify the macro-level approach to cybercrime. Drawing on these theoretical and empirical grounds, recent studies have found significant associations between macro-social indicators and cybercrime (Brady, Randa, & Reyns, 2016; Holt, Burruss, & Bossler, 2016; Kigerl, 2012; Maimon et al., 2013, 2015; Song, Lynch, & Cochran, 2016; Williams, 2016).

Based on the applicability of a macro-level perspective to cybercrime, this dissertation examines relationships between macro-social indicators and macro-level rates of cybercrime, especially financially-oriented cybercrime perpetration. Regarding the response (dependent) variable, specifically, the current study employs aggregate financially-oriented cybercrime rates across fifty states in the United States provided by the Internet Crime Complaint Center. As for possible predictors, each state's social indicators gathered by the U.S. Census Bureau and other governmental and non-governmental organizations are applied. In sum, this dissertation attempts to discover whether structural characteristics affect the reported rates of cybercrime and examine how much a variance of macro-level cybercrime perpetration is explained by these structural indicators.

Scope of the Study

The primary research interest of the current study is crimes perpetrated online with financial orientation. There are three definitions that can be related to the research interest: 1) *Internet crime* (Internet Crime Complaint Center [hereafter, IC3]), 2) *online property crime* (Tcherni et al., 2016), and 3) *cyberdeception/theft* (Wall, 2001). The scope and element that each definition covers are introduced to compare which definition is more appropriate to indicate the research interest of the current study.

Internet Crime. This term has the broadest scope of the three term. Internet crime, as defined by the IC3, covers overall all crimes committed on the Internet including many types of financially-oriented cybercrime. According to the IC3's website[2], this concept includes "Intellectual Property Rights (IPR) matters, computer intrusions (hacking), economic espionage

[2] http://www.ic3.gov/about/default.aspx

(theft of trade secrets), online extortion, international money laundering, identity theft, and a growing list of Internet-facilitated crimes."

Online property crime. Tcherni and colleagues' term, online property crime (OPC), fits well with the scope of the current study as it indicates two essential elements: crime committed 1) online and 2) having a financial orientation. It embraces many types of property crime committed online such as "identity theft, credit card theft and fraud, cyberattacks on organizational networks resulting in security breaches, the buying and selling of personal data online, and the use of unsuspecting people's computers for spamming/phishing/illegal hosting" (Tcherni et al., 2016, p.891).

Cyberdeception/theft. This term also refers to illicit behaviors with financial motives by means of computer and the Internet. In particular, Wall (2001) stated that this concept included traditional fraud/theft (e.g., credit card fraud) committed via ICT devices and digital piracy (e.g., music, texts, images).

The three definitions above all address financial Internet crimes. The Internet crimes examined in the current study, however, are best represented by Tcherni and colleagues' term, *online property crime*. In contrast, the concept of *Internet crime* is too broad to delineate the range of behaviors in this study because this concept covers some non-financial cybercrimes (e.g., cyberstalking, online forum abuse). In addition, the *cyberdeception/theft* definition is also problematic because it excludes cyberattacks or computer intrusions (e.g., hacking, virus, and malware writing crimes). While these activities have been categorized as computer-focused crime or cybertrespass as a distinguishable form of cybercrime (Furnell, 2002; Wall, 2001) and not every cyberattack or computer intrusion aims to make illicit profits, it is also undeniable that monetary orientation is often related to hackings and malware writings[3] (Furnell, 2002). Such mixed forms of online crime thus should be included in this study, which focuses on financially-oriented online crimes.

Outline of the Dissertation

This dissertation starts in Chapter Two with a discussion concerning the development of ICT over the last two decades, how it has affected changes in our daily routine activities, and examines those changes across structural contexts. Chapter Two also discusses cybercrime in general and online property crime (OPC), especially focusing on attributes of cybercrime and OPC such as their definitions, extents, scales, and trends. Then, it reviews prior empirical studies on OPC categorizing them to whether they were on either micro- or macro-level perspective.

Chapter Three reviews macro-social predictors of traditional street crimes to explore potential macro-level predictors of OPC. This chapter first reviews existing macro-social predictors for traditional crime, which have been examined by prior empirical studies. This review especially focuses on discussions about theoretical concepts related to each predictor, specific indicators employed as a measure, and effects of each predictor on violent and property crime rates. It also discusses potential online opportunity predictors; predictors that have not been considered as a predictor for traditional crime but may have a close relationship with OPC rates. Drawing on these discussions about potential macro-social predictors, research questions and the current focus of this dissertation are presented in this chapter.

[3] If hacking tools or malwares are installed in a victim's computer, it allows cybercriminals to access their computer and obtain their financial information. This may result in identity theft and credit card fraud victimization.

Chapter Four presents methodological elements such as the data, variables, and analytical techniques in this dissertation. Specifically, this chapter addresses properties of the data and variables such as how the data were collected and how the predictors were measured. For analytic strategies, the current study applies a partial least square regression approach to examine relationships among variables. Thus, this chapter presents the principles and backgrounds of the partial least square regression approach and discusses why this analytical technique is useful for the current study.

In Chapters Five and Six, findings and implications are presented and discussed respectively. Chapter Five addresses the results of descriptive statistics and bivariate/multivariate analyses. Chapter Six provides implications of these findings. Chapter Six also discusses suggestions for future research and limitations of the current study.

CHAPTER TWO:

ONLINE ENVIRONMENT AND CYBERCRIMINOLOGY

Since Daniel Bell (1973)'s discussion of the emergence of a post-industrial service economy, analyses of the relationships between the growth of Information and Communication Technology (ICT) and social structures such as economy, politics, and culture have been subject to discussions among sociologists (e.g., Bell, 1973; Castells, 1996; Giddens, 1987; Schiller, 1989, 1996; Webster, 1995). Some scholars (e.g., Daniel Bell, Manuel Castells) emphasized that technology leads to an emergence of a new form of society differentiated from the existing society, while others (e.g., Anthony Giddens, Herbert Schiller, Frank Webster) focused more on the continuities in the existing social structures. That is, the former speculated that the progress of ICT would supersede the old social systems, its hierarchies, values, and rules, whereas the latter believed that the influence of ICT would be largely embedded in existing structural characteristics and result in being integrated into existing power relations, institution, and rules (see Webster, 1995).

Considering these two contrasting approaches toward understanding the relationships between ICT and society, this chapter discusses how the development of ICT has changed our everyday routine activities over the last two decades and how disproportionately these changes have appeared across geographical and structural characteristics. This chapter also discusses cybercrime and cybercriminology. Specifically, it introduces various characteristics and definitions that can be embraced by the inclusive term, cybercrime. Then, it concentrates on the concept of online property crime (OPC), the main research interest of this dissertation, and discusses its definition, nature, and extent. This chapter also reviews prior micro- and macro-level studies on OPC to understand what we know about OPC, especially about what structural and opportunistic conditions related to OPC have been identified by the prior studies.

Our Daily Life in the Information Era

Changes in Our Everyday Routine Activities

Over the past few decades, ICT has advanced rapidly and changed our lifestyles. We do not have to go to a bank to wire money to others or to a store to buy clothes; instead, we can now conduct these transactions through the Internet. Many face-to-face courses at colleges and universities have been converted to online formats so that a college education is now available at home. Also, people can share useful information and knowledge with others without being physically present during interactions. Moreover, ICT might make a significant contribution to important political and social changes. For instance, a recent study has found a relationship between users of social media (e.g., Facebook, Twitter) and their involvement in the recent democratic movement in Egypt in 2011 (Brym, Godbout, Hoffbauer, Menard, & Zhang, 2014).

In fact, many statistics indicate that ICT devices are currently widespread. According to the Pew Research Center (2017), the percentage of American adults using the Internet has significantly increased over the past sixteen years from 52% in 2000 to 88% in 2016. This has been facilitated as temporal and spatial limitations of access to the Internet have been disappearing due to increases in the usage of smartphones and the availability of wireless Internet. As of 2015, approximately 68% of American adults had smartphones, an increase from

35% in 2011 (Anderson, 2015). That is, the majority of American people can access the Internet anytime and anywhere by using their smartphones.

Along with the increase in the number of people using the Internet and smartphones, there has been a parallel increase in people's dependence on them. For example, approximately 73% of American adults access the Internet every day, 21% reported that they access it almost constantly and another 42% reported access several times a day (Perrin, 2015). As reported by the Center for the Digital Future at the University of Southern California (2015), American adults spent an average of 21.5 hours per week online in 2014, which increased by more than a factor of two since 2000 (9.4 hours). The increase in the number of people with ICT devices and their dependence on them have allowed ICT to become more fully integrated into our everyday lives including shopping, socializing, and entertainment. In turn, it has transformed the patterns of these practices (Christensen & Røpke, 2010).

With regard to shopping, for instance, a new pattern of buying products online has increased for the last two decades, absorbing a significant portion of the traditional form of shopping. As of 2015, approximately 78% of Internet users reported that they purchased products online, which increased from 45% in 2000. About 64% of the Internet users who buy online agreed their online purchasing reduced their traditional retail purchasing (Center for the Digital Future, 2015). This is supported by national statistics indicating that the proportion of e-commerce sales to total retail sales increased from 0.2% in 1998 to 2.9% in 2006, and to 6.4% in 2014 (U.S. Census Bureau, 2015). According to the American Time Use Survey[4] (ATUS) conducted by the U.S. Bureau of Labor Statistics, the average number of hours spent shopping per day has been gradually reduced about 12% from 0.9 hours in 2004 to 0.79 in 2014. This

[4] See the ATUS website at: http://www.bls.gov/tus/home.htm

might be derived from the fact that an increase in online shopping reduces travel-time for traditional shopping.

Patterns of socializing with others are changing as well. According to the Center for the Digital Future (2015), time spent with friends face-to-face decreased from 10 hours per week in 2000 to 8 hours in 2014. As of 2014, a majority of respondents (62%) considered texting to be important in maintaining social relationships, versus 43% just two years earlier. Likewise, people visiting websites for video sharing or social networking one or more times a day increased from 24% in 2008 to 59% in 2014, and the average number of people with whom the Internet users have regular contact through Facebook, Twitter, and Google Plus was 6 in 2012 but 7.4 in 2014. These patterns of online socializing indicate that our relationships with others are increasingly built and maintained via ICT.

Leisure activities have also been integrated with ICT, and activities such as watching television online, and playing computer games/general computer use have gradually increased while reading, socializing/communicating, and other non-online leisure/sports activities have dropped (see ATUS). The average time spent on weekend and holiday leisure activities increased from 6.3 hours in 2004 to 6.5 hours in 2014 along with a rise in watching television (3.35 in 2014, an 11.3% increase from 3.01 in 2004) and playing computer games/general computer use (0.52 in 2014, an 44.4% increase from 0.36 in 2004). In contrast, socializing and communicating (1.13 in 2004 to 1.02 in 2014), reading (0.46 in 2004 to 0.35 in 2014), and other leisure and sports activities including travel (0.7 in 2004 to 0.62 in 2014) decreased. Two implications can be drawn from these statistics: 1) hours spent watching television and using the computer may have been taken away other leisure activities, and 2) reduced hours spent in face-to-face socializing/communicating may be indicative of increased online contacts for socializing/communicating.

Transformation Embedded in Existing Social Structures

Despite many examples indicating how our everyday routine activities have extensively changed due to the progress of ICT, the influence of ICT on our routine activities may vary systematically across some socio-demographic and geographical features such as class, race/ethnicity, occupation, and locality. Comparing data related to the ICT industry at the end of the 1990s and the beginning of the 2000s, when Internet use was rapidly growing, Castells (2001) pointed out that huge qualitative and quantitative differences in both production and consumption of the Internet services across geographical areas were observed. Specifically, it was found that most of the production and consumption of Internet services were made in a handful of developed countries (e.g., U.S., England), especially in largest cities (e.g., New York, Los Angeles, San Francisco, London). He speculated that this trend appeared due to physical/structural advantages that these countries/cities have. In other words, they have better infrastructures for the development of ICT businesses such as local industrial complex, other well-developed high value-added businesses (e.g., finance, law, marketing/advertisement), and a well-educated and trained labor force.

This tendency regarding the urban concentration of production and consumption of information implies that social inequalities in Internet access, often called the "digital divide," are also likely (Castells, 1996, 2001; DiMaggio et al., 2004). According to a recent survey conducted by the Pew Research Center (Zickuhr & Smith, 2012), approximately 80% of non-Hispanic Whites reported that they accessed the Internet, while only 71% of Blacks (non-Hispanic) and 68% of Hispanics did. Differences in age, income, and educational attainment in

Internet use indicate significantly greater gaps. For instance, more than 94% of people between the ages 18 to 29 accessed the Internet, while only 41% of those who over 65 did. Regarding household income, more than 90% of households with annual incomes over $50,000 reported Internet access, whereas only 62% of household with less than $30,000 did. Finally, about 88% of those with a college degree reported Internet access, while only 43% for those who did not have high school diploma accessed the Internet.

These digital divides across socio-demographic categories are also evident across different types of Internet access (e.g., wired vs. wireless), activities (e.g., email, social networking, watching television shows, reading articles, online learning etc.), and degrees of digital skill (e.g., required skills/knowledge to access online contents/resources). For example, a recent nationwide survey provided by the Pew Research Center (Horrigan, 2016) focusing on "digital readiness," a concept representing people's preparedness and confidence in using online tools and resources for their learning activities, categorized American adults into five hierarchical groups. According to the findings of the survey, the most proficient group, called "Digital Ready," were between age 30-40, and represented 17% of respondents. This group also had higher household incomes, and higher education levels. In contrast, the least proficient group, "The unprepared," who comprised 14% of the total, were more likely to be female, aged 50 and older, and to have lower household incomes and lower levels of educational attainment.

Furthermore, some empirical studies have found diverse forms of the digital divide after controlling for effects of various risk/protective factors. Mossberger and colleagues (2006) pointed out that place effects were important for understanding of the digital disparities. Using multi-level models, they found that community-level concentrated poverty and lower educational attainment had negative effects on access to computers and Internet controlling for individual-level socioeconomic and demographic factors. Hargittai and Hinnant (2008) have found heterogeneous Internet activities among young adults with different educational attainment. They reported that those who had higher educations and greater Internet skills were more likely to engage in Internet activities for enhancing their knowledge and for accessing information. Also, young adults who had greater Internet skill reported that they used the Internet more frequently and were more able to access it at home. Ren and colleagues (2013) have also found that gender, occupation, socioeconomic status, and living in a high-density community have significant effects on differences in both the timing and duration of the Internet use. They concluded that not only individual's socioeconomic status but also geographical and temporal contexts affected these digital inequalities. They also pointed out that these complex variations in the patterns of Internet use might be key concerns to understand digital inequalities.

As some sociologists speculated earlier, ICT appears to have affected our daily lifestyles but, at the same time, ICT use seems to have been influenced by existing social structures and settings in which people are embedded as well. Consequently, this implies that changes in our routine activities derived from the progress of ICT might be disproportionately distributed depending on variations in structural characteristics. This, in turn, may lead us to the conclusion that cybercrime is also disproportionately distributed across structural conditions.

Cybercriminology and Online Property Crime

Nature and Extent of Cybercrime

The transformation of our everyday practices integrated with ICT has led to a new form of crime committed in virtual space and by means of ICT devices, referred to as cybercrime. Since our lifestyles and routine activities are closely related to criminal opportunities (Cohen &

Felson, 1979; Hindelang, Gottfredson, & Garofalo, 1978), changes in our routine activities due to our reliance on ICT lead to new forms of criminal opportunity (Wall, 2007). That is, the more often people use ICT devices and access the Internet, the more potential victims are exposed to motivated offenders online.

In addition, characteristics of virtual space are also sources of criminal opportunities for cybercrime. Unlike the face-to-face context, motivated offenders can conveniently contact potential victims in cyberspace with few physical limitations of space and time. It is possible for the motivated offenders online to target multiple potential victims at the same time. Drawing on anonymity in virtual space, they can also easily disguise their identity and manipulate their profile to deceive people online for their illicit financial or sexual advantages. Yar (2006, p.12) designated these novel features of the online environment as "the collapse of space-time barrier," "many-to-many connectivity," and "the anonymity and changeability of online identity," and pointed out that these characteristics made new patterns and forms of crime distinctive from traditional crime.

The concept of cybercrime thus can be understood as crimes led by these novel criminal opportunities that our contemporary lifestyles integrated with ICT and that the attributes of virtual space can make. Regarding cyberfraud and identity theft, for example, the rapid growth of online shopping and e-commerce can provide a source of and access to attractive targets for motivated offenders seeking pecuniary interests. Private information leakage and cyberbullying are new concerns because many people are using social network services and posting their private information without effective safeguards in place. Digital piracy is another form of cybercrime because knowledge, information, and copyright protected materials are easily stored and shared online without financial compensation for the producers.

Ransomware, a kind of malware that covertly encrypts files in victims' computers and demands them to make a payment to decrypt it, is a growing concern. How it works is based largely on people's increased reliance on their computers as a means to access information and store data. In other words, many of the victims might want to resolve this problem by sending money to criminals because they store important data (e.g., software, pictures, documents) on their computers and frequently access them so that they do not want to lose them. Thus, criminals disseminating ransomware may take advantage of this growing willingness to pay that potential victims might appear. Finally, some forms of traditional crimes such as terrorism (e.g., recruitment for extremist group members) and illegal trades (e.g., arms/drug trafficking) are increasingly committed on the Internet through ICT devices because cybercriminals, in the online setting, can communicate with many random people in an anonymous way.

Although cybercrime is an expansive, inclusive, and intuitive concept with its emphasis on the understanding of the characteristics of virtual space and our lifestyles affected by the online setting, this term is still somewhat vague because there are heterogeneous sub-groups of cybercrime (Wall, 2007). For example, Furnell (2002) categorized cybercrime into two types: 1) *computer-assisted crimes*, which are traditional forms of crime but committed in virtual space (e.g., cyberfraud, cybertheft, cyberpornography), and 2) *computer-focused crimes*, which directly target and damage computers or networks by exploiting new technologies (e.g. hacking, virus; see also Grabosky's (2016) typology of cybercrime). Wall (2001) proposed a more sophisticated classification of cybercrime with four categories: 1) *cybertrespass* (illegal intrusions of computers and networks owned by others; e.g., hacking/cracking, malicious software), 2) *cyberdeception/theft* (illicit behaviors to achieve financial purposes by means of computers and the Internet; e.g., cyberfraud, identity theft, piracy), 3) *cyberpornography/obscenity* (illicit behaviors that produce and distribute illicit pornographies on cyberspace; e.g. childpornography), and 4) *cyberviolence* (aggressive and violent behaviors against others on cyberspace; e.g., cyberbullying, cyberharassment, cyberstalking). According to the target of the offense, Yar (2006, pp.10-11) reclassified Wall's categorization (2001). He designated cybertrespass and cyberdeception/theft as "crimes against property," cyberpornography/obscenity as "crimes against morality," and cyberviolence as "crimes against the person."

Aside from these discrete classifications, Gordon and Ford (2006, p.15) suggested a continuum of cybercrime ranging from crime which is purely technological in nature to crime which is entirely people-centric. Each type of cybercrime lies in a certain point on the continuum based on how much it has cyber/technological element and interpersonal online communications are required for it. For instance, if crimeware programs such as hacking codes or viruses are used to commit online fraud, this type of online fraud will be situated in a point closer to the former ("technology crime"). On the other end of the spectrum, some types of online fraud will be closer to the opposite direction ("people crime") because these crimes are committed by offenders who directly communicate with victims and deceive them by using email and messenger clients.

To sum, the concept of cybercrime is useful to understand its nature and extent more intuitively as considering features of online environment, our contemporary lifestyles integrated with ICT devices, and novel criminal opportunities online derived from both. At the same time, however, there are many heterogeneous attributes across subtypes of cybercrime according to its motivation, target, and modus operandi. Due to its expansive coverage, the concept of cybercrime might have little suitability for academic discussions to explore relevant factors or correlates having an association with each subtype of cybercrime. Thus, more specific classifications extracting commonalities from each type of cybercrime are required for this purpose.

Online Property Crime

Extent, Scale, and Trends. While cybercrime has recently become a popular research topic, online crimes with financial orientation, or online property crimes (OPC), are one of the forms of cybercrimes that remain under-explored and need further research. As discussed earlier, OPC can be defined as crimes committed through the Internet via ICT devices with a financial motivation. OPC includes many types of cybercrime such as "identity theft, credit card theft and fraud, cyberattacks on organizational networks resulting in security breaches, the buying and selling of personal data online, and the use of unsuspecting people's computers for spamming/phishing/illegal hosting" (Tcherni et al., 2016, p.891). Based on Wall's (2001) typology, Holt and Bossler (2014) have extensively reviewed studies on cyberrelated crimes and suggested that researchers pay more attention to some forms of cybercrime falling into cyberdeception/theft and cybertrespass, what Yar (2006, p.10) called "crimes against property," because relatively little research on these categories has been conducted compared to the domains of cyberpornography/obscenity and cyberviolence. Cybercrimes in the former two categories can be included in the extent of OPC because these types of cybercrime are primarily committed for illicit financial advantage.

Rapidly growing damage and losses are an additional reason we need to pay more attention to OPC. Financial losses caused by these types of cybercrime have become worse over the last decade. The latest annual report published by the Internet Crime Complaint Center (IC3) indicates that 288,012 complaints about OPC were reported in 2015, an increase from 16,838 in 2000 and 269,422 in 2014, though slightly less than the 303,809 cybercrime offenses reported in 2010. Financial losses have rapidly increased as well. Reported financial losses to the IC3 was $17.8 million in 2001, and increased approximately sixty times to $1 billion in 2015 (see Figure 2.1 and Figure 2.2).

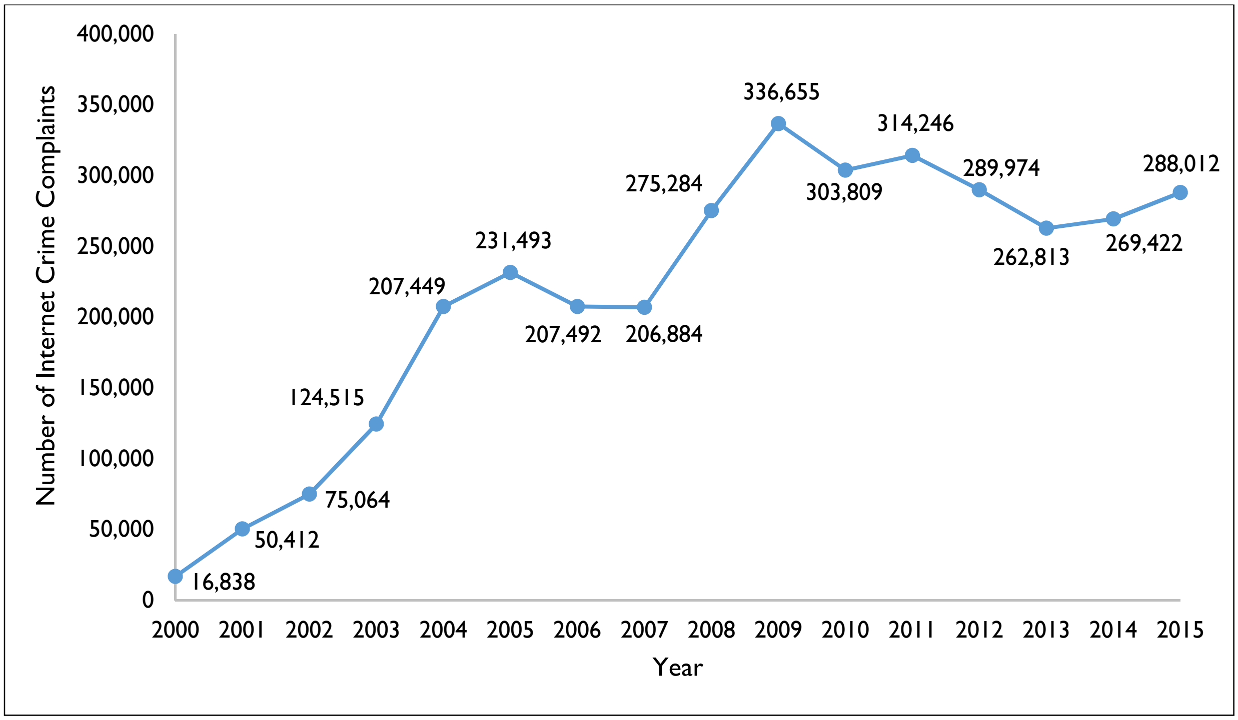

Figure 2.1. Internet Crime Complaints Reported, 2000-2015

Source: Internet Crime Complaint Center

As well as the U.S., other developed countries such as Australia, Canada, Germany, Hong Kong, Sweden, and the U.K. also seem to have experienced a substantial rise in cyberrelated fraud and identity theft (see Levi, 2017). In addition, it seems that victims can hardly recover these financial losses. Using reported fraud victimization data in the U.K., Levi and colleagues (2017) found that only approximately 5% of total victims of cyberrelated frauds (e.g., dating/romance scam, online shopping and auctions, rental fraud, ticket fraud) had managed to recover their financial losses either completely or partly.

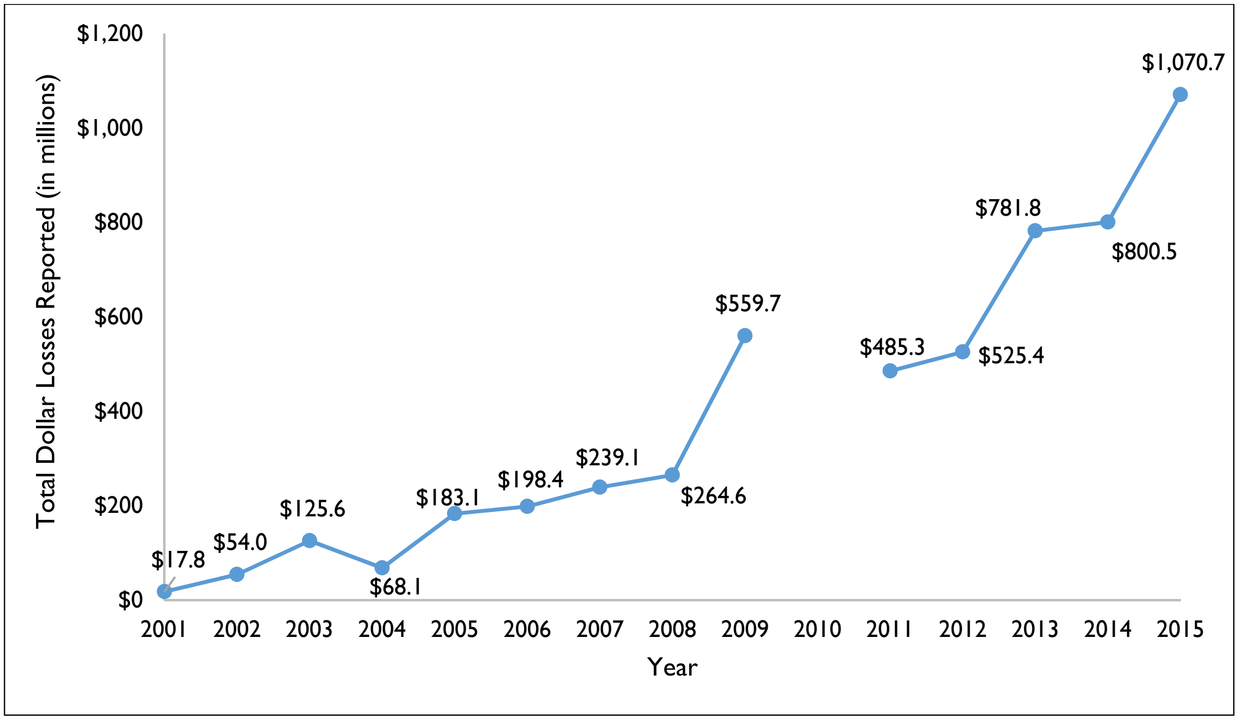

Figure 2.2. Total Financial Losses of Internet Crime Reported, 2001-2015

Note: Total financial losses were not reported in 2010

Source: Internet Crime Complaint Center

These cybercrime estimates are contrary to the decreasing rates of traditional property crimes observed over the last two decades in the U.S. In the U.S., property crime rates have gradually decreased since 1991. According to the Uniform Crime Report (UCR), property crime rate per 100,000 people in the U.S. was 5,140.2 in 1991 and it dropped to 3,618.3 in 2000 and to 2,859.2 in 2012. Similarly, victimization rates of traditional property crimes in the U.K. sharply decreased during 1995-2015 (Office for National Statistics, 2016a): vehicle-related theft (19.7% in 1995 to 4% in 2015), criminal damage/vandalism (10.1% to 3.7%), bicycle theft

(6.1% to 2.3%), domestic burglary (8.7% to 2.3%), and other household theft (5.1% to 2.3%). In contrast, fraud and computer misuse (e.g., hacking, virus, malware) indicated greater victimization rates than those of traditional forms of property crime (6.5% for fraud and 3.6% for computer misuse in 2015).

Comparing trends of traditional property crime and OPC, Tcherni and colleagues (2016) estimated that financial losses of OPC ($54 billion in 2009) have surpassed those of traditional property crime (between $15.2 to $30.4 billion in 2009). If we consider that victims do not always report their victimization when they do not recognize their losses, their losses are minor, the losses have already been compensated by others, or they believe that police cannot do anything about their victimization (Skogan, 1984), the estimated losses of cybercrime might have been less than actual losses. Thus, the extent of and losses from cybercrime are likely much worse than what we can observe (Grabosky, 2016; Reyns & Randa, 2017; Tcherni et al., 2016; Wall, 2007).

In addition, Anderson and colleagues (2013) argued that not only direct costs of cybercrime (e.g., victims' immediate financial losses) but also indirect (e.g., loss of trust in online services and transactions) and defensive costs of cybercrime (e.g., cost of development and implementation of security services and programs) should be considered to estimate costs of cybercrime. They also pointed out that these indirect and defensive costs of cybercrime might be greater than its direct costs as technological sophistication of cybercrime rapidly evolves. That is, it may require huge investment for setting and running an effective cybercrime defensive system with an ability to respond to newly evolved cybercrime promptly. This rapid evolution of cybercrime may also lead to misallocation of resources for enforcing cybercrime (e.g., adjustment of police force and jurisdiction), which may cause additional costs of cybercrime, given that administrative decisions to allocate resources can hardly overtake the speed of technological progress that makes cybercrime more sophisticated. Considering these direct, indirect, and defense costs of cybercrime, the total cost that can possibly be derived from OPC might surpass our estimates.

Prior Studies with Micro-Level Perspectives. Many empirical studies in criminology and criminal justice have attempted to apply some mainstream theories of crime such as self-control (Gottfredson & Hirschi, 1990), social learning (Akers, 1998), and routine activities (Cohen & Felson, 1979) theories to account for OPC perpetration and victimization. Studies on OPC perpetration have primarily focused on computer hacking and digital piracy and most of them employed samples of students and young adults. These studies have examined how well individual offenders' low self-control or their associations with delinquent peers predict their propensities for committing some types of OPC.

Consistent with Gottfredson and Hirschi's (1990) argument that the concept of low self-control accounts for all types of delinquent and analogous behavior, studies have found that an individual's low self-control was associated with computer hacking and digital piracy (Burruss et al., 2013; Higgins, 2004, 2006, 2007; Higgins et al., 2006, 2007; Holt et al., 2012; Kerstens & Jansen, 2016; Kim & Kim, 2015; Malin & Fowers, 2009; Moon et al., 2010) as well as other offline delinquent behaviors (see Donner, Jennings, & Banfield, 2015). In addition, OPC research based on social learning theory have also been widely conducted. Studies in this domain have found significant effects of cyberdeviant peers and acceptance of cyberdeviant definitions on hacking and digital piracy (Brunton-Smith & McCarthy, 2016; Burruss et al., 2013; Higgins, 2004, 2006; Higgins & Makin, 2004; Higgins et al., 2006, 2007, 2009; Holt et al., 2010, 2012; Malin & Fowers, 2009; Morris & Higgins, 2010; Skinner & Fream, 1997).

Despite these findings, there have been some mixed results. Hohn, Mutfic, and Wolf (2006) reported that low self-control had no effects on Internet piracy. Using panel data from South Korean youths, Moon and colleagues (2010, 2013) have also found that significant effects of low self-control on illegal downloading disappeared once opportunity factors (e.g., time spent computer use, being a member of cyber club) were included in the model. Some studies have found that both concepts, low self-control and associations with deviant peers, had independent effects on OPC (Burruss et al., 2013; Higgins, 2004, 2006; Higgins & Makin, 2004; Higgins et al., 2006, 2007; Holt et al., 2012; Malin & Fowers, 2009). In contrast, some studies have found that low self-control had a significant effect but delinquent peers did not (Kim & Kim, 2015), while some others studies reported the opposite results (Higgins et al., 2009).

Effects of gender and opportunity factors on OPC are considerable. Independent effects of gender on OPC, which indicates that males are more likely to commit OPC than females, have been found in many studies (Brunton-Smith & McCarthy, 2016; Higgins, 2006, 2007; Holt et al., 2012; Kerstens & Jansen, 2016; Kim & Kim, 2015; Malin & Fowers, 2009; Moon et al., 2010, 2013; Skinner & Fream, 1997). Some studies examined not only the direct effects of gender on OPC but also indirect ones mediated by theoretical concepts such as low self-control and social learning constructs (Higgins, 2006; Holt et al., 2010; Morris & Higgins, 2010). That is, males are more likely to have low self-control, associate with cyberdeviant peers, and accept online deviant definitions than females so that being male indirectly leads to a greater likelihood of being involved in OPC perpetration. Likewise, opportunity factors such as time spent online/computer (Higgins, 2004; Kerstens & Jansen, 2016; Kim & Kim, 2015; Holt et al., 2012; Malin & Fowers, 2009; Moon et al., 2010, 2013), computer skills (Burruss et al., 2013;

Holt et al., 2010, 2012), and being a member of online club (Moon et al., 2010, 2013), were consistently reported as significant predictors of OPC perpetration.

Regarding OPC victimization, empirical studies have primarily focused on exploring individual-level situational factors and examining its effects on OPC victimization based on the perspective of routine activities theory since Yar's (2005) inception. While a majority of these studies used samples of youths or college students (Bossler & Holt, 2009, 2010; Choi, 2008; Holt & Bossler, 2013; Holt & Turner, 2012; Ngo & Paternoster, 2011), some studies employed regionally or nationally representative samples (Leukfeldt, 2014; Leukfeldt & Yar, 2016; Pratt et al., 2010; Reyns, 2013; Van Wilsem, 2013). Many types of OPC victimization have been studied such as consumer fraud (Leukfeldt & Yar, 2016; Pratt et al., 2010; Van Wilsem, 2013), credit card/identity theft (Bossler & Holt, 2010; Holt & Turner, 2012; Leukfeldt & Yar, 2016; Reyns, 2013), phishing (Leukfeldt, 2014; Ngo & Paternoster, 2011), and malware/computer virus infection (Bossler & Holt, 2009, 2010; Choi, 2008; Holt & Bossler, 2013; Leukfeldt & Yar, 2016; Ngo & Paternoster, 2011).

Effects of various types of opportunity factors on OPC victimization were also examined and found significant in these studies. Predictors indicating an increase in exposure to motivated online offenders, online use (e.g., frequency of computer/Internet use or time spent computer/online — Kerstens & Jansen, 2016; Leukfeldt & Yar, 2016; Pratt et al., 2010; Van Wilsem, 2013), types of online activity (e.g., online banking, shopping, gaming, downloading — Leukfeldt, 2014; Leukfeldt & Yar, 2016; Pratt et al., 2010; Reyns, 2013; Van Wilsem, 2013), and cyberdeviance or risky online activities (e.g., pirating software/media, pornography — Bossler & Holt, 2009; Choi, 2008; Holt & Bossler, 2013; Ngo & Paternoster, 2011) have been examined and found to have significant effects on OPC victimization. Some situational protective factors such as installation of security programs (Choi, 2008; Holt & Bossler, 2013; Holt & Turner, 2012; Ngo & Paternoster, 2011) and having computer skill/knowledge (Holt & Bossler, 2013) were found significantly to reduce the likelihood of being an OPC victim. Socio-demographic characteristics such as gender and age have produced mixed findings. Some studies have found that females were more likely to experience OPC victimization than males (Bossler & Holt, 2009; Holt & Bossler, 2013; Holt & Turner, 2012), whereas some other studies reported that males were more likely to be a victim (Kerstens & Jansen, 2016; Reyns, 2013). Likewise, there have been some studies reporting that those who are younger were more likely to be victimized for consumer frauds than their older counterparts (Leukfeldt & Yar, 2016; Van Wilsem, 2013), while others reported that those who are older were more likely to be victimized for identity theft (Reyns, 2013).

Prior Studies with Macro-Level Perspectives. While OPC studies with a macro-level perspective have rarely been conducted, some scholars have recently attempted to explore probable macro-social predictors and examine their effects on variations in perpetration/victimization rates of OPC across geographical boundaries, mostly relying on the theoretical perspectives of routine activities and crime opportunity theories.

Using cross-country data on 132 countries, Kigerl (2012) found that macro-social economic factors such as unemployment rates and Gross Domestic Product (GDP) per capita, an opportunity factor measured by the number of Internet users per capita, and demographical/geographical factors such as each country's population and location, had significant direct and indirect effects on both spamming and phishing rates. Specifically, this study reported that GDP per capita had direct effects on both spamming and phishing rates. The number of Internet users per capita had a direct effect only on the cross-national rate of spamming, while unemployment rates had a direct effect on phishing rates. In addition, unemployment was a moderator enhancing effects of the number of Internet users per capita on spamming. An increase in population was associated with lower rates of phishing, but did not affect the spamming rate. North American countries had significantly higher rates of spamming, whereas continents other than North America and the Middle East had significantly higher rates of phishing attacks.

With a focus on household activities, which has been considered a protective factor reducing a likelihood of traditional crime victimization from routine activities theory (Cohen & Felson, 1979), Song and colleagues (2016) speculated that this protective factor for traditional crimes could be a risk factor for OPC victimization. Using state-level data provided by the Internet Crime Complaint Center (IC3), they found that rates of OPC victimization were positively associated with an increase in the proportions of those who access the Internet only at home.

Applying time-series OPC victimization data (2001-2013) provided by the Internet Crime Complaint Center (IC3), Brady and colleagues (2016) examined whether an increase in online activities over time, an indicator of an increased criminal opportunity on the Internet, was significantly related to an increase in OPC victimization. They measured temporal changes in online activities for annual changes in total dollars spent online per capita and found that a strong correlation with annual changes in total reported monetary losses derived from OPC victimization.

Working from perspective of routine activities theory, Williams (2016) also examined the direct and indirect effects of individual- and country-level opportunity predictors on online identity theft victimization. The maturity of national cybersecurity strategies, the proportion of the total population who access the Internet, GDP per capita, and the percentage of the urban population were employed as country-level opportunity predictors. This study has found that countries with a greater proportion of the population accessing the Internet was negatively associated with online identity theft victimization. This suggested that countries with more advanced online infrastructures are likely to have lower rates of online identity theft victimization. Additionally, both country-level guardianship variables, having more mature cybersecurity strategies and greater proportions of Internet users, were found to enhance protective effects of individual-level passive physical guardianship (e.g., using anti-virus programs, spam filtering) on online identity theft victimization.

Maimon and colleagues (2013, 2015) focused on physical conditions associated with computer-focused crimes (e.g., Denial of Service attack, network trespassing, password guessing). Employing Honeypot computers, they found that temporal availability (e.g., official business hours) and geographical proximity (e.g., users of foreign network, proximity to the location of target computers) were closely related to these types of cybercrime. Specifically, they reported that these crimes were more likely to be committed during official business hours and physical locations closer to target computers. In addition, a network system with more users of foreign networks was found to have more attacks from the corresponding foreign IP addresses. These findings implied that online criminal opportunities might be, to a certain degree, reflected by structural characteristics of the real world rather than simply determined by attributes of online settings.

Employing open-source self-reported data across countries, Holt and colleagues (2016) also explored macro-level correlates for malware infection victimization. They found that countries with greater technological infrastructure and with more political freedoms were more likely victimized for malware infections. That is, malware writers are more likely to target these countries because there are more potential victims in these countries and they tend to have greater accessibility to the Internet. In addition, having a democratic government can be another opportunity factor for malware attackers as these countries have fewer restrictions and controls on individuals' Internet access and activities. To conclude, these two macro-level conditions significantly predict malware infection victimization as these social characteristics result in increasing the criminal opportunity: greater exposure to motivated malware writers.

Conclusions

In this chapter, relationships among ICT, social structure, and our transformed routine activities are discussed. It addressed how advancement of ICT has changed our daily routine activities and how structural conditions have affected disproportionate distributions of people's accessibility to ICT and ability to use it. It also discussed nature and extent of cybercrime in general including its definitional issues. In addition, it discussed OPC, the primary interest of this dissertation, focusing on its extent, scale, and trends. It specifically emphasized that there are growing victims of OPC, their financial losses due to OPC are increasing, and that indirect/defense costs of OPC might be more problematic than its direct costs. Finally, previous studies on OPC, based on either micro- or macro-level perspective, were reviewed in this chapter. These empirical studies, especially studies with the macro-level perspective, have primarily focused on exploring criminal opportunistic predictors of OPC and examining its relationships with OPC. They consistently found that the opportunity predictors indicating high accessibility to Internet and ICT devices were significantly associated with OPC perpetration and victimization.

Since most forms of cybercrime are committed via ICT devices and in the context of online settings, greater accessibility to the Internet and ICT devices, which represent more frequent online criminal opportunities, may lead to greater OPC. A degree of the online accessibility may also depend on social conditions since the features of the online settings, as discussed earlier, tend to vary across certain social contexts such as economic and educational conditions. In other words, disproportionate online accessibility across macro-level units may be determined by their structural conditions and characteristics, and this, in turn, may also lead to OPC rates. To understand overall criminogenic structure of OPC, it is necessary to look into 1) whether these macro-level online accessibility, or online criminal opportunities, are directly related to OPC rates, 2) what macro-social conditions are significantly associated with the online accessibility, and 3) whether these macro-social conditions also have a direct relationship with OPC rates.

For this approach, the following chapter reviews probable macro-social predictors expected to have a significant relationship to OPC. Specifically, it reviews existing macro-social predictors for traditional crime, which have been examined and discussed in prior studies. While they differ in terms of medium and modus operandi, both traditional crime and OPC commonly share the concept of criminality (Grabosky, 2001), existing structural conditions closely related to traditional crime may be significantly associated with OPC as well. Moreover, these social characteristics may also have an indirect effect on OPC through macro-level online accessibility, which is expected to increase online criminal opportunity. In addition, it discusses potential online opportunity predictors for OPC that may indicate greater Internet and computer accessibility, and that are expected to have a close relationship with OPC. Since greater Internet/computer accessibility may increase criminal opportunities online, these predictors may also be significantly related to OPC. Based on these discussions, the following chapter also addresses the current focus of this dissertation.

CHAPTER THREE:

PROBABLE MACRO-SOCIAL PREDICTORS OF ONLINE PROPERTY CRIME

In criminology, a macro-level approach focuses on relationships between structural characteristics of social aggregates such as cities, states, or countries and their crime rates. Since Durkheim (1895) proposed the rules of sociological methodology and suggested that one social fact has to be explained by other social facts, several sociological/criminological theories of crime, for example, routine activities (Cohen & Felson, 1979), social disorganization (Sampson & Groves, 1989; Shaw & McKay, 1942), deterrence (Blumstein, Cohen, & Nagin, 1978; Gibbs, 1968, 1975; Tittle, 1969), economic deprivation (Blau, 1977; Blau & Blau, 1982), and anomie/strain (Agnew, 1999; Merton, 1938, 1968; Messner & Rosenfeld, 1994) theories, have attempted to account for a variation in crime rates by applying their theoretical propositions.

While the theoretical concepts proffered by these macro-level theories are distinct from one another, empirical assessments of macro-level criminological theories have been criticized for indirectly measuring concepts and for using social indicators to measure multiple distinct theoretical concepts (Baumer & Arnio, 2015; Pratt & Cullen, 2005). As Pratt and Cullen (2005) pointed out, for example, macro-social predictors in the domains of unemployment and economic deprivation (e.g., unemployment rates, the percent of population below the poverty line, Gini coefficients, etc.) have broadly been employed as a variable measuring multiple distinct theoretical constructs based on social disorganization, structural anomie, conflict, and criminal opportunity theories. This might be because these indicators are the only systematically collected forms of data accessible to researchers (Baumer & Arnio, 2015). As such, it is difficult to say that a macro-level theory of crime exclusively possesses specific indicators.

Given this limitation, this chapter focuses on reviewing a series of macro-social predictors closely related to traditional crime. While they are predictors of traditional crime, these indicators may also be able to predict OPC as well, since OPC is basically regarded as one of the types of property crime despite its unique modus operandi (Grabosky, 2001). Thus, this chapter reviews prior macro-level criminological theories and empirical studies, especially concentrating on the macro-social indicators that have been applied as predictors of crime. These existing macro-social predictors of crime include: racial/ethnic composition, family disruption, household activity ratio, residential instability/urbanization, economic social support, non-economic social institutions, poverty/absolute deprivation, economic inequality/relative deprivation, unemployment, and deterrence.

This chapter also discusses potential macro-social predictors of OPC. First of all, applicability of the existing macro-social predictors of traditional street crime to OPC is assessed by discussing connections of their theoretical assumptions to OPC. In addition to these existing predictors of traditional crime, discussions about potential online opportunity predictors of OPC, which may have a close relationship to OPC, are following. Since these potential online opportunity predictors may also be related to the existing macro-social predictors of crime, and it is possible that the latter might have indirect effects on OPC via the former, these possible structural relationships are also discussed in this chapter. Drawing on all these discussions, this chapter also addresses research questions and current focus of this dissertation.

Existing Macro-Social Predictors of Traditional Crime

Racial / Ethnic Composition

Racial/ethnic composition refers to the proportion of a certain racial/ethnic group in a social aggregate. A majority of macro-level empirical studies found that societies with high proportions of racial/ethnic minorities or those that are very racially/ethnically heterogeneous tend to have high crime rates. For example, Pratt and Cullen (2005) conducted a meta-analysis to assess effects of macro-level predictors on crime. They reported that indicators relevant to racial/ethnic composition such as the percent Black (or non-White) and racial heterogeneity index had high to moderate strength and stability of mean effect size estimates, which implies that these predictors have strong and consistent associations with crime rates. Nivette (2011) also applied a meta-analysis for cross-national studies and reported that measures of racial/ethnic heterogeneity were significant predictors of cross-national homicide rates.

Indicators in this domain have been used in assessments of some macro-level theories of street crime. According to social disorganization theory, racial/ethnic heterogeneity is a concept immediately related to social bonds and informal social control in a community, with both forms of bonds affecting the likelihood of crime within communities. If a community has a high level of racial/ethnic heterogeneity, for example, members of the community are less likely to interact with one another, and thus are less likely to build common values or strengthen trust and interdependency. In this context, it is difficult for them to cooperate with their neighbors to solve common problems of their community such as crime and juvenile delinquency because they do not share common values, identities, and mutual trust/interdependency with their community neighbors. Thus, racial/ethnic heterogeneity may weaken social bonds among community members, and the weakened social bonds, in turn, may lead to a lack of informal social control in their communities, which in more homogeneous communities is built by community residents' attachment to their communities, their concern with the fate of their communities, and created collective responses to solve community problem. Consequently, racial/ethnic heterogeneity results in higher crime rates as it erodes informal social control in a community (Bursik, 1988; Kornhauser, 1978; Sampson & Groves, 1989).

From the perspective of conflict theory, on the other hand, an increase in racial/ethnic heterogeneity may increase majority racial/ethnic groups' demands for reinforced formal control/criminal justice system because they feel threatened by the growth in minority racial/ethnic group concentrations (Chamlin, 1989; Liska, Lawrence, & Benson, 1981; Stults & Baumer, 2007). Conflict theorist thus emphasize that greater arrest and imprisonment rates are a byproduct stemming from reinforced formal control and criminal justice system rather than that racial/ethnic heterogeneity itself causes more crimes (Liska, 1992).

Regarding measurement, criminologists have typically measured racial/ethnic composition in two ways: 1) percent of Black or non-White, and 2) racial/ethnic heterogeneity index. The racial/ethnic heterogeneity index measures the degree of racial/ethnic diversity within a population. Using Lieberson's (1969, p.851) concept for measuring population diversity, the racial/ethnic heterogeneity index can be defined as "a continuum ranging from homogeneity to heterogeneity" in regard to one or more racial/ethnic group(s) in a society. This index is calculated as: $1-\Sigma Pi^2$, where Pi are the proportions of each racial/ethnic group to the total population. This index indicates greater racial/ethnic heterogeneity when it approximates to one (1.0), while it is computed at zero (0) if a society consists of only one racial/ethnic group.

Prior macro-level studies found that racial/ethnic composition measured by these indicators is consistently related to both violent and property crime rates. Messner (1983a) found that racial composition measured by the percent of the population Black was significantly and positively associated with homicide rates in standard metropolitan statistical areas (SMSA) while controlling for the effects of other predictors (e.g., age structure, poverty, economic inequality, population density). Land, McCall, and Cohen (1990) reported that the percent Black had stable effects on homicide rates across time periods (1960, 1970, 1980) as well as across different macro-social units of analysis (city, SMSA, State). Applying longitudinal data, Liska, Logan, and Bellair (1998) found that the percent non-White had a significant relationship with violent crime rates in suburban cities.

In terms of the heterogeneity index, Miethe, Hughes, and McDowall (1991) found strong effects of ethnic heterogeneity on both violent (homicide, robbery) and property (burglary) crime rates in 584 U.S. cities. According to their findings, ethnic heterogeneity was the only independent variable with significant effects on both crime rates and changes in crime rates. Kubrin (2000) also examined effects of racial heterogeneity index on crime rates controlling for the percent Black and found that the racial heterogeneity index had a stronger effect on violent crime than the percent Black.

Other studies that included predictors relevant to the racial/ethnic composition in their analytic models consistently found significant relationships with both violent (Gartner, 1990; Hipp, 2007; Kposowa, Breault, & Harrison, 1995; Kovandzic, Vieraitis, & Yeisley, 1998; Krivo & Peterson, 1996; Messner, 1983b; Osgood & Chambers, 2000; Rosenfeld, 1986; Sampson &

Groves, 1989; Smith & Bennett, 1985; Warner & Rountree, 1997) and property crime rates (Chamlin & Kennedy, 1991; Higgins, Hughes, Ricketts, & Wolfe, 2008; Hipp, 2007; Kposowa et al., 1995; Warner & Rountree, 1997), although some studies reported that more consistent results were found for violent crimes (Kubrin, 2000; Messner & Blau, 1987; Rosenfeld, 1986; Sampson & Groves, 1989).

Family Disruption

Family disruption refers to proportions of families within a population disrupted form (e.g., divorced, single-parent families) exist in a social aggregate. Prior studies consistently reported that a greater proportion of disrupted families predicted a high rate of crime. Predictors within this domain were also found to be critical correlates of crime rates. Pratt and Cullen (2005) reported that family disruption was one of the macro-social predictors that had high strength and stability of effects on crime rates. Nivette's (2011) assessment also observed that divorce rate was a significant predictor of homicide rates cross-nationally.

Theoretically speaking, family disruption has been regarded as a concept that may indirectly affect an increase in crime rates as undermining informal social control (Sampson & Groves, 1989) and degrading social support network (Cullen, 1994). Based on the perspective of social disorganization theory, Sampson and Groves (1989) found that family disruption had an indirect effect on both violent and property crimes as it was directly associated with one of the indicators of social disorganization, unsupervised peer group. They pointed out that an increase in disrupted families in a community could weaken informal social control processes in the community because effective surveillance by responsible adults over juveniles is reduced in the context of high levels of family disruption.

In terms of the motivational aspect, Agnew (1999) argued that communities with a high proportion of disrupted families are more likely to have a high crime rate as the disrupted family settings are a major source of strain or negative emotional status such as anger, which is directly related to criminal behaviors. Cullen (1994) pointed out that a close relationship between family disruption and crime could be attributed to deficiency of social support provided by family. When families are disrupted, it makes it difficult to provide others with needed emotional and material support that can reduce criminal motivations. These tangible and intangible family supports may work as a protective factor for those who are exposed to greater criminal opportunities, which deters them from turning into committing a criminal behavior.

Family disruption has primarily been measured by 1) divorce rates, 2) percent single-parent families (or two-parent families), and 3) percent female-headed families. For instance, Sampson (1986a) examined effects of divorce rates and the percent of two-parent families on both homicide and robbery rates across the U.S. cities. He found that divorce rates were positively associated with these two violent crimes, while the proportion of two-parent families had negative effects. Sampson (1986b) also found that divorce was strongly related to not only violent crime but also property crime victimization (theft). In his subsequent study (1987), family disruption, measured by the percent of female-headed households, was found to have strong effects on violent crime for both white and black juveniles. Using a sample of 153 American cities, Messner and Sampson (1991) also found that the percent of female-headed families had a significantly positive association with violent crime and its effect still remained significant when the family disruption variable was disaggregated by race (e.g., female-headed white families and female-headed black families).

Other studies also reported significantly positive relationships of family disruption with not only violent crime (Chamlin & Cochran, 1997; Gartner, 1990; Hannon & DeFronzo, 1998a; Hipp, 2007; Kposowa et al., 1995; Kubrin, 2000; Maume & Lee, 2003; Messner & Golden, 1992; Osgood & Chambers, 2000; Patterson, 1991; Piquero & Piquero, 1998; Smith & Bennett, 1985; Smith & Brewer, 1992) but property crime as well (Cochran & Bjerregaard, 2012; Chamlin & Cochran, 1995, 1997; Hannon & DeFronzo, 1998a; Hipp, 2007; Kposowa et al., 1995; Kubrin, 2000; Patterson, 1991; Piquero & Piquero, 1998; Smith & Jarjoura, 1988). In addition, family disruption was significantly associated with total victimization rate, which is combined both street violent and property crime victimization (Lowenkamp, Cullen, & Pratt, 2003; Sampson & Groves, 1989; Veysey & Messner, 1999).

Household Activity Ratio

Some indicators of macro-social household structure (e.g., single-person households, female labor force participation) have also been identified as macro-social predictors of crime based on the assumption that these indicators are closely related to non-household activities. Non-household activities, referring to outdoor activities away from home such as working at a workplace long time, going to a bar at night, or having outdoor leisure activities, are more likely to provide a potential victim with a chance to encounter motivated offenders in public spaces compared to household activities such as watching television or spending time with family at home. In addition, an increase in home vacancy due to non-household activities makes the house a more suitable target for motivated offenders due to decreased guardianship.

According to routine activities/opportunity theories, family structures, especially type of household and size of household, have been understood as a precondition affecting crime victimization because they are associated with household activity patterns (Cohen & Felson, 1979; Felson & Cohen, 1980). That is, an individual's life-style and routine activities can possibly depend on the type and a size of household in which they live. As discussed earlier, greater non-household activities such as work hours and leisure activity patterns are an indicator of greater likelihood of crime victimization. In contrast, greater in household activities such as spending time with family at home can be understood as producing less exposure to motivated offenders and as generating increased capable guardianship, reducing the likelihood of victimization. For example, unmarried adults living alone are more likely to enjoy more non-household activities than married couples or married couples with children. Accordingly, an increase in the proportion of a specific type of household is closely associated with a greater ratio of non-household activities (e.g., unmarried single adult household) resulting in greater crime rates.

Macro-social household structures, such as 1) percent of female labor force participation, 2) percent of single-person households, and 3) average number of persons per household, can be used as measures of macro-social non-household activities. A high percent of single-person households may represent a greater degree of non-household activities in a social aggregate because those who live alone tend to enjoy non-household activities than married couples or married couples with children. More participations in labor force among married females may also be related to greater non-household activities as indicates that there are more individuals working outside the home (Cohen & Felson, 1979; Felson & Cohen, 1980). Accordingly, greater proportions of these forms of households are expected to be associated with greater crime rate. Results from some meta-analyses seem to support these relationships. Pratt and Cullen (2005) reported that indicators regarding household activities had moderate strength and stability of effects on crime rates. Nivette (2011) also pointed out that one of the predictors in this domain, rates of female labor force participation, was significantly associated with homicide rates across countries.

Cohen and Felson (1979) initially hypothesized that the concept of non-household activities indirectly measured by macro-social household structures could explain an increase in crime rates. They measured the concept with the household activity ratio, which is the ratio of the sum of "the number of married, husband-present female labor force participants" and "the number of non-husband-wife households" to "the total number of households in the U.S." (p.600-601) That is, a greater ratio means a greater degree of non-household activities. They found that this measure was significantly associated with increasing trends in the rate of crime in the U.S. during 1947-1974.

Consistent with Cohen and Felson's (1979) findings, Cohen, Felson, and Land (1980) found that the household activity ratio was positively related to property crime rates (e.g., robbery, burglary, theft, automobile theft). Applying cross-national data for 52 countries, Bennet (1991) also found that female labor force participation increased the rates of property crime although it did not have significant effects on the rates of personal crimes (murder, attempted murder). Miethe and colleagues (1991) examined effects of female labor force participation and mean household size on rates of homicide, robbery, and burglary respectively. As expected, the average of household size was negatively associated with all the three types of crime. Unexpectedly, however, female labor force participation was significantly but inversely related to crime rates; thus, increased female labor force participation was associated with decreased rates of crime. In addition to these studies, other empirical studies applied predictors belonging to this domain also reported significant relationships with homicide (Cohen & Land, 1987; Massey & McKean, 1985), property crime (Cohen & Land, 1987; Hannon & DeFronzo, 1998a; Jackson, 1984), and total crime rates (Hannon & DeFronzo, 1998a). Some studies observed no consistent, direct relationships between these predictors and crime rates (Bryant & Miller, 1997; c.f. Bennett, 1991).

Residential Mobility and Urbanization

High crime rates have also been observed in places where people frequently move in and out, which is often conceptualized as residential mobility or residential instability. It is also known that urban areas are more likely to show high crime rates (Kornhauser, 1978, Sampson & Groves, 1989; Shaw & McKay, 1942). According to Pratt and Cullen's (2005) assessment, predictors in the domains of residential mobility and urbanization had moderate strength and stability of mean effect sizes on macro-level crime rates.

In the tradition of social disorganization theory, high crime rates observed in central city districts and transitional zones have been posited to be related to the level of residential stability within a community. For example, Shaw and McKay (1942) found a difference in crime rates between these inner city and suburban areas in Chicago, with higher crime rates in the former and lower crime rates in the latter. They also found that these differences were maintained over time despite a change in racial/ethnic compositions of both districts. Social disorganization theory thus suggests that one of the factors which explained this macro-level crime pattern in the geography of cities was due to residential stability of communities, and the argument that urbanized communities with greater residential instability and heterogeneity also experienced weakened social bonds and informal social control (Bursik, 1988; Sampson & Groves, 1989). Based on this perspective, residential instability and urbanization have been regarded as key macro-social characteristics to indicate a level of social disorganization in a community and to examine direct and indirect effects of its theoretical concepts on crime rates.

In the perspective of routine activities/opportunity theories, urbanization has also been argued to increase the risk of crime victimization because it is highly expected to be associated with non-household activities (Cohen & Felson, 1979). Those who are living in an urban area are more likely to have non-household activities than those living in a rural area because there are, in general, more opportunities for economic activity in urban areas so that urban residents are more likely to be out of home for the economic activity. This may result in greater vacancy of house at different times of the day in urban areas due to greater non-household activities, which can make those households more suitable target for motivated offenders. In addition, non-household activities for leisure purposes (e.g., going to a bar at night for a drink) are also more likely for those living in urban areas so these outdoor activities increase a likelihood of being exposed to motivated offenders as well. In the perspective of routine activities and criminal opportunity theories, as a result, the significant difference in crime rates between urban and rural areas have been explained by the concept of growing non-household activities in urban locations.

Macro-level indicators employed as a measure of residential mobility and urbanization include: 1) percent of population living in the same place for less than three years, 2) percent of population who moved into an area in the last five years, and 3) percent of people living urban areas. Using SMSA-level data, Crutchfield, Geerken, and Gove (1982) measured residential mobility as the proportion of a population that had moved within a SMSA plus the proportion that had moved into a SMSA from different areas, and examined relationships between residential mobility and crime rates. They found that residential mobility significantly increased both violent (murder, assault, rape) and property (burglary, larceny) crime rates. Smith and Jarjoura (1988) also found significant effects of residential mobility on crime rates. They measured residential mobility with the percent of households that have lived in the same place for less than three years. They reported that residential mobility specifically had a direct positive effect on burglary rates. Similarly, Miethe and colleagues (1991) tested effects of residential mobility on homicide, robbery, and burglary. The percent of residents who moved in the last five years was employed as a measure of residential mobility, and this variable significantly predicted an increase in both robbery and burglary rates. As for urbanization, Laub (1983) identified that large cities and urban areas, in general, had greater personal crime rates than small towns and rural areas had. Cao and Maume (1993) also found that urbanization had the strongest direct effects on a variation in robbery rates across 318 SMSAs when other variables including lifestyle, economic inequality, age/race structure, and southern location were being controlled.

Predictors relevant to the domain of residential instability have been applied in other macro-level studies as well. These predictors were found to have a significant relationship with both violent (Hannon & DeFronzo, 1998a; Hipp, 2007; Kubrin, 2000; Osgood & Chambers, 2000; Patterson, 1991; Sampson & Raudenbush, 1999; Warner & Rountree, 1997) and property crime (Bruinsma, Pauwels, Weerman, & Bernasco, 2013; Hannon & DeFronzo, 1998a; Hipp, 2007; Kposowa et al., 1995; Kubrin, 2000; Patterson, 1991; Sampson, 1986b; Warner & Rountree, 1997). In terms of predictors in the domain of urbanization, some country-level studies found that more urbanized countries were more likely to report greater violent and property crime rates (Anderson & Bennett, 1996; Bennett, 1991). Predictors in this domain were also significantly related to total victimization rates (Hannon & DeFronzo, 1998a; Sampson & Groves, 1989; Veysey & Messner, 1999) as well as violent and property crime rates (Hannon & DeFronzo, 1998a; Kposowa et al., 1995; Kubrin, 2000; Piquero & Piquero, 1998).

Economic Social Support

The concept of social support can be defined as "the provision of affective and/or instrumental (or material) resources," which can be supplied by not only intimate individual relationships but a society such as communities, cities, and countries as well (Cullen, Wright, & Chamlin, 1999, p.190). The concept of social support has been discussed as a structural factor that may buffer criminogenic effects derived from economic deprivation and, in turn, reduce crime. Suggesting that criminologists pay more attention to this concept, Cullen (1994) pointed out that an individual's criminal behavior is dependent on how sufficiently the individual is granted emotional and instrumental supports from social groups around him/her such as family, school, workplace, and community. If these social groups possess ample means to support their members and properly provide them with supportive resources, social trust and bonds among members of the groups may improve so that these socially supportive processes may contribute to dissolving criminal motivations of individuals at risk (Cullen, 1994; Cullen et al., 1999). The concept of social support not only includes material/financial forms of support provided by state/local governments or non-governmental organizations but emotional support from family members or peers as well, the economic forms of social support have primarily been of research interest with regard to effects of social support on macro-level crime rates.

Although the forms of social support are not limited to material/financial support provided by state/local governments or non-governmental organizations but include emotional support from family members or peers, material/financial support has been the primary form of research interest in macro-level studies. According to Pratt and Cullen's (2005) assessment, predictors belonging to the domain of social support are overall moderate in strength and consistency in their effects on macro-level crime rates. Various social indicators have been employed as a measure of social support, which include: 1) percent of gross domestic product (GDP) spent on social welfare such as health care, pensions, education, and work-related benefits, 2) the amount of charitable donations, and 3) decommodification index.

Applying a cross-national dataset, Pratt and Godsey (2003) measured social support with the percent of the country's GDP spent on health care. They found that the social support indicator was inversely related to homicide rates. This predictor also significantly reduced the effects of relative deprivation (economic inequality) on homicide rates. Altheimer (2008) employed various social support indicators such as the percent of a nation's GDP spent on health care, public health, education, pension, work-related injury and sickness, family, housing, and social assistance benefits to measure the concept of economic social support. He found that the social support predictors were significantly associated with decreases in crime rates. He also reported that the economic support variable significantly reduced the effects of ethnic heterogeneity on crime rates.

Regarding the amount of charitable donations, this indicator measures the other form of economic social support based on the concept of social altruism. Social altruism refers to a social value regarding concerns about others and their needs. Chamlin and Cochran (1997) measured this concept with the amount of charitable donations and found its negative relationships with both violent and property crimes.

Economic social support is also corresponding to the concept of decommodification. This concept refers to "the degree to which individuals, or families, can uphold a socially acceptable standard of living independently of market participation." (Esping-Andersen, 1990, p.37). If a society provides citizens with sufficient resources and services to support their sustenance, they can reduce their reliance on the market, especially their participations in the labor market. Thus, the decommodification index consists of a combination of social indicators regarding quality of social welfare in a society such as governmental expenditure on multiple social welfare services. Messner and Rosenfeld (1997) found significantly negative relationships between the decommodification index and homicide rates across countries.

According to other studies that have employed predictors in the domain of economic social support, these predictors were consistently associated with homicide rates (Chamlin, Cochran, & LowenKamp, 2002; DeFronzo & Hannon, 1998; Maume & Lee, 2003; Pratt & Godsey, 2002; Savage, Bennett, & Danner, 2008; Savolainen, 2000; Worrall, 2009). These predictors also had significantly negative relationships with violent (Hannon & DeFronzo, 1998a) and property crime rates (Hannon & DeFronzo, 1998a, 1998b; Savage et al., 2008).

Strength of Non-Economic Social Institutions

According to institutional anomie theory (Messner & Rosenfeld, 1994), strength of non-economic social institutions in a society may be negatively related to a crime rate in the society. From this theory, criminogenic social pressures increase when the power of market mechanisms overwhelms non-economic social institutions such as polity, family, education, and religion, which play a critical role in protecting social norms and moral values. This, in turn, may increase crime rates in that the non-economic institutions fail to buffer the criminogenic effects derived from the overwhelming power of the economy (Chamlin & Cochran, 1995; Messner & Rosenfeld, 1994). That is, if the non-economic institutions within a society are stable and strong, the criminogenic pressures generated by the economy can be reduced (Messner & Rosenfeld, 1994; 1997). Although only a few studies that examined effects of non-economic institutions have been conducted thus far, social indicators in this domain were found to have high strength of effects on crime rates (Pratt & Cullen, 2005).

Predictors related to non-economic social institutions include: 1) school dropout rates, percent of population without a high school diploma, or percent of college graduates (education), 2) divorce rates or percent of single parent families (family), 3) church membership rates (religion), and 4) voters' turnout rates (polity). Chamlin and Cochran (1995) examined direct and moderating effects of three non-economic institutions (family, religion, polity) on state-level property crime rates. They measured non-economic institutions with rates of divorce (family), church membership (religion), and voters' turnout (polity). They found that some of the non-economic institutions — religion and family — had direct effects on property crime rates, and all the three variables of interest significantly buffered effects of poverty on property crime rates. Schoepfer and Piquero (2006) also examined relationships between non-economic institutions — education, polity, and family — and embezzlement. They found that weakened non-economic institutions, education and polity, had a directly positive association with state-level embezzlement rates.

In addition to these studies, other empirical studies also reported that predictors in the domain of non-economic institution had significantly negative relationships with homicide (Bjerregaard & Cochran, 2008; Cochran & Bjerregaard, 2012; Kposowa et al., 1995; Maume & Lee, 2003), overall violent crimes (Kposowa et al., 1995; Piquero & Piquero, 1998), and property crimes (Baumer & Gustafson, 2007; Bjerregaard & Cochran, 2008; Cochran & Bjerregaard, 2012; Kposowa et al., 1995; Piquero & Piquero, 1998; Schoepfer & Piquero, 2006).

Poverty / Absolute Deprivation

Poverty, or absolute economic deprivation, has been of interest in many macro-level studies as a critical concept having a significant association with crime rates. In general, poverty refers to those economic conditions that fail to meet basic human needs including food, clothing, and housing. Thus, high levels of poverty in a society indicate the prevalence of households having difficulties satisfying basic human needs for subsistence. As discussed earlier, poverty is one of the strongest and most consistent correlates of macro-level crime rates (Pratt & Cullen, 2005). Applying a meta-analysis focusing on aggregate-level violent crimes, Hsieh and Pugh (1993) pointed out that 32 out of 41 prior studies (78%) using an indicator related to the concept of poverty had at least moderate strength of effects on violent crime rates. At a cross-national level of analysis, Nivette (2011) also reported that the degree of absolute deprivation, measured by infant mortality rates, was a significant predictor of crime rates cross-nationally.

Poverty has been of interest in social disorganization and macro-level anomie/strain theories as a concept that influences crime rates. In the perspective of social disorganization, poverty has been considered as a structural condition leading to a high crime rate mediated by weakened formal social control (see Warner, 1999). That is, economically deprived communities are more likely to have fewer resources for community institutions providing formal social control such as schools, churches, and local law enforcement agencies, and this weakens formal social control and finally leads to a high crime rate (Kornhauser, 1978). Bursik and Grasmick (1993) also argued that the economically deprived communities have difficulty in soliciting resources provided by agencies located outside of them "for the development of an effective regulatory capacity" (p. 278).

Rather than the lack of control mechanism in a deprived community, macro-level anomie/strain theories emphasize the motivational aspect of crime in a community-level, which is derived from a high poverty rate in the community. In this theoretical perspective, a high crime rate in a deprived community can be explained by an increase in strain of the community residents due to the failure to achieve economic success (Agnew, 1999). In other words, residents of such deprived communities are more likely to feel negative emotions such as frustration or anger since they are more likely to have difficulty in achieving their monetary goals, and their negative emotions, in turn, result in a high crime rate.

In regard to measurement for the concept of poverty, two indicators, 1) the percent of families living below the poverty line and 2) infant mortality rates, have widely been employed in prior empirical studies. In terms of the former, the poverty line is determined by a family income threshold that is calculated it three times the cost of a minimum for food based on the size and type of family. According to the poverty thresholds for 2015, provided by the U.S. Census Bureau, for example, four people families including two minor children with an annual income less than $24,306 are regarded to be in poverty (Proctor, Semega, & Kollar, 2016). Thus, proportions of families below these poverty thresholds can be used as a measure of absolute deprivation. Messner (1983b) found that this measure was positively associated with homicide rates in non-southern cities in the U.S. Patterson (1991) also found that the percent of household below the poverty line was a strong predictor of violent crime rates even when controlling for other structural covariates including economic inequality. In regard to infant mortality rates, some cross-national studies applied this indicator as an indirect measure of poverty because each country has different criteria for measuring poverty. Pridemore (2008, 2011) measured poverty with infant mortality rates and found that it was a strong predictor of homicide rates across countries. He argued that absolute deprivation might be more important than relative deprivation to understand homicide rates across countries.

Using these measures of absolute deprivation, many studies found them to be consistently and positively related to homicide rates (Bailey, 1984; Fowles & Merva, 1996; Hipp, 2007; Jacobs & Richardson, 2008; Kposowa et al., 1995; Kovandzic et al., 1998; Messner, 1983b;

Messner, Raffalovich, & Sutton, 2010; Messner & Tardiff, 1986; Paré & Felson, 2014; Roger & Pridemore, 2013; Williams, 1984). Poverty also had positive relationships with violent (Fowles & Merva, 1996; Krivo & Peterson, 1996; Lieberman & Smith, 1986; Paré & Felson, 2014; Piquero & Piquero, 1998; Smith & Bennett, 1985) and property crimes (Fowles & Merva, 1996; Hannon & DeFronzo, 1998b; Krivo & Peterson, 1996; Paré & Felson, 2014; Piquero & Piquero, 1998), although some studies reported more consistent results for violent crime (Hipp, 2007).

Economic Inequality / Relative Deprivation

Economic inequality, or relative deprivation, refers to a degree of differences in economic conditions such as income and wealth between people or households in a reference group. This concept focuses on the ratio of a person's or a household's absolute economic status compared to those of others. Blau (1977, p.57) pointed out that relative inequality defined "each person's hierarchical position or social resources relative to those of all other persons." In macro-level, it thus evaluates the degree of economic gap between a upper-incomes and a lower-incomes regardless of the degree of economic development or prosperity across societies.

It is widely accepted that a high crime rate is associated with a greater economic gap. In Pratt and Cullen's (2005) assessment, predictors in the domain of economic inequality had moderate strength and consistency of effects on crime rates. Hsieh and Pugh (1993) also pointed out that effects of income inequality on violent crime, especially homicide, had statistical significance, reporting that 28 out of 35 prior studies (80%) examined effects of income inequality on violent crime had moderate to strong strength of effects. Similarly, Nivette (2011) reported that income inequality ratios and indices were proven as strong predictors of homicide rates cross-nationally.

From the perspective of macro-level anomie/strain theories, it is posited that individuals living in a society with a great level of economic inequality are more likely to feel deprivation, frustration, and anger, and this, in turn, may lead to a high crime rate in that society. That is, when individuals perceive that they are in a worse economic condition compared to others as well as that they have only a few legitimately available means to improve their economic circumstances, they are more likely to be frustrated, and this can be a potential motivation to commit crime in a community-level (Agnew, 1999). Thus, a level of economic inequality of a society may influence a crime rate as it is mediated by the criminogenic motivation, a series of negative emotions of members of the society.

In radical criminology, economic inequality has been accepted as a fundamental cause of crime in relation to the contradiction of the capitalist mode of production. In terms of the capitalist mode of production, Marx (1867) pointed out that it is characterized by the exploitation of labor power as a commodity to produce more values. That is, it enables capitalists to exploit laborers in that the former less compensate the latter for their labor power that reproduces additional values: a surplus value. In this contradictory system, the capitalist are becoming wealthier by capital accumulation, while the laborer are being exploited and poorer continuously. This contradiction aggravates economic inequality and relative impoverishment between the two classes: the bourgeoisie and the proletariat. Radical criminologists claim that relative economic deprivation or economic inequality derived from the contradiction of the capitalist means of production shape other types of structural difference such as gender, race/ethnicity, and educational attainment. Based on this perspective, radical criminologists consider economic inequality a critical concept and emphasize that it should be paid more attention to structural relationships between economic inequality, other intervening factors (e.g., racial/ethnic/gender inequality, family disorganization), and crime (Lynch & Michalowski, 2006).

Economic inequality has primarily been measured by the income-based Gini coefficient, which indicates how (un)equally incomes are distributed across a society. The Gini coefficient is one (1.0) when there is maximum inequality in the distribution of income, while it goes zero (0) when income is evenly distributed. Blau and Blau (1982) measured economic inequality as the Gini coefficient based on family annual incomes, and tested its effect on violent crime rates. They reported that income inequality had a consistently positive association with murder and assault rates controlling for other relevant predictors including poverty, racial composition, family disruption, and socioeconomic status inequality in race. Based on a pooled time-series and cross-sectional dataset of metropolitan areas in 1975-1990, Fowles and Merva (1996) reached a similar conclusion. Their findings showed that income inequality measured by the Gini coefficient had a robust relationship with murder/manslaughter and assault rates. Along with the income-based Gini coefficient, some studies applied multiple types of income inequality ratio, for example, the ratio of the average income of the top 10% to the bottom 10%.

In addition to the Gini coefficient, Kovandzic and colleagues (1998) applied two other inequality indicators: 1) the ratio of the income shared by the top 20% families to the one shared by the lowest 20% families, and 2) the percent of income shared by top 20% families. In SMSA-level, they found that all these three indicators were significantly associated with homicide rates. Using cross-national panel data, Fajnzylber, Lederman, and Loayza (2002) examined effects of several alternative measures of economic inequality, one of them include the income ratio of the fifth quintile to the first quintile, on both murder and robbery rates along with the Gini coefficient. They also found that the income inequality ratio significantly predicted both homicide and robbery rates as the Gini coefficient did.

Most of the prior macro-social empirical studies of crime rates have examined the effects of relative deprivation. In these studies, economic inequality had consistently significant and positive associations with homicide (Altheimer, 2008; Harer & Steffensmeier, 1992; Hipp, 2007; Jacobs & Richardson, 2008; Kposowa et al., 1995; Krahn, Hartnagel, & Gartrell, 1986; Messner, 1980; Messner, Raffalovich, & Shrock, 2002; Pratt & Godsey, 2002, 2003) and other violent crimes (Harer & Steffensmeier, 1992; Hipp, 2007; Kelly, 2000; but see Patterson, 1991). However, these predictors tend to show inconsistent relationships with property crime rates (Kelly, 2000; Patterson, 1991; Stack, 1984).

Unemployment

Effects of unemployment on crime rates have been subject to criminological discussions for long time. If a society has many people who do not have a job, it is expected to show a high crime rate since unemployment is likely related to macro-level strain (Agnew, 1999) derived from economic deprivation (e.g., Bursik & Grasmick, 1993; Devine, Sheley, & Smith, 1988). In the routine activities theory perspective, on the other hand, unemployment has been considered as a protective factor of crime victimization. Since a greater proportion of unemployed population directly decreases periods of household vacancy, a greater unemployment rate leads to increased guardianship and decreased criminal opportunities, and this, in turn, reduces crime rates (Cantor & Land, 1985; Land et al., 1990).

Findings from systematic reviews of empirical studies reflect these contrasting assumptions and results as well. Chiricos (1987) argued that a positive relationship between unemployment and crime had been found in previous empirical studies. Reviewing more than

60 macro-level studies on the relationship between unemployment and crime, he concluded that a greater unemployment rate consistently predicted greater property crimes (larceny and theft), while it did not seem to apply to violent crimes (murder and robbery). Pratt and Cullen (2005) reported that several types of unemployment indicator, for example, age-restricted and length-considered unemployment rates, had low consistency of effects on crime, although its strength was moderate to high. Nivette (2011) also found that predictors in the domain of unemployment failed to report a significant mean effect size among cross-national homicide studies.

In terms of measures, two types of unemployment indicator have been applied in prior studies: 1) total unemployment rates, 2) gender, education, or age-specific unemployment rates (e.g., male, non-college-educated, 16-24 age group's unemployment rates), and 3) under-employment or labor instability index. Using time-series data for the U.S. 1946-1982, Cantor and Land (1985) examined contemporaneous and lagged effects of unemployment rates on multiple crime rates (murder, rape, robbery, assault, burglary, larceny-theft, auto-theft). They found negative contemporaneous effects of unemployment on murder, robbery, burglary, larceny-theft, auto-theft, while its positive lagged effects were only significant for robbery, burglary, and larceny-theft. Using state-level panel data from 1971 to 1997, Raphael and Winter-Ebmer (2001) also found that state-level unemployment rates had significantly positive effects on property crime rates (burglary, larceny, and auto-theft). Although unemployment did not have a significant effect on violent crime rates in general, they found that rape was predicted by unemployment rates.

In terms of age-specific unemployment, Britt (1997) applied five types of age-specific unemployment rate (16-17, 18-19, 20-24, 25-34, and 35-44 years) and examined their effects on arrest rates of Uniform Crime Report index crime. For homicide and assault, unemployment rates of three groups (16-17, 18-19, and 20-24 years) showed negative effects, while the oldest group (25-34 years) had a positive relationship with both homicide and assault rates. Gould, Weinberg, and Mustard (2002) focused on effects of gender and education specific unemployment rates on crime. They pointed out that unemployment for young and unskilled men dramatically increased in the 1980s, and improved in the 90s, which was the period when crime rates increased as well. They found that a change in the unemployment rates of non-college-educated men consistently had a positive effect on property crime rates across states and metropolitan areas.

To examine effects of unstable employment, or under-employment, as well as unemployment, Crutchfiled (1989) proposed the labor instability index and examined its effect on crime rates. The index was computed by a combination of the unemployment rates and the percent of employed persons with secondary occupations such as equipment cleaners, helpers, and laborers. He reported that the index had significantly positive associations with murder, assault, rape, and robbery rates across neighborhoods in Seattle, Washington. Similarly, Allan and Steffensmeier (1989) employed the percent of part-time employment as a measure of under-employment and found that under-employment was significantly and positively associated with arrest rates of robbery, burglary, larceny, and auto-theft for young adults (18-24) across states.

According to prior empirical studies using unemployment predictors, these studies found that unemployment was significantly and positively related to both violent and property crime rates (Hannon & DeFronzo, 1998a; Hooghe, Vanhoutte, Hardyns, & Bircan, 2011; Kposowa et al., 1995; Raphael & Winter-Ebmer, 2001; Rosenfeld, 1986; Savage et al., 2008).

Some studies examined its effects on homicide rates (Jacobs & Richardson, 2008; Kennedy, Silverman, & Forde, 1991; Land et al., 1990; McCall, Land, & Parker, 2010), property crime rates (Jacobs, 1981; White, 1999), or total index crime rates (Cappell & Sykes, 1991) respectively, and found significant relationships between unemployment and each type of crime rates. However, some other studies found that unemployment predictors had an inverse relationship with homicide rates (Kennedy et al., 1991; Land et al., 1990; Rosenfeld, 1986).

Deterrence

From the deterrence perspective, three elements of punishment — certainty, severity, and celerity — decrease crime rates because potential criminals are assumed to be rational and avoid committing crime when they are likely to get caught, be punished immediately, and receive longer sentences (Gibbs, 1968; Zimring & Hawkins, 1973). Macro-level studies within this perspective have specifically been interested in the certainty and severity of punishment, and their deterrent effects on aggregate-level rates of crimes (e.g., Gibbs, 1968; Tittle, 1969). Macro-level indicators based on the concepts of certainty and severity of punishment (e.g., incarceration rates, arrest rates, clearance rates, or law enforcement officers per capita) have been employed by prior empirical studies to examine their deterrent effects on crime rates. Some scholars argued that these predictors were consistently associated with crime rates (Blumstein et al., 1978; Nagin, 1998). Pratt and Cullen (2005) also pointed out that some predictors in this domain had high strength and consistency of effects on crime (e.g., effects of incarceration), although others had relatively weak strength and low consistency of effects (e.g., effects of law enforcement activity).

Predictors in this domain may include: 1) rates of prison population per 100,000 people, 2) arrest rates, and 3) size of or expenditures for law enforcement. As for the prison population, Levitt (1996) found its significant effects on both violent and property crime rates. According to his study, locking up one criminal leads to a decrease in fifteen Uniform Crime Report Index I crimes. Using state-level panel data on crime rates and prison populations, Spelman (2008) also pointed out that crime rates and prison populations were closely related to each other. To be specific, an increase in prison populations was associated with a decrease in subsequent crime rates, and an increase in crime rates was associated with an increase in subsequent prison populations. With the respect of arrest rates, Chamlin, Grasmick, Bursik, and Cochran (1992) applied ARIMA models with a city-level time-series dataset and found that an increase in arrest rates significantly reduced robbery, auto-theft, and larceny rates in short-term time lags (e.g., monthly and quarterly data). For the size of law enforcement, Marvell and Moody (1996) measured it with the number of police officer per capita and found that this predictor significantly reduced total crime rates.

In addition to these studies, other empirical studies have examined relationships between predictors in the domain of deterrence and crime rates. Some studies found significant and negative relationships of these predictors with total index crime rates (Cappell & Sykes, 1991; Logan, 1975), homicide rates (Devine et al., 1988; Marvell & Moody, 1999), and other types of economic crime rates (e.g., rates of robbery and burglary; Devine et al., 1988). However, some other studies failed to report its consistently significant relationships with crime rates (Chamlin, 1988, 1991; Parker & Smith, 1979).

Table 3.1 provides a summary of discussions in this section including 1) predictor domains as well as predictors applied in prior empirical studies, 2) relevant criminological theories, and 3) effect direction.

Table 3.1. Summary of the Macro-Social Predictors of Traditional Crime

Domain	*Relevant Theories*	*Predictors Applied*	*Effect Direction*
Racial/Ethnic Composition	Social Disorganization Theory, Conflict Theory	1) Percent of Black or non-White 2) Racial/ethnic heterogeneity index	+
Family Disruption	Social Disorganization Theory, Macro-level Strain Theory, Social Support Theory	1) Divorce rates 2) Percent of single-parent families 3) Percent of female-headed families	+
Household Activity Ratio	Routine Activities/Opportunity Theories	1) Percent of female labor force participation 2) Percent of single-person households	+
		3) Average number of persons per household	-
Residential Mobility and Urbanization	Social Disorganization Theory, Routine Activities/Opportunity Theories	1) Percent of population living in the same place for less than three years 2) Percent of population who moved into an area in the last five years 3) Percent of people living urban areas	+
Economic Social Support	Social Support Theory	1) Percent of GDP spent on social welfare such as health care, pensions, education, and work-related benefits 2) Amount of charitable donations 3) Decommodification index	-

Table 3.1. Summary of the Macro-Social Predictors of Traditional Crime (Continued)

Domain	*Relevant Theories*	*Predictors Applied*	*Effect Direction*
Strength of Non-Economic Social Institutions	Institutional Anomie Theory	1) School dropout rates (education) 2) Divorce rates (family)	+
		3) Church membership rates (religion) 4) Voters' turnout rates (polity)	-
Poverty/ Absolute Deprivation	Social Disorganization Theory, Macro-level Strain Theory	1) Percent of families (individuals) living below the poverty line 2) Infant mortality rates	+
Economic Inequality/ Relative Deprivation	Macro-level Strain Theory, Radical Theory	1) Income Gini coefficient 2) Ratio of the income shared by the top 20% families to the one shared by the lowest 20% families 3) Percent of income shared by top 20% families	+
Unemployment	Macro-level Strain Theory, Routine Activities/Opportunity Theories	1) Total unemployment rates 2) Gender, education, or age-specific unemployment rates 3) Under-employment or labor instability index	+ or -
Deterrence	Deterrence Theory	1) Rates of prison population per 100,000 people 2) Arrest rates 3) Size of or expenditures for law enforcement	-

Applicability of Macro-Social Indicators to Online Property Crime

While most of the macro-social indicators discussed above are significant predictors of both forms of traditional street crime (violent and property crime), whether these indicators and relevant theories also predict OPC has not been sufficiently addressed. Although traditional crime and OPC have different temporal and spatial attributes, both forms of crime can be understood as a consequence of macro-level criminogenic structures producing motivations and opportunistic situations. Accordingly, existing predictors of traditional crime might also be relevant for explaining the macro-level criminogenic structure of OPC because some theoretical concepts explain a crime regardless of its type. In this section, therefore, the applicability of the existing macro-social predictors of traditional street crime to OPC is discussed.

On the other hand, it should also be noted that the unique properties of OPC require addressing macro-social indicators that may be related to the unique opportunity structure for OPC. Put differently, since OPC is basically a crime committed in the virtual space, opportunistic conditions leading to OPC might depend on attributes of virtual spatiality, meaning that potential macro-level opportunity predictors of OPC could be quite different than those affecting street crime. Assessing this possibility would require paying attention to macro-level indicators that are specific to the social-structural dimensions of Internet access as well as the determinants of the physical engineered nature of the Internet. Thus, this section also discusses these probable online opportunity predictors of OPC.

Finally, relationships among the existing predictors of traditional street crime, online-specific opportunities, and OPC are discussed as well. It is possible that macro-social predictors of traditional crime have indirect effects on OPC via online opportunity because macro-level social conditions are also likely to be associated with degrees of quality and quantity of ICT infrastructure. Thus, the possible structural relationships among three subjects are discussed in this section.

Racial/Ethnic Composition and Online Property Crime

For OPC, racial/ethnic composition may affect access to the Internet, and thus affect OPC opportunities for crime and victimization. Prior research has established that computer/Internet access varies across race/ethnic groups. Fairlie (2004) found that Mexican-Americans were only about 30% as likely to have Internet access at home as White. Blacks were also reported approximately 50% of Internet access at home of Whites. Mossberger and colleagues (2006) also found that ethnicity had an independent effect on digital disparities, indicating that Latinos reported significantly lower Internet access at home than non-Hispanic Whites. This finding thus suggests that indicators in the domain of racial/ethnic composition may have a significant association with OPC through online-specific opportunities for these crimes. Thus, in contrast to explanations for street crime, specific measures of racial/ethnic composition such as percent Black or Hispanic would be negatively related to OPC. In this view, racial/ethnic composition is a measure of Internet access and thus opportunities for crime rather than a measure of criminogenic conditions that might stimulate crime.

Family Disruption and Online Property Crime

For street crime, it has been argued that family disruption can affect the extent of informal social control within communities. However, OPC is unlikely to be affected by community level informal social control, since this behavior may occur in both private and virtual settings that are unlikely to be exposed to community informal social control, except, perhaps in locations such as schools and public libraries. Thus, if indicators in the domain of family disruption have a significant effect on OPC, that is likely to related to either or both motivations and opportunities for OPC. For example, OPC could be higher in a community with a high percent of single-parent families because the deprived family setting may lead individuals to negative emotional status such as frustration or anger, and this may also increase the aggregate likelihood of committing OPC in the community. At the same time, however, those types of families are also likely to co-exist in lower income communities which is likely to decrease Internet access. Thus, it is unclear what relationships indicators in this domain would have with OPC.

Household Activity Ratio and Online Property Crime

Indicators of macro-level household structure, or indicators of household activity ratio, can be related to OPC in that these indicators are also likely to be associated with online opportunity. According to the routine activities theory perspective, household structure (e.g., size and type) closely relates to individuals' household activity ratio, and this, in turn, affects opportunities for crime as well as generates guardianship patterns that constrain or enhance crime. Thus, it is possible that household structure indicating more household activities (e.g., low percentages of female labor force participation, single-person households, greater average number of persons per household) can predict a high OPC rate as a greater level of Internet access at home is associated with greater online opportunities. Supporting this idea, Boniwell, Osin, and Renton (2015) also found that individuals having Internet access at home were more likely to have greater household sizes (see also Office for National Statistics, 2016b).

Residential Mobility / Urbanization and Online Property Crime

Studies of traditional street crime have found an association between residential mobility and crime but theoretical explanations in regard to the association are unlikely applicable to OPC. Rather, neighborhoods with a higher residential mobility are likely to have other deprived macro-level characteristics that reduce the likelihood of Internet access (e.g., poverty, concentration of minority groups, low socio-economic status). Individuals living in unstable neighborhoods and with other impaired or detrimental characteristics, are unlikely to possess sufficient and even stable access to the Internet, and perhaps, if residential mobility does have a relationship with OPC, the association would be negative.

Urbanization and urban locations may have a relationship with OPC due to certain characteristics of urban areas such as easier/enhanced access to the Internet (e.g., a broader Internet network coverage; availability in public locations such as libraries or coffee shops), or variability in urban demographical characteristics associated with population groups more likely to access the Internet routinely (e.g., a greater percentage of younger population). According to a survey conducted by the Pew Research Center in 2015 (Horrigan & Duggan, 2015), the percentage of adults who live in a rural area with broadband service was a 55%, while it was a 67% for those living in urban areas and a 70% for those in suburban areas. This suggests that urbanization could increase access to the Internet and thus increase the opportunity for OPC.

Economic Deprivation, Social Support, and Online Property Crime

In theory, various types of economic deprivation (e.g., poverty, economic inequality, and unemployment) and social support (e.g., economic, non-economic) may be applicable to OPC, especially from the perspective of macro-level anomie/strain and social support theories. As discussed previously, a society suffering from absolute/relative economic deprivation or a high unemployment rate is more likely to have individuals with motivations to commit crime as the deprived settings lead them to a high level of strain/frustration. This criminogenic mechanism would not be differently applied to OPC. Likewise, a society providing insufficient (non-) economic social support is also more likely to have a high OPC rate due to the lack of both types of social support alleviating individuals' criminal motivations derived from deprivation.

On the other hand, there is also the possibility that communities where economic deprivation and insufficient social support exist report a lower OPC rate because these deprived settings may be related to under-developed Internet infrastructure, limiting the opportunity for OPC in those communities. For example, it has been found that concentrated poverty limits computers/Internet access significantly controlling for gender, age, race, and income (Mossberger et al. 2006). Similarly, income disparities are also associated with inequalities in technology access (e.g., lower incomes predict less accessibility to the Internet; see DiMaggio et al., 2004).

Therefore, there are two contradictory hypotheses in regard to the relationships between OPC and indicators in the economic deprivation and the lack of social support domains. If these indicators are positively related to OPC, as the case of traditional crime, it would indicate that perhaps the motivations for OPC in those community contexts outweigh factors limiting access to the Internet. In contrast, if these factors are unrelated or negatively to OPC, it could indicate that lack of opportunity is sufficient to suppress motivations for OPC in the context of those communities.

Deterrence and Online Property Crime

Deterrence seems to be applicable to OPC theoretically. From the perspective of deterrence theory, certain, rapid, and harsh punishments can reduce crime regardless of the type of crime so long as offenders are rational. Consequently, rational OPC offenders would avoid committing a crime if they believe that they are likely to be apprehended and punished.

There is no direct measure, however, of the perception of the probability of capture and punishment for OPC, and this potential association can only be measured by variability in real rates of punishment or incarceration. While OPC offenses have been increasing in recent years (see Tcherni et al., 2016), there is no clear evidence that incarcerating offenders deters OPC because total incarceration rates have not been significantly dropped at the same time. It is thus unclear at present whether deterrence and OPC are related.

Potential Online Opportunity Predictors

There might be other potential macro-social indicators which have not been considered as predictors of traditional crime rates but which are likely to have an immediate relationship with OPC perpetration. These potential predictors of OPC are various indicators of Internet-related opportunistic risk factors. In terms of traditional crime, most opportunistic risk factors happen in the face-to-face situation where there is direct physical contact between potential offender(s) and victim(s) (Cohen & Felson, 1979). Thus, certain macro-social conditions leading to the physical contact between motivated offenders and potential victims can be regarded as a macro-level opportunity predictor of traditional crime. As discussed previously, some macro-level indicators, such as household activity ratio employed as macro-level measures of criminal opportunity.

For OPC, however, contacts between potential offenders and victims do not occur the face-to-face but virtually. This difference in how contacts occur, in turn, makes criminal opportunities of OPC distinct from those of traditional crime (Yar, 2005). In other words, since being online is the way for motivated OPC offenders to approach potential victims, the more people who are online, the more who are in a situation to abuse the technology for illegitimate purposes (Grabosky, 2016). Thus, indicators regarding online accessibility such as the extent to which access to the virtual space is available and how convenient or easily access can be achieved are the key measure of OPC opportunistic risk. Certain macro-social conditions allowing people to access the Internet more easily, quickly, or less costly should predict macro-level OPC rates (e.g., Holt et al., 2016; Kigerl, 2012; Maimon et al., 2013; Williams, 2016). As reviewed in the previous chapter, a majority of prior OPC studies utilized some indicators relevant to the concept of Internet/online accessibility as an opportunity predictor of OPC to examine its relationship with OPC, and found that these predictors were consistently and significantly related to OPC perpetration and victimization (Kerstens & Jansen, 2016; Leukfeldt & Yar, 2016; Pratt et al., 2010; Van Wilsem, 2013; Williams, 2016).

The measures of the concept of online accessibility, which have previously been employed by prior macro-level OPC studies, include: 1) Internet users per capita or percent of population using the Internet (Holt et al., 2016; Kigerl, 2012; Williams, 2016), 2) percent of population going online both at home and out-of-home (Song et al., 2016), and 3) percent of population currently using a smartphone (Holt et al., 2016). These predictors indicate greater online accessibility in a country or a state, and they were found to have a significant association with macro-level OPC perpetration and victimization rates. In addition to these measures, there might be other potential online opportunity predictors of OPC. These potential predictors may include the cost of home broadband, the coverage of wired/wireless Internet (e.g. service areas, number of Internet providers), the quality of Internet connection (e.g., speed, stability), and the number of public facilities (e.g., public libraries, community centers) providing public computers for free Internet access. For example, greater Internet accessibility is expected when the cost of home broadband service is less expensive, Internet providers covers broader serviced areas, available networks provide a fast speed and have few issues on disconnection, and public facilities provide more public computers for free Internet access. In sum, these social indicators can capture a degree of online accessibility in a social aggregate. To understand overall structure of macro-level OPC rates, therefore, it is necessary to examine the direct relationships between these measures of online opportunity and rates of OPC.

In addition to direct relationships between these macro-level indicators and OPC, there is also a need to consider that some of the existing macro-social predictors may not influence only OPC directly but indirectly through their effects on online opportunity risks. In other words, these existing predictors may indirectly affect variations in macro-level OPC rates through the online opportunity predictors. Quality and quantity of the ICT infrastructure may vary across social aggregates depending on their social conditions such as socio-demographic characteristics, economic development, or industrial structure (Castells, 2001). As discussed previously, many empirical studies and surveys also found that frequency of Internet access and patterns of Internet activities varied across differences in gender, age, race/ethnicity, education, occupation, location, and socioeconomic status (Fairlie, 2004; Hargittai & Hinnant, 2008; Horrigan & Duggan, 2015; Mossberger, Tolbert, & Stansbury, 2003; Mossberger et al., 2006; Office for National Statistics, 2016b; Ren et al., 2013).

In sum, macro-level indicators of online opportunities based on the concept of Internet/online accessibility are expected to have a significant and direct relationship with OPC because these are necessary preconditions for OPC perpetration. In addition, it is likely that some macro-social predictors of traditional street crime are also closely related to online opportunity indicators because social structural conditions influence ICT infrastructure and online accessibility. That is, these predictors of traditional crime may have an indirect effect on variations in OPC perpetration. Therefore, these two types of relationships relevant to macro-level opportunity risks need to be examined for better understanding of the criminogenic mechanisms of macro-level OPC perpetration.

In this section, to sum, it was discussed whether macro-level predictors of traditional street crime are also applicable in predicting OPC. Table 3.2 summarizes the description of the macro-level street crime and OPC predictors provided above.

Table 3.2. Effect Directions of Predictors of Traditional Crime and Online Property Crime

Predictor Domain	*Effect Direction*	
	Traditional Crime	*Online Property Crime*
Racial/Ethnic Composition (e.g., percent of minority)	+	-
Family Disruption	+	Unclear (+ or -)
(Non-)Household Activity Ratio	+	-
Residential Mobility / Urbanization	+	Unclear (+ or -) for residential mobility but perhaps + for urbanization
Economic Deprivation and Social Support	Economic deprivation (+) Social support (-)	Unclear (+ or -)
Deterrence	-	Unclear (perhaps insignificant)
Online Opportunity	N/A	+

Conclusions

This chapter reviewed macro-social predictors of traditional crime in the domains of: racial/ethnic composition, family disruption, household activity ratio, residential instability/urbanization, economic social support, non-economic social institutions, poverty/absolute deprivation, economic inequality/relative deprivation, unemployment, and deterrence. It specifically focused on discussing what social indicators were employed as a predictor of crime and what relationships these predictors had with macro-level violent and property crimes. Based on the research findings from prior studies, these existing predictors, in general, had significant associations with both violent and property crime rates although some exceptions were also pointed out (e.g., inconsistent relationships between economic inequality and property crime).

This chapter also discussed potential macro-level predictors of OPC. Applicability of macro-social predictors of traditional crime and relevant theoretical assumptions to OPC was discussed. Although some possible predictors are expected to have the same direction of effects as the case of traditional crime (e.g., household activity ratio, urbanization, economic deprivation, social support), most predictors are also likely to be associated with macro-level online opportunity, and this makes it difficult to reckon directions of relationships between the possible predictors and OPC.

It also discussed online opportunity predictors expected to have an immediate relationship with OPC. Since OPC, in general, occurs in the online setting via ICT devices, how easily Internet access is available is the most fundamental concept that the potential online opportunity predictors necessarily include. Thus, macro-level conditions related to ICT infrastructure that can be potential macro-level online opportunity predictors of OPC are addressed. It is also emphasized that these online opportunity predictors might be intervening between the existing predictors of traditional crime and OPC. Thus, it needs to examine relationships between these two types of probable predictor of OPC, and to discuss what implications, if any, the relationship between them would be has to understand the macro-social structure of OPC.

Current Focus of the Study

As discussed above, although it is likely that existing predictors of traditional street crime can also be a significant predictor of OPC, what direction of the effects of the existing predictors on OPC would be is still unclear due to the influence of online opportunity disproportionately structured by various macro-social conditions. In other words, since OPC is a new mode of property crime with the unique attribute, which it does not occur in a face-to-face context but in a virtual space, traditional macro-level criminological theories, especially those emphasizing social control mechanisms in the face-to-face context such as social disorganization theory do not seem to fully account for OPC. It is thus difficult, at least at this point, to hypothesize that what types of relationship (e.g., negative, positive, or null) with OPC each macro-social indicator would have and whether the existing theoretical explanations are applicable to understanding the meaning of the relationships. In this context, it is more appropriate for the current study to focus on exploring probable predictors of OPC and identifying what types of relationship these predictors have with OPC rather than examining generalizability of the relationships by hypothesis testing and confirming theoretical explanations about them. Based on these purposes, this dissertation thus raises the research questions below:

1) *What are the influential macro-social predictors of rates of online property crime (OPC) perpetration? What existing macro-social predictors of crime can predict OPC? Are there any influential online opportunity predictors of OPC? How much variance in OPC can be explained by both types of predictors?*

2) *Are there any influential relationships between the existing predictors and the online opportunity predictors? How much variance in the online opportunity predictors can be explained by the existing predictors?*

In sum, this dissertation examines relationships among three subjects, 1) existing macro-social predictors of traditional crime, 2) potential online opportunity predictors, and 3) rates of OPC perpetration, by applying cross-sectional state-level data in the U.S. The following chapter provides descriptions in regard to data, measurement of variables, and analytic strategies and plans.

CHAPTER FOUR:

METHODS

This dissertation aims to explore probable macro-social predictors for OPC perpetration and examines how much of the distribution in OPC these predictors can explain. For these purposes, it employs the partial least square regression (PLSR) approach to analyze cross-sectional macro-level data, specifically using state-level OPC rates as a response variable and various state-level social indicators of fifty states in the U.S. as predictors. This chapter addresses the sources and attributes of data applied in this study, and provides a description of each variable including the response variable and probable macro-social predictors of OPC. In addition, it discusses analytical strategies and plans, especially focusing on the PLSR approach. Principles of PLSR will be discussed along the reasons why this approach needs to be applied in this dissertation.

Data and Measures

The unit of analysis of this study is a state in the U.S. Other than Washington D.C., the fifty states in the U.S. are subject to analyses in this dissertation. The response variable is the rates of reported OPC perpetration. Existing macro-social predictors of traditional street crime and online opportunity indicators are employed to account for variations in rates of OPC across states as probable predictors of OPC. In addition, socio-demographic characteristics such as macro-level structures of sex, age, population, and economic development are applied as well.

Response Variable: Rates of Online Property Crime

The Internet Crime Complaint Center (IC3) annually provides the rates of online property crime perpetration per 100,000 population across fifty states in the U.S. The current study utilized the IC3 data as a response (dependent) variable. IC3, one of the subunits in the Federal Bureau of Investigation (FBI), receives complaints about cybercrime victimization including information about types of cybercrime and amounts of monetary losses. IC3 forwards these complaints to local or federal law enforcement agencies considering jurisdiction to facilitate investigations of each cybercrime victimization. Based on information collected by these complaints, IC3 annually publishes a report that includes several statistics regarding types of cybercrime, characteristics of victims and perpetrators, and amounts of financial losses. IC3's annual report also provides state-level cybercrime statistics such as the rates of Internet crime complaints and perpetrators per 100,000 population across fifty states in the U.S. Although these statistics include not only OPC but some computer-focused crimes such as hacking, virus, and malware as well, a majority of the reported cybercrime can be categorized into OPC[5]. Even though computer-focused crimes are not a direct form of OPC, additionally, they are, as discussed earlier, often motivated by financial goals. Thus, this dissertation employs the IC3 state-level data on cybercrime perpetration as an indicator for OPC perpetration rates across fifty states in the U.S.

The response variable in this study was measured by the average rates of OPC perpetrators per 100,000 population across fifty U.S. states for three consecutive years from

[5] According to a recent IC3 annual report (2010, p.9), top five crime types reported by referred complaints include non-delivery payment/merchandise fraud (21.1%), identity theft (16.6%), and auction fraud (10.1%), credit card fraud (9.3%), and miscellaneous fraud (7.7%). Computer crimes took 6.1%. Other than computer crime, other types of cybercrime in the top ten crime types seem to have a relationship with OPC. These types of crime include advance fee fraud (4.1%), spam (4.0%), overpayment fraud (3.6%), and FBI-related scam (3.4%).

2007 to 2009. The three-year average OPC rates were applied in that annual fluctuations in reporting are likely to occur. That is, since it is possible that each year indicates an unusually high or low rate of reported OPC, applying the three-year average may reduce a possible random bias. It should also be noted that Washington D.C. is excluded in the analyses because the statistics from Washington D.C. may be inflated by complaints regarding FBI-related scams; that is, complainants who reported FBI-related scams to IC3 may believe that the incident has occurred in Washington D.C., although perpetrators generally commit these scams in another place rather than Washington D.C. (see IC3, 2008). Due to this misconception, it is more advisable to exclude data of Washington D.C. from the analysis to avoid biased results.

Some limitations of IC3 data should be noted. First of all, this dataset does not include all OPC committed in the U.S. As indicated, it is because the IC3's OPC data was only collected when victims report their OPC victimization to the IC3. Thus, this dataset only represents the cases reported to the IC3; actual OPC rates including unreported cases are likely much higher. In addition, although the IC3 receives victims' reports, the dataset only includes a case when the IC3 hands over the victimization reports to local law enforcement agencies. The local agencies then open those cases, begin investigations, and they identify offenders' information such as gender, age, and location. Through this long complicated process, a significant portion of the all reported cases can be omitted. Bias of the data may also occur if there are any significant differences in characteristics of local law enforcement agencies across states (e.g., how much effort they give to OPC cases, whether they have advanced technological skills or ample resources to enforce/investigate OPC, etc.). It is also possible that the dataset includes many missing cases because Internet offenders can commit cybercrime anywhere, even outside of the country. If it is the case, the IC3 data drops the case and this, in turn, may be able to represent only a part of OPC offenses. This issue becomes more problematic if there are more cybercriminals who live outside of the country and target victims living in the U.S. In sum, these limitations need to be considered when research findings are discussed.

Possible Predictors: Macro-Social Indicators

Racial / Ethnic Composition. In the domain of racial/ethnicity composition, three indicators are used: 1) percent Black, 2) percent Hispanic-origin, and 3) percent Non-Hispanic White populations. These indicators were estimated from Census data collected in 2008 (U.S. Census Bureau, 2010, p.8).

Family Disruption. Three indicators related to family disruption are applied: 1) divorce rates[6], 2) percent of female-headed households, and 3) percent of single-parent households with children under 18 years. State-level data during 2005-2007 were utilized for the two indicators, divorce rates (National Center for Health Statistics), and female-headed households (U.S. Census Bureau, 2010, p.9). For the proportion of single-parent households with minor children, U.S. Census data collected in 2010 was employed (U.S. Census Bureau, 2012, p.10).

Household Activity Ratio. Three indicators on the concept of household activity ratio applied in this study are: 1) percent of female labor force participation, 2) percent of single-person households except 65 years and over, and 3) average number of people per household. All three indicators were obtained from the U.S. Census data (2010). The percent of female labor force participation was collected in 2008 (p.33). The percent of single-person households and the average number of people in household were measured during 2005-2007 (p.9).

[6] Six states — California, Georgia, Hawaii, Indiana, Louisiana, and Minnesota — do not report divorce rates. To impute these missing values, predictive mean matching (PMM) imputation was applied by using five relevant variables: 1) percent of female-headed household, 2) percent of single-parent household, 3) percent of female employment, 4) percent of single-adult household, and 5) average number of people in household.

Residential Mobility / Urbanization. This domain has four macro-social indicators: 1) percent of population who lived in the same house one year ago, 2) percent of population living in the state where they were born, 3) percent of population living in an urban area, and 4) percent of the land urbanized in the state. Regarding the percent of people who lived in the same house one year ago, it measures the difference between two years, 2008 and 2009 (U.S. Census Bureau, 2012, p.38). The other three indicators, lifetime mobility (Ren, 2011), urban population, and urban land use (see the website below[7]) were estimated by the 2010 U.S. census data.

Economic Social Support. Five indicators in the domain of economic social support were employed: 1) percent of welfare expenditure to the state's total gross domestic product (GDP), 2) percent of education expenditure to the state's total GDP, 3) percent of welfare expenditure to the state's total expenditure, 4) percent of education expenditure to the state's total expenditure, and 5) percent of total amount of charitable contribution to adjusted gross income. To measure these indicators, state-level GDP data in 2007 provided by the U.S. Bureau of Economic Analysis and state governments' expenditure data in 2007 (U.S. Census Bureau, 2010, p.90) were utilized. Regarding the indicator of charitable contribution, data were measured in 2009 and provided by the Urban Institute (2011).

Strength of Non-Economic Social Institutions. Three macro-social indicators relevant to the concept of strength of non-economic social institutions were applied: 1) percent of people aged 25 and older who do not have a high school diploma (education), 2) voter turnout in the 2008 presidential election (polity), and 3) percent of religious adherents (religion). The education attainment was represented by the data collected during 2005-2007. Two indicators

[7] http://www2.census.gov/geo/docs/reference/ua/PctUrbanRural_State.xls

regarding education and polity were provided by the U.S. Census Bureau (2010, pp.25, 101). For religious adherents, the Religious Congregation and Membership Study (RCMS; see Grammich et al., 2012) provides relevant data applied in this study. The original data were collected in 2010.

Poverty / Absolute Deprivation. The domain of poverty, absolute deprivation, includes three macro-social indicators: 1) percent of families under the poverty line, 2) percent of individuals under the poverty line, and 3) rates of infant mortality. Both indicators manifesting the proportions of families and individuals below the poverty line were obtained by census data during 2005-2007 (U.S. Census Bureau, 2010, p.40). Infant mortality indicates the rate of infant mortality per 1,000 live births in 2009 (Mathews & MacDorman, 2013).

Economic Inequality / Relative Deprivation. Four indicators relevant to the concept of economic inequality are applied: 1) Gini coefficient of income inequality, 2) percent of the top 1% share of all income, 3) change of percent points in income share of the top 1% during 1979-2007, and 4) ratio of incomes between top and bottom 20% of households during 2008-2010. Gini coefficients of income inequality across states were measured by the average of Gini coefficients during five years, from 2005 to 2009, which is provided by the results of the American Community Survey (Weinberg, 2011). Top 1% share indicates their portions of all income in 2007. Also, the change in income share of the top 1% during 1979-2010 was added because it reflects a change in income inequality across states over time. Both indicators were provided by Sommeiller and Price's (2015, pp.16-17) study. To include a broader range than top 1%, the ratio of average incomes between top and bottom 20% of households during 2008-2010 was also applied (McNichol, Hall, Cooper, & Palacios, 2012, p.17).

Unemployment. U.S. Bureau of Labor Statistics (BLS) provides six alternative measures of unemployment rates to capture labor underutilization (see their website[8] for details). In the current study, two indicators are employed: 1) total unemployment rates, and 2) total unemployment rates including discouraged workers. For the former indicator, which is officially utilized unemployment rate and referred to as U-3 unemployment rate, it is defined as the percent of total unemployed to the civilian labor force. The U.S. BLS defines the unemployed as "all jobless persons who are available to take a job and have actively sought work in the past four weeks." The latter, which is also referred to as U-5 unemployment rate, covers all marginalized working conditions in addition to the total unemployed population. The U.S. BLS defines this indicator as "total unemployed, plus discouraged workers, plus all other marginally attached workers, as a percent of the civilian labor force plus all marginally attached workers." Discouraged workers are defined as "persons who are not in the labor force, want and are available for work, and had looked for a job sometime in the prior 12 months." Marginally attached workers include discouraged workers, "with the exception that any reason could have been cited for the lack of job search in the prior four weeks." For both indicators, the average of annual data from 2005 to 2007 was applied.

Deterrence. In the domain of deterrence, three indicators were employed in this dissertation: 1) rates of incarceration, 2) change in prison population across states, and 3) tightness/looseness index. The rate of incarceration indicates the number of prisoners per 100,000 population across states in 2008 (Sabol, West, & Cooper, 2009). The change in prison population refers to the percentage of the difference in prison population between 2008 and 2009 to prison population in 2008 (Sabol et al., 2009; West, Sabol, & Greenman, 2010). For

[8] https://www.bls.gov/lau/stalt.htm

tightness/looseness index, the concept of tightness/looseness is defined as "the strength of punishment and the degree of permissiveness in a social system." (Harrington & Gelfand, 2014, p.7991) It is the composite index of several state-level social indicators related to strengths of punishment (e.g., rate of executions, the legality of corporal punishment in school), latitude/permissiveness (e.g., the legality of same-sex civil union), and reinforcement of moral order (e.g., religiosity) across states (see Harrington & Gelfand, 2014, p.7991 for more details). Thus, this index can be expected to manifest overall strength of deterrence in a society through not only formal punishment but cultural and implicit forms of social control as well.

Online Opportunity Indicators. Four online opportunity indicators were employed as probable predictors of OPC: 1) percent of households using Internet at home, 2) percent of households using Internet anywhere, 3) number of public-use Internet computers in public libraries, and 4) frequency of uses of public-use Internet computers in public libraries. The first two predictors indicate Internet accessibility of households across states from 2007 census survey (U.S. Census Bureau, 2010, p.82). The other two predictors related to public libraries were obtained from a survey of public libraries conducted in 2009 (Miller et al., 2011, pp. 81-82). The number of public-use Internet computers in public libraries refers to the number of public-use Internet computers in public libraries per 5,000 people. The frequency of uses of public-use Internet computer in public libraries indicates how frequently Internet computer in public libraries have been used by visitors of public libraries in 2009.

Socio-Demographic Structure. Four indicators relevant to socio-demographic structure were included in this study as well: 1) total population, 2) sex ratio, 3) age structure, and 4) total gross domestic products (GDP). Total population was measured by each state's population in 2008 (U.S. Census Bureau, 2010, p.3). Sex ratio refers to the ratio of males to

100 females in 2008 (U.S. Census Bureau, 2010, p.6). Age structure is the percent of population between 18 and 65 years to total population in 2008 (U.S. Census Bureau, 2010, p.6). GDP was obtained from state-level GDP data in 2007 provided by the U.S. Bureau of Economic Analysis as addressed previously.

Table 4.1 summarizes the variables addressed above. Abbreviated names for each variable are provided as well.

Table 4.1. Summary of the Variables Applied in the Current Study

Variable domain	*Indicators*
Online Property Crime	1) Average rates of online property crime 2007-2009
Racial/Ethnic Composition	1) Percent of Black 2) Percent of Hispanic-origin 3) Percent of Non-Hispanic White populations
Family Disruption	1) Divorce rates 2) Percent of female-headed households 3) Percent of single-parent households with children under 18 years
Household Activity Ratio	1) Percent of female labor force participation 2) Percent of single-person households except 65 years and over 3) Average number of people per household
Residential Mobility / Urbanization	1) Percent of population who lived in the same house one year ago 2) Percent of population living in the state where they were born 3) Percent of population living in an urban area 4) Percent of the land urbanized in the state
Economic Social Support	1) Percent of welfare expenditure to the state's total gross domestic product (GDP) 2) Percent of education expenditure to the state's total GDP 3) Percent of welfare expenditure to the state's total expenditure 4) Percent of education expenditure to the state's total expenditure 5) Percent of total amount of charitable contribution to adjusted gross income

Table 4.1. Summary of the Variables Applied in the Current Study (Continued)

Variable domain	*Indicators*
Strength of Non-Economic Social Institutions	1) Percent of people aged 25-older who don't have a high school diploma (education) 2) Voter turnout in the 2008 presidential election (polity) 3) Percent of religious adherents (religion)
Poverty / Absolute Deprivation	1) Percent of family under the poverty line 2) Percent of individuals under the poverty line 3) Rates of infant mortality
Economic Inequality / Relative Deprivation	1) Gini coefficient of income inequality 2) Percent of the top 1% share of all income 3) Change of percent points in income share of the top 1% during 1979-2007 4) Ratio of incomes between top and bottom 20% of households during 2008-2010
Unemployment	1) Total unemployment rates 2) Total unemployment rates including discouraged workers
Deterrence	1) Rates of incarceration in 2008 2) Change in prison population across states (2008-2009) 3) Tightness/looseness index
Online Opportunity	1) Percent of households using internet at home 2) Percent of households using internet anywhere 3) Number of public-use internet computers in public libraries 4) Frequency of uses of public-use internet computers in public Libraries
Socio-demographic Structure	1) Total population 2) Ratio of males to 100 females 3) Percent of population between 18-65 years 4) Total GDP

Analytic Strategies and Plans: Partial Least Square Regression

Overview of Partial Least Square Regression

To explore macro-social predictors of OPC and examine how much variance in OPC can be explained by these predictors, this dissertation applies the approach of partial least squares regression (PLSR). PLSR is one of the statistical techniques based on the partial least square (PLS) algorithm initiated by Herman Wold (see Wold, 1973, 1976, 1980a, 1980b, 1985), a Swedish econometrician and statistician. It has been advanced by Svante Wold (see Wold, Martens, & Wold, 1983; Wold, Ruhe, Wold, & Dunn, 1984), a son of Herman Wold, and has primarily been applied by research in Chemistry. Recently, some areas in social science such as marketing and organization studies have been using PLSR as well as partial least squares path modeling (PLSPM; or PLS-SEM), which is another approach based on the PLS algorithm (Sosik, Kahai, & Piovoso, 2009). The PLS algorithm, often referred to as soft-modeling, is designed to examine relationships between observed predictors and response variables without parametric inference, especially when the number of predictors is greater than the number of cases (Falk & Miller, 1992; Jöreskog & Wold, 1982; Wold, 1980b).

The approach of classical statistics such as ordinary least square (OLS) regression and structural equation modeling (SEM) have been widely applied in social science studies. This approach, which is also referred to as hard-modeling, aims to examine multivariate relationships between independent and dependent variables relevant to theoretical concepts based on some statistical assumptions for inferential statistics, especially null-hypothesis significance testing (NHST). That is, the hard-modeling approach focuses on examining whether relationships between variables of interest observed from sampled data can be generalized to a population as it estimates parameters (Thompson, 2013). The problem is, the hard-modeling approach is underpinned by several unrealistic assumptions. For example, the hard-modeling approach requires data to meet assumptions such as multivariate normality, independence between variables, homoscedasticity of error variance, and a large sample size to estimate parameters efficiently and unbiasedly. However, social science studies often employ data that violate these assumptions due to many limitations in the process of data collection. Violation of these assumptions may lead to inefficiency for NHST and biased estimation of parameters (Wilcox, 1998).

In contrast, the soft-modeling approach focuses on how effectively probable predictors and their latent structures account for variance in response variable(s) within observed data (Falk & Miller, 1992; Lohmöller, 1989). Put differently, it is the data-oriented and non-parametric approach that concentrates more on identification of predictors and latent structures to maximize predictability of response variable(s) confining its implications to a sample (predictability) rather than a population (generalizability). The soft-modeling approach can be liberalized from the strict and unrealistic assumptions as it discards the goal of generalization, which is the idea that characteristics of a population can be extrapolated by a sample when the sample approximates a known distribution of the population (Falk & Miller, 1992). While the soft-modeling does not perform the purpose of generalization, it still provides useful information regarding what predictors have greater effects on response variable(s) and how much variance in response variable(s) is explained by the predictors. Thus, the soft-modeling approach can be more appropriate to examine relationships between variables when relevant theories do not exist or they are undeveloped thus development of a new theory is needed (Falk & Miller, 1992; Hair, Hult, Ringle, & Sarstedt, 2016; Lohmöller, 1989). In sum, the soft-modeling approach can be used to identify an undiscovered structure of research interest when relevant theories are underdeveloped and prior studies are insufficient, and to predict variance in response variable(s) depending on observed predictors within the sampled data.

Specifically, PLSR can be a useful approach especially when 1) there are a number of predictors, 2) these predictors are highly correlated with each other, and 3) a size of case, or sample size, is relatively small (Garthwaite, 1994; Sawatsky, Clyde, & Meek, 2015; Sosik et al., 2009). Using OLS regression under these circumstances makes it difficult to control multicollinearity as generating greater error variance due to both interdependent relationships between variables and a small sample size, and this may, in turn, result in inefficient results of the significance test and biased estimates. Taking an example from the covariance-based structural equation modeling, often referred to as SEM or LISREL, it also requires a large sample size (n= 200-400) to estimate parameters because of its estimating method, a maximum likelihood estimation (Jackson, 2001).

In contrast, PLSR responds to these methodological issues with two steps. First, it constructs a latent component(s) maximizing explained variance in a response variable by applying a weighted linear combinations of observed variables. Through the least square estimation, the response variable is subsequently regressed on the constructed latent components (Abdi, 2007). Regression coefficients of the latent components and the percentage of explained variance in the response variable are estimated by the ordinary linear regression. This procedure sounds similar to principal component analysis (PCA), which is one of the data reduction techniques producing fewer numbers of components based on communalities that explanatory variables share with one another. The difference between PCA and PLSR is how component variables are constructed. That is, PCA only uses explanatory variables or predictors (x-variables) to extract their communalities and to construct component variables, while PLSR includes, to produce component variables, correlations between a response variable (y-variable) and predictors (x-variables) in addition to the communalities among predictors. Through this procedure, it extracts the latent components to maximize explained variance in the response variable (Mateos-Aparicio, 2011). Reducing the number of explanatory variables, critical issues about multicollinearity and small sample sizes become controllable. PLSR is also free from the assumption of normality because components calculated by linear combinations have normality according to the central limit theorem (Sosik et al., 2009; Wold, 1985).

Application of Partial Least Square Regression to the Current Study

These attributes of PLSR are the reasons that PLSR needs to be applied in this study. Since no macro-level theories explaining a structure of OPC rates have been proposed thus far, the current study does not attempt to examine validity and reliability of macro-level criminological theories in explaining macro-level OPC but aims to explore relevant macro-social predictors and a latent structure constructed by these possible predictors of OPC. With this purpose, PLSR is more appropriate as it does not assume a known distribution of a population. As mentioned previously, the soft-modeling is more advisable for searching for unidentified variables (Falk & Miller, 1992; Hair et al., 2016; Lohmöller, 1989).

In addition, an application of PLSR is also preferred for this study due to the units of analysis, fifty states in the U.S. Since state-level data that indicate many macro-social characteristics of fifty states in the U.S. are employed in this study, it does not have to be a study that estimates characteristics of a population by applying inferential statistics because observed data used in this study can be regarded as a population. In other words, this study pays more attention to predictability of a number of macro-social indicators of OPC and their capabilities to explain variance in OPC within the observed data of the fifty states in the U.S. rather than estimating parameters and generalizing research findings into a population. In this context, statistical approaches with PLS algorithm are highly recommended (Lohmöller, 1989).

This study also has a small number of observation (n=50) but a relatively large number of predictors (n=41). This is problematic in the hard-modeling approach because of a low statistical power (greater error variance due to a small sample size) and inefficiency of estimating coefficients (multicollinearity due to a large number of aggregate-level predictors). With this data structure, PLSR can be a useful method to examine relationships between variables because it generally provides best results when there are many predictors and the size of error variance is large (Garthwaite, 1994).

While PLSR can be a good choice for the current study considering its research purpose and data structure, some limitations of the soft-modeling approach with the PLS-algorithm should also be discussed. It should be foremost noted that the soft-modeling approach including PLSR does not consider measurement error of observed variables (Goodhue et al., 2012; Rönkkö & Evermann, 2013). On the other hand, covariance-based SEM (or LISREL) allows for entering measurement error into an equation for modeling thus guarantees an advanced level of certainty or generalizability when it comes to examining relationships between variables based on a given theory. As with OLS regression, results of PLSR thus are more likely to be biased due to the absence of the consideration of measurement error. This is one important reason that the soft-modeling approach is not recommended to test a theoretical model. Despite this methodological limitation, the current study can apply PLSR since it focuses on exploring possible predictors of OPC and a preliminary model for predicting OPC rather than examining generalizability of criminological theories in regard to OPC.

Some criticisms of the argument that the soft-modeling approach is robust in the contexts of using small-sized samples or non-normality data have also been raised. That is, there is no firm evidence that the approach with PLS-algorithm guarantees a greater statistical power for small-sized samples or data with non-normality compared to other statistical techniques such as OLS and SEM (Goodhue et al., 2012; Rönkkö & Evermann, 2013; Rönkkö, McIntosh, & Antonakis, 2015). These criticisms seem to be related to concerns about the growing popularity of the approach with the PLS-algorithm, mostly PLS-SEM. Recently, many empirical studies applying small-sized samples have tended to adopt the soft-modeling approach, insisting that it is robust for a small-sized sample. However, the soft-modeling approach, as discussed previously, produces results more efficiently for data with fewer observations as it abandons the purpose of generalizability. In other words, the benefit of those loose assumptions is achieved at the expense of generalizability of results, thus the results should not be utilized for a global application but limited to data-specific predictability within a sample. For instance, if a study has a small-sized individual-level sample but still pursues testing a theory and generalizability of the results, the soft-modeling cannot be an alternative because results of the study cannot be simply extrapolated to a global population. The current study, by contrast, is not subject to these criticisms. As discussed above, the unit of analysis of the current study is fifty states in the U.S. and the data employed covers all the fifty U.S. states. Therefore, generalization of the results based on NHST is not necessary for the current study, especially in the context of the number of observations (n=50), but data-driven predictability is sufficient to identify relationships between variables as the data employed is equal to a population (Lohmöller, 1989).

Plan of Analysis

To examine bivariate relationships between variables, Spearman's rank-order correlations will be reported since some of the variables employed in the current study including OPC rates appear to have non-normality with high skewness and kurtosis (see Table 5.1 in Chapter Five), For multivariate PLSR analyses, two types of relationships are examined: 1) relationships between OPC and macro-social indicators, and 2) relationships between a composite of online opportunity indicators and macro-social indicators. PLSR modeling for these two types of relationships includes two stages of analyses. For the initial analysis, it aims to select an optimal number of latent components through cross-validation and to identify best possible predictors of the response variable, including all possible predictors in the model. In terms of cross-validation, it estimates the predictability of potential models and provides information about an optimal number of latent components. The initial PLSR model computes PRESS (predicted residual sum of squares) values for each model with different numbers of latent components and the model with the lowest PRESS will be considered the best model in the perspective of parsimony (Garson, 2016; Sawatskyet et al., 2015). For the selection of possible predictors, VIP (variable importance in projection) values, which indicate relative importance of each predictor for a latent component(s), is utilized to identify influential predictors of each response variable (OPC and online opportunity). The greater VIP values the more influential. If a predictor has a VIP value more than 1.0, the predictor is considered an influential predictor. Possible predictors with VIP less than 0.8 will be eliminated at the initial stage (Garson, 2016; Sawatskyet et al., 2015; Wold, 1995).

For the second stage of PLSR analysis, all influential predictors other than eliminated predictors (VIP less than 0.8) will be included in the model and re-analyzed. As in the initial model, results of cross-validation and VIP values will be reported in the second model. In addition, although a parametric significance test is not available in PLSR, a non-parametric test by applying a bootstrapping method can be conducted. Thus, both standardized and unstandardized regression coefficients, and significance of those coefficients for each predictor will be reported as well based on the results of bootstrapping with 500 replications. Finally, it compares state-by-state predicted values of both OPC and online opportunity computed by PLSR modeling to actual values of them to examine how well the PLSR models predict those actual values and what states are outliers with predicted values significantly deviated from the actual values.

In the following chapter, it provides descriptive statistics of each variable including state-by-state OPC rates. It also reports results of Spearman's rank-order correlation matrix to identify bivariate relationships with variables. As for multivariate relationships, PLSR modeling examines relationships between possible predictors and latent components, and their relationships with OPC. For all PLSR analyses, a statistical software package with PLSR modules, Tanagra 1.4, is applied.

CHAPTER FIVE:

RESULTS

This chapter reports findings of several bivariate and multivariate analyses examining relationships between OPC rates and an array of macro-social indicators including predictors of traditional crime and indicators of online opportunity. This chapter begins by providing descriptive statistics for the response variable (OPC rates) and macro-social predictors. This is followed by bivariate relationships among these variables. Finally, partial least square regression (PLSR) models are employed to examine the multivariate relationships between OPC and these macro-social indicators. Through these examinations, the current study identifies influential indicators of both OPC perpetration rates and online opportunity structures, and examines how effectively these indicators predict both types of response variables.

Descriptive Statistics

Table 5.1 reports the means, standard deviations, minimum and maximum values, and skewness and kurtosis for 42 variables (1 response variable and 41 possible predictors) employed in the current study. The mean and standard deviation of the rate of OPC perpetrators per 100,000 population across fifty states in the U.S. 2007-2009 are 27.29 and 13.26 respectively.

Table 5.2 and Figure 5.1 provide state-by-state information about the response variable. Table 5.2 reports that the state of *Nevada* had the highest figure (84.34) followed by *Washington* (56.22), *Montana* (49.28), *Florida* (48.56), and *Delaware* (48.34), while the state of *Mississippi* reported the lowest OPC rate (10.32) followed by *Louisiana* (14.54), *Arkansas* (14.66), *Wisconsin* (15.11), and *West Virginia* (15.34). Figure 5.1 shows a histogram displaying OPC rates in descending order from left to right by state. Top 10 states with the highest OPC rates include: *Nevada, Washington, Montana, Florida, Delaware, Utah, New York, California, Arizona,* and *Wyoming*. Bottom 10 states with the lowest OPC rates are: *Mississippi, Louisiana, Arkansas, Wisconsin, West Virginia, Iowa, New Mexico, Kentucky, South Carolina,* and *Oklahoma*.

Table 5.1. Descriptive Statistics

Variables	*Mean*	*S.D.*	*Min*	*Max*	*Skewness*	*Kurtosis*
Online Property Crime rates	27.29	13.26	10.32	84.34	2.03	8.36
Percent Black population	10.53	9.52	.70	37.20	1.08	3.29
Percent Hispanic population	9.86	9.83	1.10	44.90	1.94	6.32
Percent Non-Hispanic White population	73.06	15.19	24.90	95.30	-.85	3.64
Divorce rates	3.94	1.00	2.27	6.93	.65	3.19
Percent female-headed households	11.73	2.18	7.40	18.20	.42	3.37
Percent single-parent households with children under 18 years	9.34	1.07	7.40	12.40	.60	3.32
Percent female labor force participation	57.88	4.44	48.40	68.10	.29	2.55
Percent single-person households except 65 years and over	18.06	1.32	13.30	21.00	-.84	5.08
Average number of people per household	2.55	.15	2.25	3.12	1.38	5.77
Percent population who lived in the same house one year ago	58.11	12.12	24.30	78.80	-.51	2.77
Percent population living in the state where they were born	84.27	2.47	77.70	90.10	-.19	3.35
Percent population living in an urban area	73.58	14.57	38.66	94.95	-.45	2.55
Percent land urbanized in the state	7.41	10.39	.05	39.70	2.22	6.97
Percent welfare expenditure to state's total GDP	2.82	.84	1.25	4.96	.77	3.11
Percent education expenditure to state's total GDP	4.04	1.15	2.27	8.70	1.56	6.81
Percent welfare expenditure to the state's total expenditure	22.54	4.17	13.45	32.28	.03	2.96
Percent education expenditure to the state's total expenditure	32.40	5.16	21.59	43.11	-.08	2.31
Percent total amount of charitable contribution to adjusted gross income	2.03	.55	1.20	4.60	2.12	10.98

Table 5.1. Descriptive Statistics (Continued)

Variables	*Mean*	*S.D.*	*Min*	*Max*	*Skewness*	*Kurtosis*
Percent people aged 25-older who don't have a high school diploma	14.50	3.67	9.30	22.00	.42	1.95
Voter turnout in the presidential election	59.35	6.44	45.50	73.40	-.26	2.62
Percent religious adherents	48.34	10.34	27.60	79.10	.23	3.12
Percent families under the poverty line	9.32	2.68	4.90	16.60	.72	2.85
Percent individuals under the poverty line	12.90	3.09	7.70	21.10	.55	2.81
Rates of infant mortality	6.50	1.21	4.59	10.09	.48	2.93
Gini coefficient of income inequality	.45	.02	.41	.50	.08	2.63
Top 1% share of all income	18.83	4.73	12.80	33.40	1.66	5.32
Change in income share of the top 1% (1979-2007)	9.63	4.09	3.90	22.30	1.68	5.71
Ratio of incomes between top and bottom 20% of households (2008-2010)	7.47	1.05	5.60	9.90	.40	2.69
Total unemployment rates	4.63	.90	2.90	6.85	.33	2.79
Total unemployment rates including discouraged workers	5.42	1.10	3.60	8.23	.52	3.15
Rates of incarceration in 2008	411.28	145.77	151.00	853.00	.62	3.49
Change in prison population across states (2008-2009)	.14	3.01	-9.20	5.40	-.74	3.92
Tightness/looseness index	50.14	12.60	27.37	78.86	.43	2.62
Percent households using internet at home	61.64	6.52	46.00	74.90	-.27	2.54
Percent households using internet anywhere	71.67	5.81	58.20	84.30	-.18	2.84
Number of public-use internet computers in public libraries	4.43	1.30	2.10	7.80	.69	3.16
Frequency of uses of public-use internet computers in public libraries	1.29	.37	.40	2.70	.80	5.91
Total population	6,069.28	6,748.63	533.00	36,757.00	2.55	10.73
Ratio of males to 100 females	97.65	3.09	93.80	108.80	1.14	4.74
Percent population between 18-65 years	62.90	1.34	60.00	66.50	.11	3.04
Total GDP	285,949.00	348,882.40	24,759.00	1,951,997.00	2.86	12.61

Table 5.2. Online Property Crime Rates across the U.S. States

State	*Online Property Crime*	*State*	*Online Property Crime*
Alabama	19.22	Montana	49.28
Alaska	31.59	Nebraska	23.01
Arizona	35.43	Nevada	84.34
Arkansas	14.66	New Hampshire	22.44
California	38.37	New Jersey	28.89
Colorado	31.07	New Mexico	16.34
Connecticut	24.57	New York	43.88
Delaware	48.34	North Carolina	19.29
Florida	48.56	North Dakota	32.97
Georgia	29.43	Ohio	20.34
Hawaii	30.84	Oklahoma	17.96
Idaho	21.75	Oregon	24.29
Illinois	24.15	Pennsylvania	20.23
Indiana	19.96	Rhode Island	27.54
Iowa	15.77	South Carolina	17.53
Kansas	19.73	South Dakota	24.22
Kentucky	16.98	Tennessee	20.10
Louisiana	14.54	Texas	24.72
Maine	31.42	Utah	45.91
Maryland	25.48	Vermont	25.15
Massachusetts	21.71	Virginia	21.20
Michigan	19.69	Washington	56.22
Minnesota	19.44	West Virginia	15.34
Mississippi	10.32	Wisconsin	15.11
Missouri	20.78	Wyoming	34.51

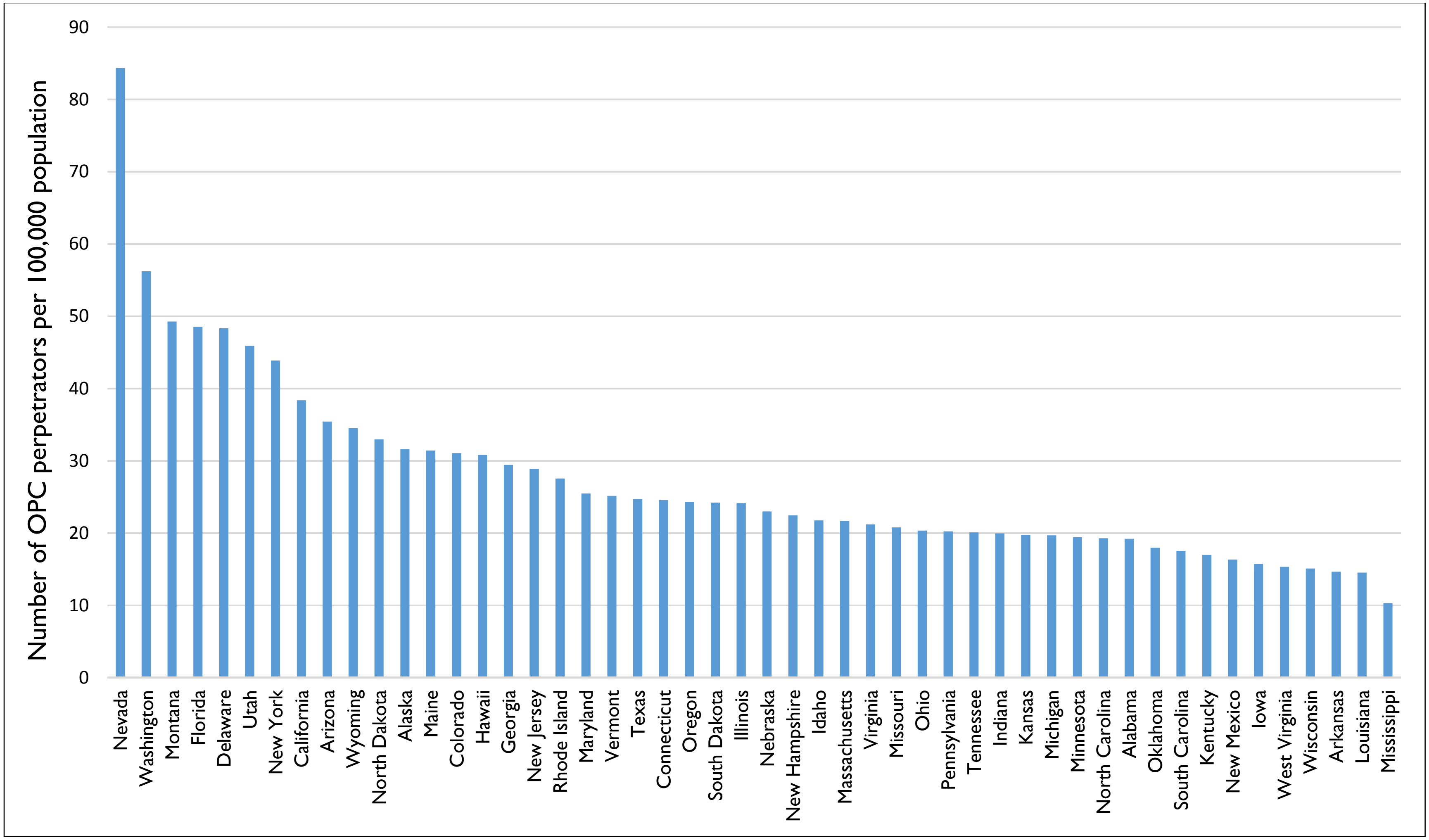

Figure 5.1. Online Property Crime Rates across the U.S. States (Descending Order)

Bivariate Results

Table 5.3 and Table 5.4 report bivariate relationships between all 42 variables examined in the current study. Firstly, Table 5.3 indicates the Spearman's rank-order correlation matrix. As indicated, OPC rates had significantly positive relationships with nine indicators: *percent Hispanic population*; *percent of female labor force participation*; *average number of people per household*; *percent of population living in an urban area*; *percent of the top 1% share of all income*; *change in income share of the top 1% during 1979-2007*; *percent of households using Internet at home*; *percent of households using Internet anywhere*; and *ratio of males to females*. It is also reported that OPC rates had significantly negative relationships with eleven indicators: *percent of people who lived in the same house one year ago*; *percent of welfare expenditure to the state's total GDP*; *percent of education expenditure to the state's total GDP*; *percent of people without high school diploma*; *percent of religious adherents*; *percent of families under the poverty line*; *percent of individuals under the poverty line*; *infant mortality rates*; *total unemployment rates*; *total unemployment rates including discouraged workers*; and *tightness/looseness index*.

Table 5.4 shows six groups that categorize 30 predictors with significant correlations with OPC rates based on direction (positive or negative) and effect size (small, medium, or large; see Cohen, 1988). Among these 30 predictors, four predictors, *percent of households using Internet at home* (r_s=.582), *change in income share of the top 1% during 1979-2007* (r_s=.536), *percent of people who lived in the same house one year ago* (r_s=-.636), and *tightness/looseness index* (r_s=-.576), were found to have large effect sizes (r_s > 0.5), while only one, *percent of female labor force participation* (r_s=.287), had a small effect size (r_s < 0.3). The rest of the fifteen predictors with medium effect sizes (0.3 < r_s < 0.5) includes: *percent of households using Internet anywhere* (r_s=.489); *percent of population living in an urban area* (r_s=.461); *percent of the top 1% share of all* *income* (r_s=.456); *percent Hispanic population* (r_s=.437); *ratio of males to females* (r_s=.394); *average number of people per household* (r_s=.329); *percent of welfare expenditure to the state's total GDP* (r_s=-.465); *percent of individuals under the poverty line* (r_s=-.442); *percent of religious adherents* (r_s=-.426); *percent of families under the poverty line* (r_s=-.415); *infant mortality rates* (r_s=-.397); *percent of education expenditure to the state's total GDP* (r_s=-.386); *total unemployment rates* (r_s=-.370); *percent of people without high school diploma* (r_s=-.355); and *total unemployment rates including discouraged workers* (r_s=-.347).

Multivariate Results: Relationships between Online Property Crime and Possible Macro-Social Predictors

To explore characteristics of multivariate relationships between OPC and possible macro-social predictors, the current study applies the two stages of PLSR analyses. For the first step of the analyses, all 41 possible predictors are included in the initial PLSR model and analyzed to extract influential predictors of OPC. In the second stage, a final PLSR model is estimated by including these influential predictors identified by the initial analysis. That is, predictors relatively less influential on the response variable in the initial model were eliminated from the second analysis to extract a parsimonious model.

Results of the Initial PLSR Analysis

To construct the best model for predicting actual OPC rates across states, the initial PLSR analysis began with cross-validation. Since firm theoretical grounds regarding characteristics of the latent components of OPC have not been established, a hypothetical model with five latent components was temporarily assumed and an optimal number of latent components were selected based on the cross-validation. The number of latent components with the lowest PRESS is accepted as the best model for predicting a response variable.

Table 5.3. Spearman's Rank-Order Correlation Matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*
(1) *Online property crime rate*	1.000													
(2) *% Black*	-.282	1.000												
(3) *% Hispanic*	.437*	.062	1.000											
(4) *% White*	-.171	-.595*	-.637*	1.000										
(5) *Divorce rate*	-.033	-.031	-.030	-.088	1.000									
(6) *% female-headed households*	-.215	.836*	.159	-.742*	.036	1.000								
(7) *% single-parent households*	-.243	.671*	.134	-.604*	.233	.756*	1.000							
(8) *% female labor force participation*	.287*	-.525*	-.059	.439*	-.413*	-.686*	-.554*	1.000						
(9) *% single-person households*	.161	.030	.096	-.059	-.143	-.072	.117	.277	1.000					
(10) *Average number of people per household*	.329*	.299*	.631*	-.775*	.071	.476*	.366*	-.304*	-.142	1.000				
(11) *% people lived in the same house one year ago*	-.636*	.206	-.542*	.325*	-.248	.096	.018	-.174	-.146	-.374*	1.000			
(12) *% people living in the state where they were born*	-.247	.234	-.323*	.173	-.410*	.260	-.085	-.091	-.267	-.142	.399*	1.000		
(13) *% urban population*	.461*	.221	.813*	-.617*	-.258	.258	.054	-.031	.046	.648*	-.330*	-.016	1.000	
(14) *% land urbanized*	-.068	.662*	.113	-.334*	-.349*	.616*	.240	-.296*	-.155	.249	.111	.625*	.455*	1.000
(15) *% welfare expenditure to state's total GDP*	-.465*	.061	-.388*	.189	-.061	.242	.203	-.362*	-.124	-.251	.432*	.450*	-.364*	.125
(16) *% education expenditure to state's total GDP*	-.386*	-.169	-.427*	.215	.320*	-.017	.030	-.219	-.138	-.195	.242	-.068	-.544*	-.339*
(17) *% welfare expenditure to the state's total expenditure*	-.261	.182	-.080	.152	-.268	.178	.088	-.246	-.123	-.231	.360*	.441*	-.007	.407*
(18) *% education expenditure to the state's total expenditure*	-.184	-.064	-.031	.102	.266	-.154	-.048	-.019	-.038	-.123	.018	-.397*	-.194	-.279*
(19) *% total amount of charitable contribution*	-.168	.397*	.075	-.204	.130	.235	.259	-.288*	.014	.116	.037	-.296*	-.096	-.067
(20) *% people without a high school diploma*	-.355*	.662*	.095	-.522*	.316*	.779*	.714*	-.834*	-.125	.258	.198	.059	.071	.356*
(21) *Voter turnout*	-.062	-.277	-.509*	.589*	-.300*	-.485*	-.348*	.596*	.252	-.535*	.126	.226	-.397*	-.142
(22) *% religious adherents*	-.426*	.298*	-.065	-.036	-.275	.202	.105	-.113	-.156	-.011	.588*	.089	-.031	.091

Table 5.3. Spearman's Rank-Order Correlation Matrix (Continued)

(23) *% families under the poverty line*	-.415*	.354*	-.067	-.256	.425*	.506*	.602*	-.809*	-.051	.079	.321*	-.169	-.241	-.062
(24) *% individuals under the poverty line*	-.442*	.281*	-.171	-.156	.400*	.429*	.538*	-.753*	-.030	-.051	.361*	-.156	-.356*	-.131
(25) *Infant mortality rate*	-.397*	.610*	-.420*	-.136	.302*	.465*	.518*	-.430*	-.020	-.101	.308*	.031	-.343*	.208
(26) *Gini coefficient*	-.224	.669*	.186	-.512*	.011	.729*	.473*	-.677*	-.027	.233	.209	.237	.209	.500*
(27) *Top 1% share of all income*	.456*	.160	.617*	-.330*	-.124	.119	.022	-.122	.067	.329*	-.401*	.031	.581*	.312*
(28) *Change in income share of the top 1%*	.536*	-.030	.580*	-.262	-.123	-.048	-.119	.031	.109	.329*	-.511*	.003	.522*	.169
(29) *Ratio of incomes between top and bottom 20% households*	-.009	.593*	.457*	-.731*	.035	.684*	.556*	-.563*	.140	.505*	-.058	.060	.471*	.431*
(30) *Total unemployment rates*	-.370*	.407*	-.110	-.164	.078	.450*	.557*	-.531*	.137	.097	.354*	.125	-.058	.228
(31) *Total unemployment rates including discouraged workers*	-.347*	.433*	-.087	-.196	.061	.501*	.552*	-.569*	.146	.119	.311*	.178	-.022	.299*
(32) *Incarceration rate*	-.213	.569*	.051	-.474*	.463*	.505*	.666*	-.598*	-.089	.285*	-.012	-.324*	-.021	.078
(33) *Change in prison population across states*	-.185	-.308*	-.324*	.303*	.297*	-.272	-.023	-.023	-.010	-.333*	.043	-.238	-.490*	-.421*
(34) *Tightness/looseness index*	-.576*	.495*	-.376*	.016	.195	.311*	.385*	-.392*	-.098	-.236	.463*	-.125	-.441*	.024
(35) *% households using internet at home*	.582*	-.313*	.334*	.017	-.351*	-.343*	-.415*	.619*	.141	.216	-.510*	.038	.461*	.085
(36) *% households using internet anywhere*	.489*	-.462*	.209	.190	-.346*	-.543*	-.494*	.775*	.196	.033	-.427*	-.089	.240	-.191
(37) *Number of internet computers in public libraries*	-.156	-.353*	-.331*	.579*	-.161	-.416*	-.227	.491*	.114	-.488*	.256	.167	-.419*	-.278
(38) *Frequency of uses of internet computers in public libraries*	.013	-.193	.173	.227	-.086	-.339*	-.084	.403*	.317*	-.085	-.064	-.165	.034	-.180
(39) *Total population*	-.081	.596*	.338*	-.452*	-.194	.465*	.296*	-.417*	.068	.285*	.188	.166	.482*	.582*
(40) *Ratio of males to 100 females*	.394*	-.652*	.310*	.088	.189	-.646*	-.384*	.413*	.159	.110	-.386*	-.688*	.062	-.693*
(41) *Percent population between 18-65 years*	.250	-.067	-.041	.053	-.222	-.028	-.215	.262	.471*	.027	-.244	.306*	.082	.226
(42) *Total GDP*	-.021	.595*	.410*	-.491*	-.224	.447*	.260	-.336*	.091	.338*	.122	.162	.569*	.605*
	(15)	*(16)*	*(17)*	*(18)*	*(19)*	*(20)*	*(21)*	*(22)*	*(23)*	*(24)*	*(25)*	*(26)*	*(27)*	*(28)*
(15) *% welfare expenditure to state's total GDP*	1.000													
(16) *% education expenditure to state's total GDP*	.486*	1.000												

Table 5.3. Spearman's Rank-Order Correlation Matrix (Continued)

(17) *% welfare expenditure to the state's total expenditure*	.642*	-.149	1.000											
(18) *% education expenditure to the state's total expenditure*	-.121	.464*	-.130	1.000										
(19) *% total amount of charitable contribution*	-.160	.095	-.067	.283*	1.000									
(20) *% people without a high school diploma*	.272	.039	.251	.041	.254	1.000								
(21) *Voter turnout*	-.010	.001	-.099	-.147	-.229	-.630*	1.000							
(22) *% religious adherents*	.128	-.026	.167	.021	.369*	.275	-.207	1.000						
(23) *% families under the poverty line*	.365*	.308*	.219	.137	.373*	.777*	-.468*	.226	1.000					
(24) *% individuals under the poverty line*	.379*	.360*	.199	.152	.353*	.725*	-.381*	.223	.981*	1.000				
(25) *Infant mortality rate*	.139	.223	.034	.154	.319*	.493*	-.087	.147	.471*	.471*	1.000			
(26) *Gini coefficient*	.189	-.208	.347*	-.193	.261	.765*	-.432*	.374*	.590*	.547*	.317*	1.000		
(27) *Top 1% share of all income*	-.289*	-.578*	.155	-.141	.192	.079	-.288*	.044	-.119	-.186	-.293*	.351*	1.000	
(28) *Change in income share of the top 1%*	-.329*	-.531*	.019	-.159	.130	-.116	-.188	-.092	-.259	-.311*	-.398*	.164	.920*	1.000
(29) *Ratio of incomes between top and bottom 20% households*	.031	-.320*	.206	-.177	.135	.685*	-.481*	.177	.455*	.382*	.195	.831*	.406*	.269
(30) *Total unemployment rates*	.421*	.113	.302*	-.217	.012	.485*	-.120	-.020	.565*	.517*	.289*	.415*	-.118	-.237
(31) *Total unemployment rates including discouraged workers*	.471*	.114	.341*	-.235	-.001	.512*	-.164	-.033	.552*	.499*	.277	.454*	-.079	-.196
(32) *Incarceration rate*	-.136	.021	-.156	.124	.460*	.651*	-.332*	.090	.586*	.542*	.602*	.449*	.064	-.037
(33) *Change in prison population across states*	.125	.338*	-.078	.214	-.084	-.046	.069	-.068	.268	.338*	.161	-.125	-.291*	-.187
(34) *Tightness/looseness index*	.123	.266	.090	.329*	.529*	.495*	-.181	.528*	.550*	.566*	.745*	.326*	-.239	-.402*
(35) *% households using internet at home*	-.346*	-.385*	-.155	-.149	-.373*	-.625*	.309*	-.389*	-.788*	-.821*	-.598*	-.410*	.254	.385*
(36) *% households using internet anywhere*	-.396*	-.266	-.264	-.025	-.263	-.780*	.441*	-.337*	-.811*	-.807*	-.575*	-.600*	.121	.292*
(37) *Number of internet computers in public libraries*	.108	.057	.043	-.091	-.200	-.439*	.552*	.069	-.208	-.152	-.096	-.270	-.247	-.221
(38) *Frequency of uses of internet computers in public libraries*	-.108	-.046	-.019	.028	.090	-.431*	.237	-.056	-.197	-.221	-.163	-.266	.096	.140
(39) *Total population*	.000	-.342*	.385*	-.003	.197	.428*	-.232	.118	.275	.207	.109	.597*	.403*	.303*

Table 5.3. Spearman's Rank-Order Correlation Matrix (Continued)

(40) *Ratio of males to 100 females*	-.472*	.044	-.463*	.313*	-.097	-.490*	-.009	-.245	-.255	-.239	-.443*	-.554*	.023	.206
(41) *Percent population between 18-65 years*	.027	-.148	.005	-.239	-.346*	-.292*	.360*	-.426*	-.425*	-.428*	-.235	-.069	.097	.192
(42) *Total GDP*	-.089	-.411*	.329*	-.029	.160	.355*	-.216	.088	.158	.082	.055	.556*	.443*	.350*

	(29)	*(30)*	*(31)*	*(32)*	*(33)*	*(34)*	*(35)*	*(36)*	*(37)*	*(38)*	*(39)*	*(40)*	*(41)*	*(42)*
(29) *Ratio of incomes between top and bottom 20% households*	1.000													
(30) *Total unemployment rates*	.312*	1.000												
(31) *Total unemployment rates including discouraged workers*	.344*	.980*	1.000											
(32) *Incarceration rate*	.446*	.314*	.283*	1.000										
(33) *Change in prison population across states*	-.203	-.039	-.049	.068	1.000									
(34) *Tightness/looseness index*	.108	.156	.135	.546*	.230	1.000								
(35) *% households using internet at home*	-.190	-.300*	-.272	-.509*	-.250	-.746*	1.000							
(36) *% households using internet anywhere*	-.392*	-.372*	-.371*	-.553*	-.162	-.631*	.910*	1.000						
(37) *Number of internet computers in public libraries*	-.343*	-.092	-.151	-.335*	.127	-.044	.019	.198	1.000					
(38) *Frequency of uses of internet computers in public libraries*	-.175	.065	.036	-.148	-.042	-.156	.192	.316*	.568*	1.000				
(39) *Total population*	.629*	.392*	.402*	.317*	-.210	.121	-.060	-.203	-.373*	-.071	1.000			
(40) *Ratio of males to 100 females*	-.312*	-.333*	-.384*	-.135	.190	-.308*	.293*	.473*	.021	.264	-.257	1.000		
(41) *Percent population between 18-65 years*	.003	.104	.162	-.383*	-.227	-.516*	.569*	.484*	.058	.092	.024	-.044	1.000	
(42) *Total GDP*	.619*	.338*	.353*	.278	-.266	.046	.048	-.104	-.379*	-.027	.985*	-.216	.082	1.000

* *indicates $p < .05$ (two-tailed).*

Table 5.4. Effect Directions and Sizes of Predictors Significantly Correlated with Online Property Crime Rates

		Effect Direction	
		Positive	*Negative*
Effect Size	*Small*	Percent of female labor force participation (.287)	-
	Medium	Percent of households using Internet anywhere (.489) percent of population living in an urban area (.461) Percent of the top 1% share of all income (.456) Percent Hispanic population (.437) Ratio of males to females (.394) Average number of people per household (.329)	Percent of welfare expenditure to the state's total GDP (-.465) Percent of individuals under the poverty line (-.442) Percent of religious adherents (-.426) Percent of families under the poverty line (-.415) Infant mortality rates (-.397) Percent of education expenditure to the state's total GDP (-.386) Total unemployment rates (-.370) Percent of people without high school diploma (-.355) Total unemployment rates including discouraged workers (-.347)
	Large	Percent of households using Internet at home (.582) Change in income share of the top 1% during 1979-2007 (.536)	Percent of people who lived in the same house one year ago (-.636) Tightness/looseness index (-.576)

Note: Parenthesis indicates Spearman's Rank-order correlation coefficient significant at p <.05 (two-tailed) level.

As indicated in Table 5.5, one latent component is the optimal number according to the results of this initial analysis (PRESS=6354.8). That is, the model with one latent component is the most appropriate model to predict the response variable with respect to explanatory parsimony. While the proportion of the explained variance in the response variable gradually increased as the number of latent components increases, it is likely an over-fitted consequence that the more variables the more proportions of explained variance. Table 5.5 also reports how much variance in predictors (X) and the response variable (Y; OPC rates) was explained by each model. The model with one component explained 46.6% of the variance in the response variable (Y) as well as 20.7% of the variance in predictors (X).

Table 5.5. Model Selection and Validation for Online Property Crime: Initial Analysis

		PRESS	*Proportion of Variance Explained*			
			Predictor Variables (X)		*Response Variable (Y)*	
			Current (%)	*Cumulative (%)*	*Current (%)*	*Cumulative (%)*
Number of Latent Components	*1*	6354.8	20.7	20.7	46.6	46.6
	2	6388.4	19.4	40.1	8.0	54.6
	3	7593.2	9.6	49.6	6.1	60.7
	4	9419.3	8.4	58.0	4.0	64.7
	5	12642.8	4.2	62.2	5.9	70.6

Table 5.6 reports variable importance in projection (VIP) values of each predictor. As shown in Table 5.6, significantly influential predictors with VIP more than 1.0 include: *percent of population who lived in the same house one year ago* (2.183); *tightness/looseness index* (1.677); *change in income share of the top 1% during 1979-2007* (1.657); *percent of the top 1% share of all income* (1.594); *percent of households using Internet at home* (1.487); *ratio of males to 100 females* (1.467); *percent of population living in an urban area* (1.410); *percent of welfare expenditure to the state's total GDP* (1.362); *percent of households using Internet anywhere* (1.259); *percent of welfare*

expenditure to the state's total expenditure (1.198); *percent of families under the poverty line* (1.167); *percent of individuals under the poverty line* (1.160); *percent Hispanic population* (1.146); *percent of religious adherents* (1.116); *infant mortality rates* (1.116); and *percent of population living in the state where they were born* (1.078).

Nineteen predictors reported VIP values less than 0.8, which include: *voter turnout* (.724); *percent of people without a high school diploma* (.711); *percent Black population* (.709); *percent of female-headed households* (.686); *percent Non-Hispanic White population* (.666); *Gini coefficient of income inequality* (.613); *percent of single-parent households with children under 18 years* (.528); *total GDP* (.490); *rates of incarceration* (.483); *change in prison population across states* (.423); *percent of female labor force participation* (.382); *total population* (.371); *percent of population between 18-65 years* (.282); *frequency of uses of public-use internet computers in public libraries* (.243); *percent of single-person households except 65 years and over* (.220); *percent of education expenditure to the state's total expenditure* (.082); *ratio of incomes between top and bottom 20% of households* (.061); *percent of land urbanized in the state* (.023); and *percent of total amount of charitable contribution to adjusted gross income* (.006). As discussed earlier, these predictors were eliminated from the final model due to their weak influence on the response variable.

Results of the Second PLSR Analysis

In the second stage of the analysis, the final model is estimated based on inclusion of 22 out of 41 predictors, those with VIP more than 0.8. Table 5.7 reports the results of cross-validation of the second PLSR analysis. As the results of the initial model, one latent component model with the lowest PRESS was found to be the optimal model (PRESS=5742.6). In terms of the amount of the explained variance in the second model, it is reported that the explained variance in the predictors (X) increased approximately 50% (20.7% → 30.7%) and that in the response variable (Y) also increased slightly (46.6% → 49.0%).

Table 5.6. Variance Importance in Projection (VIP) for Online Property Crime: Initial Analysis

Predictors	*VIP*
Percent of population who lived in the same house one year ago	2.183
Tightness/looseness index	1.677
Change in income share of the top 1% (1979-2007)	1.657
Percent of the top 1% share of all income	1.594
Percent of households using internet at home	1.487
Ratio of males to 100 females	1.467
Percent of population living in an urban area	1.410
Percent of welfare expenditure to state's total GDP	1.362
Percent of households using internet anywhere	1.259
Percent of welfare expenditure to the state's total expenditure	1.198
Percent of families under the poverty line	1.167
Percent of individuals under the poverty line	1.160
Percent Hispanic population	1.146
Rates of infant mortality	1.116
Percent of religious adherents	1.116
Percent of population living in the state where they were born	1.078
Average number of people per household	.983
Number of public-use internet computers in public libraries	.922
Percent of education expenditure to state's total GDP	.907
Total unemployment rates	.902
Total unemployment rates including discouraged workers	.900
Divorce rates	.860
Voter turnout	.724
Percent of people aged 25-older who don't have a high school diploma	.711
Percent Black population	.709
Percent of female-headed households	.686
Percent Non-Hispanic White population	.666
Gini coefficient of income inequality	.613

Table 5.6. Variance Importance in Projection (VIP) for Online Property Crime: Initial Analysis (Continued)

Predictors	*VIP*
Percent of single-parent households with children under 18 years	.528
Total GDP	.490
Rates of incarceration in 2008	.483
Change in prison population across states (2008-2009)	.423
Percent of female labor force participation	.382
Total population	.371
Percent of population between 18-65 years	.282
Frequency of uses of public-use internet computers in public libraries	.243
Percent of single-person households except 65 years and over	.220
Percent of education expenditure to the state's total expenditure	.082
Ratio of incomes between top and bottom 20% of households (2008-2010)	.061
Percent of land urbanized in the state	.023
Percent of total amount of charitable contribution to adjusted gross income	.006

Table 5.7. Model Selection and Validation for Online Property Crime: Second Analysis

		PRESS	*Proportion of Variance Explained*			
			Predictor Variables (X)		*Response Variable (Y)*	
			Current (%)	*Cumulative (%)*	*Current (%)*	*Cumulative (%)*
Number of Latent Components	*1*	5742.6	30.7	30.7	49.0	49.0
	2	5846.5	14.5	45.2	7.6	56.6
	3	6969.5	8.3	53.5	3.0	59.6
	4	8691.6	3.8	57.3	3.7	63.3
	5	9572.6	4.9	62.1	2.3	65.6

Table 5.8 indicates VIP values of each predictor included in the second model. The majority of the predictors, other than six predictors, showed a meaningful influence on the response variable (VIP > 0.8). In the second PLSR model, the order of the VIP sizes of each predictor was identical to that of the initial model although VIP decreased slightly compared to the initial model. That is, *percent of population who lived in the same house one year ago* (1.689), *tightness/looseness index* (1.297), *change in income share of the top 1% during 1979-2007* (1.282), *percent of the top 1% share of all income* (1.233), and *percent of households using Internet at home* (1.151) were found to be five predictors with the greatest influence on OPC.

Table 5.8. Variance Importance in Projection (VIP) for Online Property Crime: Second Analysis

Predictors	*VIP*
Percent of population who lived in the same house one year ago	1.689
Tightness/looseness index	1.297
Change in income share of the top 1% (1979-2007)	1.282
Percent of the top 1% share of all income	1.233
Percent of households using internet at home	1.151
Ratio of males to 100 females	1.134
Percent of population living in an urban area	1.091
Percent of welfare expenditure to state's total GDP	1.054
Percent of households using internet anywhere	.974
Percent of welfare expenditure to the state's total expenditure	.927
Percent of families under the poverty line	.903
Percent of individuals under the poverty line	.897
Percent Hispanic population	.887
Rates of infant mortality	.864
Percent of religious adherents	.863
Percent of population living in the state where they were born	.834
Average number of people per household	.761
Number of public-use internet computers in public libraries	.713
Percent of education expenditure to state's total GDP	.702
Total unemployment rates	.697
Total unemployment rates including discouraged workers	.696
Divorce rates	.665

Table 5.9 reports unstandardized and standardized PLSR regression coefficients predicting OPC rates. It also reports the results of non-parametric significance tests applied Jack-knife bootstrapping including 95% confidence intervals for coefficients of each predictor. According to the results, all of the predictors other than three predictors (*divorce rates*, *percent of population living in the state where they were born*, and *number of public-use internet computers in public libraries*) were significantly associated with OPC rates. Specifically, predictors with a positive relationship to OPC include: *percent Hispanic population* (b=.071); *average number of people per household* (b=3.894); *percent of population living in an urban area* (b=.059); *percent of the top 1% share of all income* (b=.205); *change in income share of the top 1% during 1979-2007* (b=.247), *percent of households using Internet at home* (b=.139); *percent of households using Internet anywhere* (b=.132); and *ratio of males to 100 females* (b=.289). That is, a state is more likely to have a greater OPC rate when it has a greater proportion of Hispanic population, a greater average number of people per household, a greater proportion of the top 1% share of all income, a more aggravated change in income share of the top 1% during 1979-2007, a greater proportion of people who access the Internet at home, and a greater proportion of people who access the Internet anywhere.

On the other hand, some predictors were found to have a significantly negative relationship to OPC. These predictors include: *percent of population who lived in the same house one year ago* (b=-.110); *percent of welfare expenditure to the state's total GDP* (b=-.983); *percent of education expenditure to the state's total GDP* (b=-.481); *percent of welfare expenditure to the state's total expenditure* (b=-.175); *percent of religious adherents* (b=-.066); *percent of families under the poverty line* (b=-.265); *percent of individuals under the poverty line* (b=-.229); *infant mortality rates* (b=-.561); *total unemployment rates* (b=-.611); *total unemployment rates including discouraged* *workers* (b=-.499), and *tightness/looseness index* (b=-.081). That is, a state is more likely to have a lower OPC rate when it has a greater proportion of people who lived in the same house one year ago, greater proportions of education/welfare expenditure to the total GDP or the total government expenditure, a greater proportion of religious adherents, greater proportions of both families and individuals below the poverty line, higher unemployment rates, and greater cultural tightness.

In regard to effect sizes, *percent of population who lived in the same house one year ago* (B=-.100), *tightness/looseness index* (B=-.077), *change in income share of the top 1% during 1979-2007* (B=.076), *percent of the top 1% share of all income* (B=.073), and *percent of households using Internet at home* (B=.068) are five predictors reporting the highest standardized coefficients. That is, these predictors have the largest effects on the response variable. It should also be noted that this order is exactly the same as that of VIP. In the descending order, the rest of the predictors are followed by *percent of population living in an urban area* (B=.065), *percent of welfare expenditure to the state's total GDP* (B=-.062), *percent of households using Internet anywhere* (B=.058), *percent of welfare expenditure to the state's total expenditure* (B=-.055), *percent of families under the poverty line* (B=-.054), *percent of individuals under the poverty line* (B=-.053), *percent Hispanic population* (B=.053), *percent of religious adherents* (B=-.051), *infant mortality rates* (B=-.051), *average number of people per household* (B=.045), *percent of education expenditure to the state's total GDP* (B=-.042), *total unemployment rates* (B=-.041), and *total unemployment rates including discouraged workers* (B=-.041).

Finally, Table 5.10 and Figure 5.2 provide information about both predicted and actual OPC rates. In Table 5.10, state-by-state predicted OPC rates based on the second PLSR model and actual OPC rates are presented. As reported previously, five states with the highest

Table 5.9. Unstandardized/Standardized Regression Coefficients and Standardized Bootstrap Confidence Intervals on Online Property Crime

Variables	*Unstandardized Coefficient*	*Standardized Coefficient*	*95% Confidence Interval (Standardized)*	
			Lower Bound	*Upper Bound*
% Hispanic	.071	.053*	.008	.100
Divorce rates	.521	.039	-.034	.094
Average number of people per household	3.894	.045*	.012	.083
% people lived in the same house one year ago	-.110	-.100*	-.129	-.061
% people living in the state where they were born	-.266	-.049	-.083	.002
% urban population	.059	.065*	.032	.093
% welfare expenditure to state's total GDP	-.983	-.062*	-.089	-.019
% education expenditure to state's total GDP	-.481	-.042*	-.065	-.016
% welfare expenditure to the state's total expenditure	-.175	-.055*	-.092	-.004
% religious adherents	-.066	-.051*	-.095	-.003
% families under the poverty line	-.265	-.054*	-.073	-.032
% individuals under the poverty line	-.229	-.053*	-.072	-.033
Infant mortality rate	-.561	-.051*	-.084	-.016
Top 1% share of all income	.205	.073*	.033	.109
Change in income share of the top 1%	.247	.076*	.039	.109
Total unemployment rates	-.611	-.041*	-.073	-.014
Total unemployment rates including discouraged workers	-.499	-.041*	-.072	-.012
Tightness/looseness index	-.081	-.077*	-.097	-.055
% households using internet at home	.139	.068*	.042	.098
% households using internet anywhere	.132	.058*	.028	.091
Number of internet computers in public libraries	-.433	-.042	-.080	.006
Ratio of males to 100 females	.289	.067*	.027	.093
Constant	18.968	-	-	-

Note:
* *indicates regression coefficient significant at p <.05 (two-tailed) level.*

measured OPC rates are: *Nevada* (84.34); *Washington* (56.22); *Montana* (49.28); *Florida* (48.56); and *Delaware* (48.34), but the order changed to *Nevada* (50.79); *Wyoming* (42.62); *Colorado* (39.39); *California* (38.87); and *Washington* (38.74) when it comes to the predicted OPC rates. Likewise, the five states with the lowest measured OPC rates include: *Mississippi* (10.32); *Louisiana* (14.54); *Arkansas* (14.66); *Wisconsin* (15.11); and *West Virginia* (15.34), but that order also changed to *Mississippi* (3.96); *West Virginia* (11.90); *Louisiana* (14.14); *Alabama* (14.57); and *Kentucky* (14.62) as to the predicted OPC rates.

Figure 5.2 shows the scatter plot of the predicted and actual OPC rates. As indicated in both Table 5.10 and Figure 5.2, the predicted OPC rates seem to correspond to the actual OPC rates in general as the predicted OPC rates had a linear relationship to actual OPC rates. Some states, however, reported their predicted OPC rates far from their actual OPC rates. For example, states such as *New Hampshire* and *Connecticut* reported greater predicted OPC rates compared to their actual rates, while *New York*, *Delaware*, *Montana*, *Washington*, and *Nevada* had lower predicted rates than their actual OPC rates.

Multivariate Results: Relationships between Online Opportunity and Possible Macro-Social Predictors

In addition to identification of OPC structure, the PLSR approach was also applied to explore what macro-social indicators can predict characteristics of the online opportunity structure. As the PLSR analyses explored influential predictors of the OPC rates, the two steps of PLSR analyses, 1) screening influential predictors, and 2) remodeling the final predictive model with the selected predictors, were also employed to identify the best model for predicting online opportunity structure. Since three out of four online opportunity predictor

Table 5.10. Measured and Predicted Online Property Crime Rates across the U.S. States

State	*Measured OPC*	*Predicted OPC*	*Predicted OPC – Measured OPC*
Alabama	19.22	14.57	-4.65
Alaska	31.59	37.50	+5.91
Arizona	35.43	36.75	+1.32
Arkansas	14.66	14.63	-0.03
California	38.37	38.87	+0.5
Colorado	31.07	39.39	+8.32
Connecticut	24.57	37.59	+13.02
Delaware	48.34	30.64	-17.7
Florida	48.56	38.03	-10.53
Georgia	29.43	25.98	-3.45
Hawaii	30.84	37.86	+7.02
Idaho	21.75	31.71	+9.96
Illinois	24.15	28.07	+3.92
Indiana	19.96	22.28	+2.32
Iowa	15.77	23.38	+7.61
Kansas	19.73	25.60	+5.87
Kentucky	16.98	14.62	-2.36
Louisiana	14.54	14.14	-0.4
Maine	31.42	19.91	-11.51
Maryland	25.48	32.52	+7.04
Massachusetts	21.71	30.54	+8.83
Michigan	19.69	18.08	-1.61
Minnesota	19.44	27.17	+7.73
Mississippi	10.32	3.96	-6.36
Missouri	20.78	21.67	+0.89
Montana	49.28	28.55	-20.73
Nebraska	23.01	27.14	+4.13
Nevada	84.34	50.79	-33.55
New Hampshire	22.44	36.55	+14.11
New Jersey	28.89	34.19	+5.3
New Mexico	16.34	25.41	+9.07
New York	43.88	28.93	-14.95
North Carolina	19.29	21.12	+1.83
North Dakota	32.97	24.41	-8.56
Ohio	20.34	18.43	-1.91
Oklahoma	17.96	19.93	+1.97
Oregon	24.29	34.91	+10.62
Pennsylvania	20.23	21.19	+0.96
Rhode Island	27.54	23.83	-3.71
South Carolina	17.53	17.82	+0.29
South Dakota	24.22	25.47	+1.25
Tennessee	20.10	17.63	-2.47
Texas	24.72	28.92	+4.2
Utah	45.91	38.30	-7.61
Vermont	25.15	23.91	-1.24
Virginia	21.20	32.53	+11.33
Washington	56.22	38.74	-17.48
West Virginia	15.34	11.90	-3.44
Wisconsin	15.11	25.91	+10.8
Wyoming	34.51	42.62	+8.11

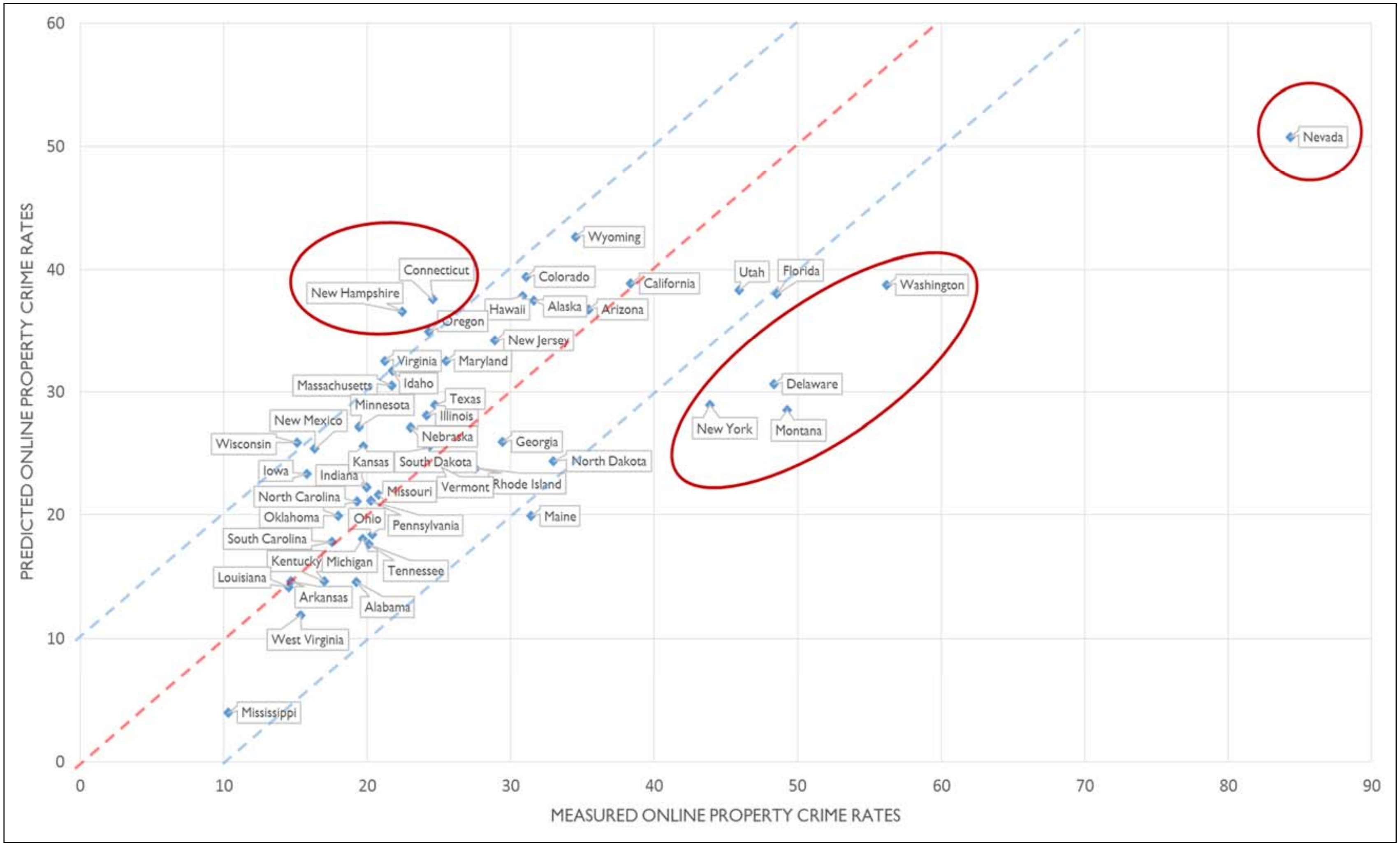

Figure 5.2. Scatter Plot of Measured and Predicted Online Property Crime

(*percent of households using Internet at home, percent of households using Internet anywhere*, and *number of public-use internet computers in public libraries*) had high internal consistency (α=.734), they were standardized and combined into one final response variable.

Results of the Initial PLSR Analysis

As in the PLSR approach previously conducted for OPC rates, cross-validation was also applied to decide an optimal number of latent components and to identify influential predictors of online opportunity structure. As indicated in Table 5.11, the lowest PRESS was reported when the optimal number of latent components was one (PRESS=103.9). In this model, approximately 25.7% and 70.6% of variance in predictors (X) and the response variable (Y; online opportunity composite variable) respectively was explained.

Table 5.11. Model Selection and Validation for Online Opportunity: Initial Analysis

			Proportion of Variance Explained			
		PRESS	*Predictor Variables (X)*		*Response Variable (Y)*	
			Current (%)	*Cumulative (%)*	*Current (%)*	*Cumulative (%)*
Number of Latent Components	*1*	103.9	25.7	25.7	70.6	70.6
	2	117.3	11.8	37.6	6.5	77.1
	3	130.4	9.4	47.0	4.6	81.7
	4	135.8	9.0	55.9	2.6	84.2
	5	136.6	7.3	63.3	1.7	85.9

Table 5.12 reports VIP values of each predictor. Predictors with VIP more than 1.0 include: *percent of people without a high school diploma* (1.922); *percent of families under the poverty line* (1.918); *percent of female labor force participation* (1.866); *percent of individuals under the poverty line* (1.855); *tightness/looseness index* (1.496); *rates of incarceration* (1.452); *percent of*

female-headed households (1.437); *infant mortality rates* (1.378); *Gini coefficient of income inequality* (1.365); *voter turnout* (1.230); *percent of Black population* (1.213); *percent of single-parent households with children under 18 years* (1.164); and *percent of population between 18-65 years* (1.043).

Twenty predictors with VIP less than 0.8 were categorized as predictors with marginal influence on online opportunity so were removed from the second PLSR analysis. These predictors include: *percent of population who lived in the same house one year ago* (.758); *total unemployment rates* (.745); *total unemployment rates including discouraged workers* (.726); *percent of religious adherents* (.648); *percent of total amount of charitable contribution to adjusted gross income* (.562); *change in income share of the top 1% during 1979-2007* (.540); *percent of welfare expenditure to state's total GDP* (.520); *total population* (.446); *percent of education expenditure to state's total GDP* (.434); *percent of single-person households except 65 years and over* (.354); *percent of welfare expenditure to the state's total expenditure* (.347); *total GDP* (.314); *percent of population living in an urban area* (.223); *percent of the top 1% share of all income* (.215); *percent education expenditure to the state's total expenditure* (.202); *percent of land urbanized in the state* (.195); *percent Hispanic population* (.138); *change in prison population across states* (.123); *average number of people per household* (.096); and *percent of population living in the state where they were born* (.040).

Table 5.12. Variance Importance in Projection (VIP) for Online Opportunity: Initial Analysis

Predictors	*VIP*
Percent of people aged 25-older who don't have a high school diploma	1.922
Percent of families under the poverty line	1.918
Percent of female labor force participation	1.866
Percent of individuals under the poverty line	1.855

Table 5.12. Variance Importance in Projection (VIP) for Online Opportunity: Initial Analysis (Continued)

Predictors	*VIP*
Tightness/looseness index	1.496
Rates of incarceration in 2008	1.452
Percent of female-headed households	1.437
Rates of infant mortality	1.378
Gini coefficient of income inequality	1.365
Voter turnout	1.230
Percent Black population	1.213
Percent of single-parent households with children under 18 years	1.164
Percent of population between 18-65 years	1.043
Ratio of incomes between top and bottom 20% of households (2008-2010)	.974
Ratio of males to 100 females	.919
Divorce rates	.870
Percent Non-Hispanic White population	.807
Percent of population who lived in the same house one year ago	.758
Total unemployment rates	.745
Total unemployment rates including discouraged workers	.726
Percent of religious adherents	.648
Percent of total amount of charitable contribution to adjusted gross income	.562
Change in income share of the top 1% (1979-2007)	.540
Percent of welfare expenditure to state's total GDP	.520
Total population	.446
Percent of education expenditure to state's total GDP	.434
Percent of single-person households except 65 years and over	.354
Percent of welfare expenditure to the state's total expenditure	.347
Total GDP	.314
Percent of population living in an urban area	.223
Percent of the top 1% share of all income	.215
Percent education expenditure to the state's total expenditure	.202
Percent of land urbanized in the state	.195
Percent Hispanic population	.138
Change in prison population across states (2008-2009)	.123
Average number of people per household	.096
Percent of population living in the state where they were born	.040

Results of the Second PLSR Analysis

Table 5.13 indicates the results of the cross-validation for the second PLSR analysis predicting online opportunity including 17 predictors with VIP more than 0.8. The optimal model was found to have two latent components (PRESS=79.8). With these two latent components, the explained variance in predictors (X) in the second PLSR model dramatically increased compared to the results of the initial model (25.7% → 59.8%). The explained variance in online opportunity (the response variable; Y) was found to increase slightly as well in the second model (70.6% → 79.5%).

Table 5.13. Model Selection and Validation for Online Opportunity: Second Analysis

		PRESS	*Proportion of Variance Explained*			
			Predictor Variables (X)		*Response Variable (Y)*	
			Current (%)	*Cumulative (%)*	*Current (%)*	*Cumulative (%)*
Number of Latent Components	*1*	87.9	49.4	49.4	71.2	71.2
	2	79.8	10.4	59.8	8.3	79.5
	3	81.4	7.2	67.0	2.6	82.1
	4	85.4	4.3	71.3	1.9	84.0
	5	85.0	7.1	78.4	0.7	84.7

Table 5.14 reports VIP of each predictor in the second PLSR model. Other than three predictors (*percent Non-Hispanic White population*, *divorce rates*, and *ration of males to females*), all predictors had VIP more than 0.8 in at least more than one component. As the results of the initial model, the most influential predictors of online opportunity include: *percent of people without a high school diploma* (comp1=1.378; comp2=1.307); *percent of families under the poverty line* (comp1=1.375; comp2=1.317); *percent of female labor force participation* (comp1=1.337;

comp2=1.310); *percent of individuals under the poverty line* (comp1=1.329; comp2=1.285); and *tightness/looseness index* (comp1=1.072; comp2=1.033).

Table 5.14. Variance Importance in Projection (VIP) for Online Opportunity: Second Analysis

Predictors	*VIP*	
	Component 1	*Component 2*
Percent of families under the poverty line	1.375	1.317
Percent of people aged 25-older who don't have a high school diploma	1.378	1.307
Percent of female labor force participation	1.337	1.310
Percent of individuals under the poverty line	1.329	1.285
Tightness/looseness index	1.072	1.033
Percent of female-headed households	1.030	1.057
Rates of incarceration in 2008	1.041	1.008
Rates of infant mortality	.988	.935
Gini coefficient of income inequality	.978	.935
Percent of single-parent households with children under 18 years	.834	1.058
Percent Black population	.870	.907
Voter turnout	.882	.869
Percent of population between 18-65 years	.747	.869
Ratio of incomes between top and bottom 20% of households (2008-2010)	.698	.801
Ratio of males to 100 females	.658	.623
Divorce rates	.624	.634
Percent Non-Hispanic White population	.578	.599

Table 5.15 indicates unstandardized and standardized PLSR regression coefficients for 17 predictors of online opportunity as well as 95% confidence intervals based on the non-parametric bootstrapping estimation. According to the results, nine predictors were found to have a significant relationship to the response variable. Three predictors, *percent of female labor force participation* (b=.088), *voter turnout* (b=.041), and *percent of population between 18-65 years*

(b=.260), were positively associated with online opportunity. That is, a state is more likely to enjoy better online opportunity/accessibility when it has a greater proportion of female labor force participation, a greater voter turnout, and a greater proportion of people aged 18 to 65. It was found that there were six predictors with a negative relationship to online opportunity, which include: *percent of people without a high school diploma* (b=-.080); *percent of families under the poverty line* (b=-.127); *percent of individuals under the poverty line* (b=-.116); *infant mortality rates* (b=-.149); *Gini coefficient of income inequality* (b=-6.723); and *tightness/looseness index* (b=-.022). It can be said that a state is more likely to have limited online opportunity/accessibility when it has a greater proportion of people without a high school diploma, greater proportions of both families and individuals below the poverty line, a higher infant mortality rate, higher income inequality (a greater Gini coefficient), and greater cultural tightness. With regard to the effect sizes, the predictor that appeared to have the greatest effects on online opportunity was *percent of female labor force participation* (B=.167) followed by *percent of individuals under the poverty line* (B=-.153), *percent of population between 18-65 years* (B=.149), *percent of families under the poverty line* (B=-.145), *percent of people without a high school diploma* (B=-.125), *tightness/looseness index* (B=-.119), *voter turnout* (B=.113), *infant mortality rates* (B=-.077), and *Gini coefficient of income inequality* (B=-.055).

Both Table 5.16 and Figure 5.3 show predicted and measured online opportunity across states. Specifically, Table 5.16 reports standardized state-by-state predicted and measured online opportunity. The top three states with the highest measured online opportunity were: *Vermont* (5.301); *Alaska* (4.077); and *New Hampshire* (3.895). However, the three states with the highest predicted online opportunity were: *New Hampshire* (3.596); *Alaska* (3.308); and *Minnesota* (3.258). That is, Vermont, Alaska, New Hampshire, and Minnesota tend to have

Table 5.15. Unstandardized/Standardized Regression Coefficients and Standardized Bootstrap Confidence Intervals on Online Opportunity

Variables	*Unstandardized Coefficient*	*Standardized Coefficient*	*95% Confidence Interval (Standardized)*	
			Lower Bound	*Upper Bound*
% Black	-.001	-.002	-.062	.041
% White	.000	.003	-.095	.141
Divorce rates	-.211	-.090	-.151	.015
% female-headed households	-.011	-.010	-.077	.025
% single-parent households	.127	.058	-.040	.141
% female labor force participation	.088	.167*	.081	.237
% people without a high school diploma	-.080	-.125*	-.164	-.076
Voter turnout	.041	.113*	.015	.198
% families under the poverty line	-.127	-.145*	-.177	-.091
% individuals under the poverty line	-.116	-.153*	-.194	-.084
Infant mortality rate	-.149	-.077*	-.137	-.015
Gini coefficient	-6.723	-.055*	-.112	-.002
Ratio of incomes between top and bottom 20% households	.054	.024	-.039	.083
Incarceration rates	-.001	-.045	-.125	.013
Tightness/looseness index	-.022	-.119*	-.173	-.054
Ratio of males to 100 females	.042	.056	-.048	.144
Percent population between 18-65 years	.260	.149*	.048	.241
Constant	-19.443	-	-	-

Note:
* *indicates regression coefficient significant at p <.05 (two-tailed) level.*

better Internet infrastructure or online accessibility compared to other states. The three states with the lowest measured online opportunity were: *West Virginia* (-5.007); *Mississippi* (-4.992); and *Arkansas* (-3.786). However, the three states with the lowest predicted online opportunity were: *Mississippi* (-5.033); *Arkansas* (-3.837); and *Louisiana* (-3.684). Thus, West Virginia, Mississippi, Arkansas, and Louisiana tend to have worse Internet infrastructure or online accessibility compared to other states.

Figure 5.3 shows the scatter plot of the predicted and measured online opportunity. As in the case of OPC rates, the predicted data had a linear relationship to the measured online opportunity. However, some states were found to have a difference between the predicted and measured data. For states such as *West Virginia*, *Pennsylvania*, *Hawaii*, *Montana*, *North Dakota*, and *Massachusetts*, their predicted values were greater than their measured ones. In contrast, *Louisiana*, *Utah*, *Nebraska*, *Kansas*, and *Vermont* reported lower predicted online opportunity compared to their measured ones.

Summary of Results

Table 5.17 summarizes the findings of the current study regarding the multivariate relationships among three subjects: 1) OPC, 2) online opportunity, and 3) various macro-social indicators. As indicated, predictors found to have a significantly positive association with OPC are (in descending order based on effect sizes): *change in income share of the top 1% during 1979-2007* (B=.076); *percent of the top 1% share of all income* (B=.073); *percent of households using Internet at home* (B=.068); *ratio of males to females* (B=.067); *percent of population living in an urban area* (B=.065); *percent of households using Internet anywhere* (B=.058); *percent Hispanic population* (B=.053); and *average number of people per household* (B=.045), while predictors with

Table 5.16. Measured and Predicted Standardized Online Opportunity across the U.S. States

State	*Measured Online Opportunity*	*Predicted Online Opportunity*	*Predicted Online Opportunity – Measured Online Opportunity*
Alabama	-3.389	-3.512	-.123
Alaska	4.077	3.308	-.769
Arizona	-.973	-1.556	-.583
Arkansas	-3.786	-3.837	-.051
California	-.630	-.571	+.059
Colorado	2.315	1.780	-.535
Connecticut	1.783	1.784	+.001
Delaware	-.208	.235	+.443
Florida	-.341	-1.351	-1.010
Georgia	-.733	-.975	-.242
Hawaii	-1.287	.956	+2.243
Idaho	-.907	-.305	+.602
Illinois	.882	.278	-.604
Indiana	.275	-.785	-1.060
Iowa	2.071	2.012	-.059
Kansas	2.984	.564	-2.420
Kentucky	-2.084	-2.873	-.789
Louisiana	-2.380	-3.684	-1.304
Maine	2.256	1.608	-.648
Maryland	.908	1.976	+1.068
Massachusetts	.620	2.098	+1.478
Michigan	-.129	-.174	-.045
Minnesota	2.032	3.258	+1.226
Mississippi	-4.992	-5.033	-.041
Missouri	-1.716	-.511	+1.205
Montana	-.820	.817	+1.637
Nebraska	2.964	1.464	-1.500
Nevada	-.773	.207	+.980
New Hampshire	3.899	3.596	-.303
New Jersey	1.294	1.348	+.054
New Mexico	-1.744	-1.750	-.006
New York	-.836	-.507	+.329
North Carolina	-2.222	-1.282	+.940
North Dakota	.325	1.958	+1.633
Ohio	-.470	-.025	+.445
Oklahoma	-3.119	-3.101	+.018
Oregon	.926	1.049	+.123
Pennsylvania	-1.762	.097	+1.859
Rhode Island	1.439	.779	-.660
South Carolina	-2.565	-1.787	+.778
South Dakota	1.589	.898	-.691
Tennessee	-3.142	-2.642	+.500
Texas	-2.014	-2.853	-.839
Utah	1.981	.395	-1.586
Vermont	5.301	2.682	-2.619
Virginia	.999	1.026	+.027
Washington	2.956	1.896	-1.060
West Virginia	-5.007	-3.295	+1.712
Wisconsin	1.280	2.285	+1.005
Wyoming	2.871	2.055	-.816

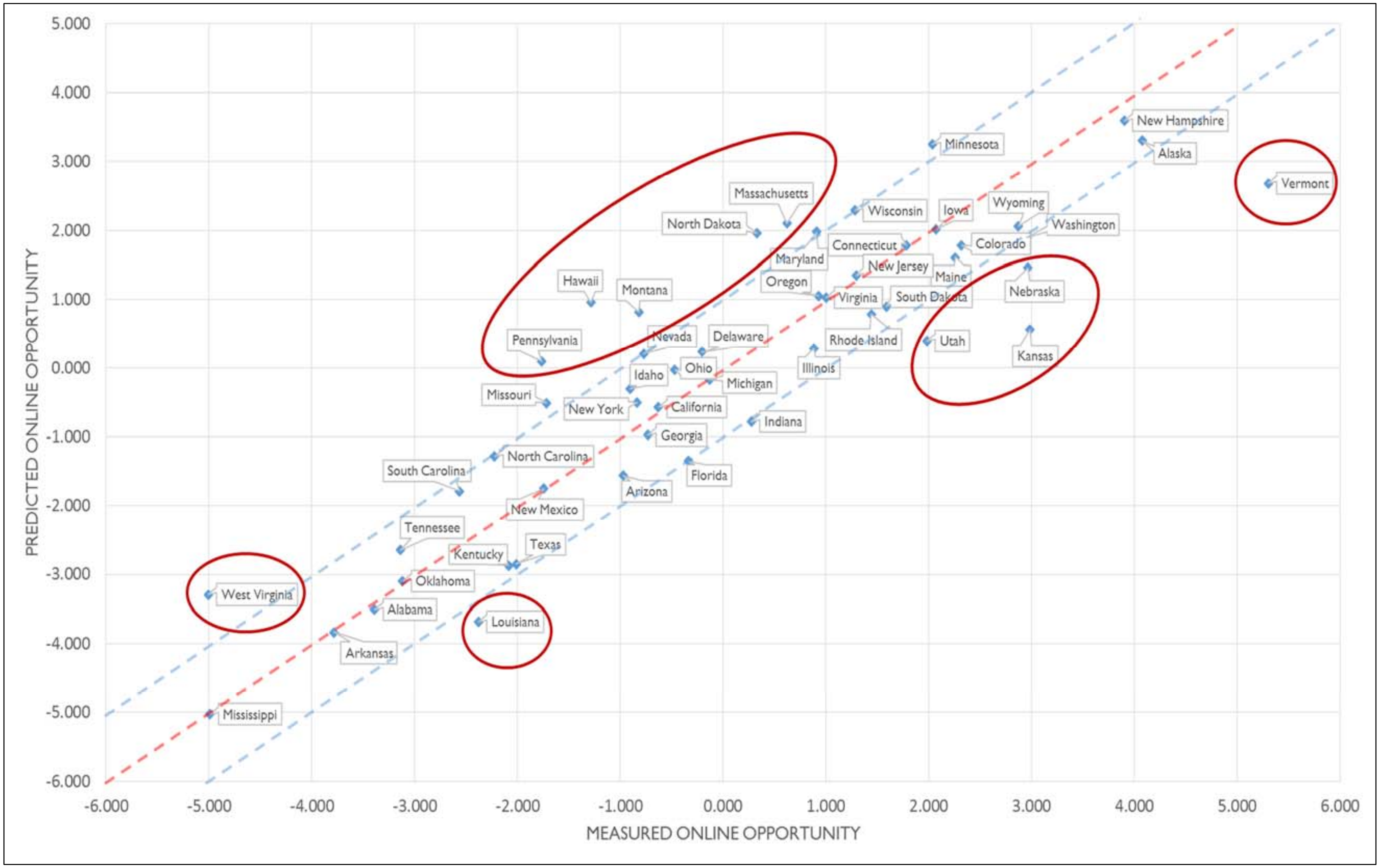

Figure 5.3. Scatter Plot of Measured and Predicted Online Opportunity

a negative association are (in descending order based on effect sizes): *percent population who lived in the same house one year ago* (B=-.100); *tightness/looseness index* (B=-.077); *percent of welfare expenditure to state's total GDP* (B=-.062); *percent of welfare expenditure to the state's total expenditure* (B=-.055); *percent of families under the poverty line* (B=-.054); *percent of individuals under the poverty line* (B=-.053); *percent of religious adherents* (B=-.051); *infant mortality rates* (B=-.051); *percent of education expenditure to state's total GDP* (B=-.042); *total unemployment rates* (B=-.041); and *total unemployment rates including discouraged workers* (B=-.041). The PLSR model for predicting OPC including these significant predictors above and the other predictors indicates that 49% of variance in OPC was explained by the predictors included in the model.

In terms of the PLSR model for predicting online opportunity, predictors with a significantly positive association with online opportunity include (in descending order based on effect sizes): *percent of female labor force participation* (B=.167); *percent of population between 18-65 years* (B=.149); and *voter turnout* (B=.113), while predictors with a negative relationship include (in descending order based on effect sizes): *percent of individuals under the poverty line* (B=-.153); *percent of families under the poverty line* (B=-.145); *percent of people without a high school diploma* (B=-.125); *tightness/looseness index* (B=-.119); *infant mortality rates* (B=-.077); and *Gini coefficient* (B=-.055). The final PLSR model for predicting online opportunity found that predictors included in this model explained 79.5% of variance in online opportunity.

Table 5.17. Summary of the Results of the Partial Least Square Regression Predicting Online Property Crime and Online Opportunity

	Response Variable	
	Online Property Crime	*Online Opportunity*
Predictors with Positive (+) Relationship	Change in income share of the top 1% during 1979-2007 (.076) Percent of the top 1% share of all income (.073) Percent of households using Internet at home (.068) Ratio of males to females (.067) percent of population living in an urban area (.065) Percent of households using Internet anywhere (.058) Percent Hispanic population (.053) Average number of people per household (.045)	Percent of female labor force participation (.167) Percent of population between 18-65 years (.149) Voter turnout (.113)
Predictors with Negative (-) Relationship	Percent of people who lived in the same house one year ago (-.100) Tightness/looseness index (-.077) Percent of welfare expenditure to the state's total GDP (-.062) Percent of welfare expenditure to the state's total expenditure (-.055) Percent of families under the poverty line (-.054) Percent of individuals under the poverty line (-.053) Percent of religious adherents (-.051) Infant mortality rates (-.051) Percent of education expenditure to the state's total GDP (-.042) Total unemployment rates (-.041) Total unemployment rates including discouraged workers (-.041)	Percent of individuals under the poverty line (-.153) Percent of families under the poverty line (-.145) Percent of people without high school diploma (-.125) Tightness/looseness index (-.119) Infant mortality rates (-.077) Gini coefficient (-.055)
Explained Variance (R^2)	49.0%	79.5%

Note: Parenthesis indicates standardized regression coefficient significant at p <.05 (two-tailed) level.

CHAPTER SIX:

DISCUSSION AND CONCLUSION

Drawing on the research findings presented in the previous chapter, this chapter discusses implications of the results. It specifically provides possible interpretations about the background of significant relationships between macro-social indicators and OPC, and between those and online opportunity. It also discusses how effectively the two analytic models account for each OPC and online opportunity, and what implications can be expected with respect to predictability of both models. In addition to the overview of the research findings and implications, both sections of suggestions for both future research and relevant policies, and limitations of the current study are following. Based on the results and its implications, additional ideas need to be explored further and relevant research topics that should be studied are also suggested for the theoretical development to account for OPC as well as effective policies for responding to OPC. In the section of limitations of the current study, finally, methodological issues regarding the data and analytical approach employed in this study, which should be noted to prevent overgeneralization or misinterpretation of the findings, are addressed.

Overview of Results

Modeling for Predicting Online Property Crime

The primary goal of the current study is to explore significant macro-social predictors of OPC and the best model for explaining variance in OPC rates. Recall the relevant research questions regarding this goal: *What are the influential macro-social predictors of rates of OPC perpetration? What existing macro-social predictors of crime can predict OPC? Are there any influential online opportunity predictors of OPC? How much variance in OPC can be explained by both types of predictors?*

For the significant predictors of OPC based on the results of the PLSR approach, OPC rates across states were found to have a significant relationship to 19 macro-social indicators out of 41. As reported in the previous chapter, eight predictors — *change in income share of the top 1% during 1979-2007*; *percent of the top 1% share of all income*; *percent of households using Internet at home*; r*atio of males to females*; *percent of population living in an urban area*; *percent of households using Internet anywhere*; *percent of Hispanic population*; *average number of people per household* — had a positive association with OPC rates, while eleven predictors — *percent of population who lived in the same house one year ago*; *tightness/looseness index*; *percent of welfare expenditure to state's total GDP*; *percent of welfare expenditure to state's total expenditure*; *percent of families under the poverty line*; *percent of individuals under the poverty line*; *percent of religious adherents*; *infant mortality rates*; *percent of education expenditure to state's total GDP*; *total unemployment rates*; *total unemployment rates including discouraged workers* — had a negative relationship to OPC. Note that two online opportunity predictors — *percent of households using Internet at home*, *percent of households using Internet anywhere* — were also positively related to OPC rates.

Among the predictors with a significant relationship to OPC, it should be noted that predictors in the domain of economic inequality or relative deprivation were found to have the largest effects. Two other predictors in this domain (*Gini coefficient* and *ratio of incomes between top and bottom 20% of households during 2008-2010*) showed no significant association with

OPC. However, a state with a higher proportion of *the top 1% share of all income or* with a larger percentage *increase in income share of the top 1% during 1979-2007* was more likely to have a greater OPC rate. This corresponds to the results of prior empirical studies reporting consistently positive relationships between relative deprivation and traditional crime rates (e.g., Blau & Blau, 1982; Fowles & Merva, 1996; Kovandzic et al., 1998; For the results of meta-analysis studies, see Hsieh & Pugh, 1993; Nivette, 2011; Pratt & Cullen, 2005).

The significantly strong relationships between predictors in the domain of economic inequality and OPC imply that the criminogenic mechanism derived from relative deprivation, which has been argued by some macro-level criminological theories, may be applicable to OPC as well as traditional crimes. For example, macro-level strain theory explains that a society with severe economic inequality is more likely to have a high crime rate as frustration or strain becomes pervasive in the society due to the relative deprivation (Agnew, 1999). For institutional anomie theory, it maintains that a greater strength of economic institution leads to a high crime rate in a society as it weakens non-economic institutions such as prosocial morals, values, and beliefs that play a critical role in controlling criminogenic influence caused by the overwhelming power of economic institutions (Messner & Rosenfeld, 1994). Economic inequality, as one of the indicators of the strength of economic institutions, is thus expected to have a positive relationship to a high crime rate. Since OPC, as a crime responding to these theoretical concepts — strain and institutional anomie —, is not different from traditional crimes, these anomie-strain theories may also account for OPC. Perhaps, these explanations, focusing on economic conditions provoking strain and anomie, might be more appropriate for OPC since most OPC tends to be committed by pursuing illegitimate financial advantage. Furthermore, OPC might also be well-explained by the macro-level strain/anomie theories because moral perception of OPC, regarding whether it is morally wrong or not, might be relatively obscure compared to traditional crimes (Kshetri, 2016).

In addition to economic inequality, predictors in the domains of economic social support and strength of a non-economic social institution — religion — were reported to have a significant and negative association with OPC. That is, the greater *governmental expenditure for education and welfare*, the lower OPC rates. In addition, a state with a greater proportion of *religious adherents* is also more likely to have a lower OPC rate. These predictors are all macro-social indicators that reflect a degree of economic and non-economic social support for reducing criminogenic influence derived from the blind pursuit of economic success discussed above. In other words, if a society has a greater level of economic support for welfare and education, the economic success would not necessarily have to be subject to a target of achievement, and this, in turn, may be related to a lower crime rate in the society. If a society is under greater religious influence, it would also lead to a lower crime rate in the society since the religious atmosphere emphasizing moral values and beliefs can control the criminogenic effects that the blind pursuit of economic success would draw out. Thus, the significant relationships of these predictors to OPC can be understood by theoretical concepts from institutional anomie theory (Messner & Rosenfeld, 1994) and social support theory (Cullen, 1994), and results of prior empirical studies based on these theories (e.g., Altheimer, 2008; Chamlin & Cochran, 1995; DeFronzo & Hannon, 1998; Hannon & DeFronzo, 1998a, 1998b; Maume & Lee, 2003; Pratt & Godsey, 2003).

Some of the predictors in the domain of residential mobility and urbanization were found to have a significant relationship to OPC. According to the results, *percent of people who lived in the same house one year ago* was inversely related to OPC, and this relationship was reported to have the largest size effect. In addition, *percent of population living in an urban area*, an indicator of high mobility, was found to be associated with a higher OPC. That is, predictors indicating greater residential stability are significantly related to a lower OPC rate. In social disorganization theory, these predictors have been utilized to measure its key theoretical concept indirectly, a degree of social disorganization in a community. Social disorganization theory explains that social disorganization weakens social bonding, which is an informal social control mechanism to prevent criminal incidents in a community, and this, in turn, leads to a high crime rate in the community (Bursik, 1988; Sampson & Groves, 1989). For OPC, however, this explanation drawing on the perspective of social disorganization theory seems to be barely applicable because OPC occurs in the online setting where the control mechanism derived from community-level social bonding is obviously not working.

Rather than the theoretical approach, the significant association of the two predictors with OPC might be explained by lifestyle or opportunity theories based on characteristics of demographic structure. In other words, a state with lower residential stability and greater urban population is more likely to have a greater proportion of younger population, who are expected to be more familiar with ICT devices, to have more advanced skills and knowledge of the Internet, and to access the Internet more frequently, compared to a state with a greater percent of elderly population, who are less likely to move their residence, to live in urban areas, and to have frequent Internet access. As will be discussed in the next section of the results regarding online opportunity and its predictors, this alternative explanation was also supported by the finding that age structure (18 to 65 year) was positively and significantly associated with online opportunity. Thus, the potential difference in online opportunities between age groups might be the key to understanding the significant relationships of both residential stability and urban population indicators to OPC.

In terms of predictors in the domains of poverty/absolute deprivation and unemployment, interesting results were found that predictors in these two domains were reported to have a negative relationship to OPC, which contrasts to traditional crime. That is, a state with high *poverty* and *unemployment rates* are more likely to report a lower OPC rate. For poverty, specifically, empirical studies on traditional crime have consistently reported that a high poverty rate is associated with a high crime rate (Nivette, 2011; Pratt & Cullen, 2005). Two implications on the results should be noted. As in the case of indicators of residential stability and urbanization discussed previously, first of all, the negative relationship of poverty to OPC can be understood by considering its relationship to online opportunities. Put another way, a society suffering from a higher poverty rate is more likely to experience ICT limitations including high Internet costs, slow network speeds, or unstable Internet connections. This restricted accessibility to the Internet and ICT devices in the context of absolute deprivation may indicate a lower level of online criminal opportunities available in the deprived society, and this, in turn, leads to a lower OPC in that society.

The negative relationship between poverty predictors and OPC also provides an alternative perspective about poverty as one of the criminogenic conditions. Poverty has been regarded as an aggravating factor leading to high crime rates since it increases strain or frustration in a community level due to economic difficulties of that community. It is thus likely to be associated with deviant behaviors outside of social norms such as aggression and drug use, and the pursuit of illegitimate financial advantage (Agnew, 1999). According to this explanation, indicators of poverty would also have a positive relationship to OPC. Thus, the opposite direction of the relationship contrasting to our expectation may imply that intervening factors might more importantly be considered when it comes to examining effects of poverty on crime in general rather than its negative consequences directly affecting crime.

Unemployment predictors also had a significantly negative association with OPC, although they were the weakest ones among the significant predictors. Note that unemployment has been less consistently related to crime compared to poverty or economic inequality (Nivette, 2011; Pratt & Cullen, 2005). As discussed previously, it was found to have a positive relationship to high crime rates, especially for property crimes, since economic difficulties arise as a result of unemployment (Chiricos, 1987), while some other empirical studies reported the opposite results and argued that unemployment decreases crime as it increases household activity ratio, which in turn leads to an increased capable guardianship (Cantor & Land, 1985; Land et al., 1990). However, both explanations seem to be barely applicable to OPC. Instead, there is a possibility that states with higher unemployment rates or greater proportions of temporary workers are more likely to rely on the manufacturing industry rather than the ICT one, so thus more likely to include the regions often called Rust-Belt. Due to the expansion of neo-liberalism and factory automation systems, secure jobs in the manufacturing industry have been significantly decreasing for a few decades, and proportions of unemployed and temporary workers have been increasing in these regions. For workers who are engaged in this manufacturing industry, they might use ICT devices and access the Internet less frequently compared to those in the ICT or service industries because the latter are more likely to rely on the online and ICT settings, and this, in turn, may lead them to be familiar with new technological settings. Thus, the differences in ICT accessibility, familiarity, and online opportunities depending on types of the major industry of regions might be more directly related to OPC rates rather than effects of unemployment itself. Interestingly, data employed in the current study also showed that states that can be categorized as the Rust-Belt states had greater unemployment rates and lower OPC rates.[9] This finding can be one of the clues supporting the hypothetical relationships among unemployment, types of industry, and OPC.

For the rest of the significant predictors, proportions of Hispanic population and male population, and the cultural tightness/looseness index, one of the predictors in the deterrence domain, were found to have a significant relationship to OPC. That is, a state with greater *proportions of Hispanic* and *male populations*, and *cultural looseness* is more likely to report a greater OPC rate. Regarding the cultural tightness/looseness index, specifically, if a state has a criminal justice system emphasizing harsher punishment for crimes and social institutions with a marginal tolerance to culturally deviant behaviors, the state is more likely to report a lower OPC rate. It should also be noted that it had a relatively strong association with OPC, the second largest inverse effect.

As for the relationship between male population and OPC, first of all, it corresponds to the general tendency of crime in regard to gender in that males tend to commit more crimes than females. Relationships of greater Hispanic population and cultural looseness to OPC seem to be relevant to each other. A society emphasizing severe punishment for a crime and intolerance to individuals' deviant behaviors tend to protect homogeneity of the society and their own rules and culture rather than values of diversity and individuals' uniqueness and creativity. According to Harrington and Gelfand's study (2014), states with greater cultural tightness were found to have greater social discrimination and inequality measured by the

[9] Nine states, New York, Pennsylvania, West Virginia, Ohio, Indiana, Michigan, Illinois, Wisconsin, and Iowa include the regions called Rust-Belt. For unemployment, all the states other than Iowa were found to have unemployment rates above the average. For OPC, all the states except the state of New York had OPC rates above the average.

percent of minority-owned or women-owned firms, and lower creativity measured by utility patents per capita and the number of fine artists. Therefore, states with a greater cultural tightness are more likely to have a culture of discrimination against minorities so they may have a lower percent of Hispanic population. In addition, their marginal creativity, as Harrington and Gelfand (2014) pointed out, can also be directly related to limited understanding and application of ICT, which also indicates marginal online criminal opportunities. All together, levels of tolerance and creativity may affect Hispanic population and OPC simultaneously. That is, a society with a greater openness to new technology, diverse cultural backgrounds, and unique/creative ideas, which is representative of a developed and affluent society with fewer traditional crimes, may have a new type of crime based on creativity and technology-oriented social characteristics. As Durkheim (1895, 1897) discussed that socio-pathological problems in a society can be understood by other social facts of the society, OPC can be regarded as a negative byproduct of advanced social characteristics such as creativeness, openness, diversity, and tolerance in a developed society.

Finally, it was found that online opportunity predictors, as expected, had a higher OPC rate. The greater the *proportion of households using the Internet at home* as well as *households using the Internet anywhere*, the higher the OPC rates. As discussed earlier, increasing ease and affordability of Internet access creates opportunistic factors to increase OPC since Internet access is the precondition of OPC. The results support this relationship. Nevertheless, the remaining two predictors in the online opportunity domain, 1) *number of public-use internet computers in public libraries* and 2) *frequency of use of publicly available internet computers in public libraries*, did not have a significant relationship to OPC. These results may imply that the location of Internet access can be a critical factor in committing OPC. That is, Internet access at home might be more closely related to OPC compared to Internet access outside of the home. In the context of the latter, OPC are less likely to be committed because potential offenders accessing the Internet via public computers may perceive that they are monitored by bystanders around them and information security managers of the public computers. Song and colleagues (2016) also pointed out that Internet access outside of the home might reduce cybervictimization as it functions as a guardianship to deter online risky behaviors due to the existence of bystanders in public areas. To sum, Internet access location in addition to the frequency of Internet access seem to be important OPC opportunities or risk factors for both cybercrime offending and victimization.

Regarding the question about the explanatory power of the model predicting OPC, it was found that the PLSR model explained almost a half of variance in OPC (R^2=0.490). That is, although a half of variance in OPC was explained by both predictors of traditional crimes and online opportunity predictors, the remaining portion of variance still needs to be explained by undiscovered predictors of OPC. Thus, it is suggested that future studies focus on exploring these uncharted predictors and discussing how they are associated with OPC.

For the exploration, the results of the comparison between state-by-state predicted and actual OPC rates may be a good starting point. According to the results, a straight line was observed between predicted OPC rates calculated by the PLSR model and actual OPC rates for most of the states, which indicates that both types of OPC rates were overall similar. However, some states reported a relatively greater predicted OPC rate than the actual rate (*New Hampshire* and *Connecticut*) and vice versa (*New York*, *Delaware*, *Montana*, *Washington*, and *Nevada*). For these states, the greater difference between both types of OPC rates they had means there is a significant amount of error in the model predicting OPC. That is, there might be more undiscovered predictors that would explain the error, especially for these states, and they need to be identified and included in a model in addition to the predictors employed in the current study. Future studies may begin with searching for similar characteristics, especially those expected to be closely related to OPC, among the states found to have a relatively greater gap between predicted and actual OPC rates. If any kind of similar structural conditions among these states are found, they are likely to be a possible predictor of OPC, and an inclusion of these predictors may increase an explanatory power of the model predicting OPC.

Modeling for Predicting Online Opportunity

The present study also has the purpose of exploring probable predictors of online opportunity to obtain preliminary knowledge about indirect effects of macro-social predictors on OPC mediated (or moderated) by online opportunity. The research questions about this purpose are: *Are there any influential relationships between the existing predictors and the online opportunity predictors? How much variance in the online opportunity predictors can be explained by the existing predictors?*

Regarding the first question, it was found that 9 predictors out of 37 possible predictors of online opportunity were significantly associated with online opportunity; three predictors — *percent of female labor force participation*; *percent of population between 18-65 years*; *voter turnout* — had a positive relationship to online opportunity, while six predictors — *percent individuals under the poverty line*; *percent of families under the poverty line*; *percent of people without a high school diploma*; *tightness/looseness index*; *infant mortality rates*; *Gini coefficient* — had a negative relationship.

As anticipated, online opportunity had a significant relationship to predictors related to macro-level economic conditions, especially predictors in the domain of poverty/absolute deprivation. All three poverty predictors were inversely related to online opportunity, especially two of them, 1) *percent of families under the poverty line* and 2) *percent of individuals under the poverty line*, were found to have the strongest effects. If a state has greater *proportions of families or individuals below the poverty line*, or greater *infant mortality rate*, the state is more likely to have a lower level of online opportunity. These findings seem similar to prior research findings that concentrated poverty at the community-level lowers individuals' online access (Mossberger et al., 2006). These results may support the idea discussed above that a society suffering from prevailing absolute deprivation has marginal opportunities to access the Internet since that society is more likely to have difficulty in investing their resources in advanced ICT infrastructure. Thus, the consistently and significantly inverse relationships of poverty predictors to online opportunity can be partial evidence that poverty may have a negative indirect effect on OPC via online opportunity.

In contrast, predictors in the domain of economic inequality/relative deprivation did not have a significant relationship to online opportunity other than the *Gini coefficient*. This seems to be due to the fact that the Internet has become an indispensable medium recently for the general population in most societies. Given that the costs of access to the Internet and the use of ICT devices have been decreasing and become reasonable for a majority of the population, the income ratio might capture online opportunity marginally because the ratio basically does not indicate economic difficulties in meeting basic needs. If it is the case, the use of Internet will not be considered. In sum, although relative deprivation predictors had a direct effect on OPC, there is little evidence that they have an indirect effect on OPC through online opportunity.

The strongest positive association between the *percent of female labor force participation* and online opportunity was also found. This predictor has been employed as an indicator to measure the concept of household activity ratio in the perspective of routine activity theory. In the context of online opportunity, however, the relationship might be related to industrial structure in a society. For example, if a society has more jobs in education, service, and ICT industries compared to jobs in manufacturing and agricultural industries, the society may need more advanced ICT infrastructure because the former largely depends on it, and may also need more female workers as their major industries are less likely to emphasize physical skills. Weinberg's findings (2000) support these hypothetical relationships. He reported that an increase in computer use in workplace was positively correlated with female labor force participation, suggesting that the change in working conditions, de-emphasizing of physical skills due to advancement of ICT, may have benefited female workers. Thus, while the percent of female labor force participation did not have a direct relationship to OPC, this predictor should be considered as a macro-social factor that might have an indirect effect on OPC via online opportunity, as it indicates more ICT-based industries in a society.

The indicator of age structure employed in this study, *percent of population aged 18 to 65*, had also a relatively strong positive relationship to online opportunity. As is the case of female labor force participation, the relationship seems to be relevant to characteristics of economic/industrial structure of a society. In other words, since the age structure (18-65) also indicates working-age population, a higher proportion of population in this range of age is likely to be associated with more economic activities. Considering that many kinds of work currently are ICT-integrated and they require advanced ICT infrastructure for work efficiency, it is natural that a greater working-age population is positively correlated with a higher level of online opportunity due to contemporary working conditions. Although the age structure predictor did not report a significant relationship to OPC, it might still be possible that it indirectly affects OPC through online opportunity. Since a relatively broad age range, 18 to 65, was applied in the current study, using more narrowly categorized age groups might be helpful to identify relationships among age structure, types of industry/working condition, and online opportunity. For example, a region with a higher percent of younger population such as under 40 years is likely to have more population involved in industries with relatively high dependency on ICT (e.g., service, education, technology), and this, in turn, may lead to a higher level of online opportunity in that region compared to others with a higher percent of elderly population.

Two predictors in the domains of non-economic institutions, education and polity, were also found to have a significant association with online opportunity. According to the results, a state having a higher *percent of people with high school diploma* or a higher *voting turnout* was more likely to have a higher level of online opportunity. For educational attainment, specifically, the results of the current study are congruent with the findings of prior studies that low educational attainment was related to not only the quantity of online access but the quality of online activities as well (Hargittai & Hinnant, 2008; Horrigan, 2016; Mossberger et al., 2006). It seems that a region with low levels of educational attainment or political participation is more likely to have a group of people, who are not very interested in online activities and applications, which may, in turn, lead to under-developed ICT infrastructure, a lower level of online opportunity, and eventually a lower OPC rate.

Finally, *cultural tightness/looseness index* was also found to be significantly associated with online opportunity, indicating that cultural looseness was positively related to it. As discussed earlier, since the concept of cultural looseness may also indicate values of creativeness, openness, and tolerance, a state with higher cultural looseness is more likely to have a group of people, who highly depend on ICT devices and the Internet during their routine activities including both work and household activities, which may, in turn, lead to a high level online opportunity and a greater OPC rate in the end. Therefore, cultural tightness/looseness index may also indirectly affect OPC via online opportunity as well as its direct relationship to OPC.

In terms of the question how much variance in online opportunity is explained by the PLSR model, the final PLSR model explained approximately 80% of variance in online opportunity (R^2=0.795). This indicates that predictors required to explain most of the variance in online opportunity were included in the final model. The linear relationship between predicted and actual measured online opportunity also shows that the model predicted actual online opportunity well. As is the case of OPC, some states reported relatively greater differences between predicted and actual online opportunity. Five states including *Louisiana*, *Utah*, *Nebraska*, *Kansas*, and *Vermont* reported relatively higher levels of predicted online opportunity than the actual online opportunity, while six states including *West Virginia*, *Pennsylvania*, *Hawaii*, *Montana*, *North Dakota*, and *Massachusetts* were vice versa. As discussed previously, these distinctions imply that there still might be uncharted predictors to explain the variance in actual online opportunity, and the undiscovered potential predictors might be related to common characteristics of these outlier states. It is also suggested that future studies explore these possible predictors for designing a better model.

Suggestions for Future Studies and Effective Policies

For Future Studies

Drawing on the findings of the current study, some aspects that future studies might focus on are suggested. First of all, the current study attempted to search for a good model to explain a new type of property crime, OPC, applying many macro-social indicators based on macro-level criminological theories and empirical studies. As confirmed by the results, while some predictors included in the analytic model were found to have a significant relationship to OPC, it was also found that there are still many macro-social predictors left unidentified because the final model for predicting OPC only accounted for about 50% of variance in OPC. Thus, it can be suggested that future studies work on exploring these unidentified predictors of OPC to construct a better predictive model. Regarding this issue, as discussed earlier, the results analyzed the state-by-state difference between predicted and actual measured OPC rates might be useful. That is, it can be inferred that states with a relatively greater gap between predicted and measured OPC rates may have a unique macro-social characteristic, which was not included in the model but possibly affects their actual OPC rates. If common structural characteristics, expected to have a relationship to OPC and shared by these outlier states, are identified and relationships between these characteristics and OPC are examined, it seems possible to approach more accurate information about the potential predictors.

In regard to the uncharted predictors of OPC, future studies can also focus on searching for diverse forms of online opportunity predictors. Most prior studies utilizing online opportunity indicators have primarily concentrated on the quantitative aspect of online access (e.g., percent of household with a subscription of broadband service, percent of people who can access the Internet anywhere) to measure online opportunity. However, not only the quantitative aspect of online opportunity but the qualitative aspect, diverse patterns of Internet access (e.g., location, time, and ICT device for Internet access; types of online activity, etc.), might also be important to understand OPC as well as cybercrime in general. In the previous chapter, it was discussed that digital divide appeared depending on both community- and individual-level characteristics such as age, educational attainment, and income. Although the digital divide is expected to decrease as Internet access is becoming easier and more affordable due to the expansion of Internet networks and advancement in online infrastructure, the qualitative aspect of online opportunity seems likely to become more heterogeneous across different regions and groups (Hargittai & Hinnant, 2008; Horrigan, 2016; Mossberger et al., 2006; Ren et al., 2013). Future studies thus need to focus more on the qualitative aspect such as what specific patterns or types of Internet access or online opportunity have a significant effect on OPC and cybercrime in general.

Finally, it is also suggested that future studies delve into the development of OPC theory and the examination of structural relationships among macro-social indicators, online opportunity indicators, and OPC. That is, direct effects of macro-social conditions on OPC as well as their indirect effects through online opportunity need to be theorized based on appropriate speculation and relevant empirical evidence, and to be examined by advanced statistical approaches for structural modeling. Since there has been little macro-level research on OPC theory and predictors of OPC, the current study, with an exploratory purpose, applied the PLSR approach in order to identify significant macro-social predictors of OPC among many possible ones, and found some significant predictors of OPC as well as macro-social indicators of online opportunity. With these results, the current study contributes to important information about the possibility that some macro-social conditions may also indirectly affect OPC via online opportunity. Nevertheless, this possibility is based on speculation and cannot be empirically verified in the current study due to characteristics of the statistical application of PLSR. Based on the results of the current study, future studies thus should embark on theorizing OPC to provide proper explanations regarding relationships between macro-social conditions, online opportunity, and OPC, and examining the structural relationships by using advanced statistical approaches such as covariance-based structural equation modeling (CB-SEM, LISREL) or partial least square structural equation modeling (PLS-SEM).

For Effective Policies

To design effective policies responding to OPC, there is a need for a more sophisticated data collection process drawing on a more clear definition and specified categorization of OPC because it is obvious that access to precise data is a necessary condition for more effective policies, considering that OPC and cybercrimes in general include many heterogeneous types of online crime with different orientations and modus operandi. As discussed earlier, however, it is difficult to provide useful suggestions in order to design an effective policy for OPC based on the results of the current study due to some limitations of the IC3's OPC data applied in the current study. Accordingly, suggestions to establish better data collection should have a priority at this point.

In this respect, Gordon and Ford's (2006) definition, discussed in the previous chapter, might be useful for establishment of a better data collection process of OPC as well as cybercrime in general. Their definition locates a cybercrime along a certain point in a continuum according to whether it is close to technology-oriented cybercrime (Type I cybercrime) or people-related cybercrime (Type II cybercrime). Collecting OPC data based on this criteria may benefit local governments and law enforcement agencies as it allows them to use their resources more effectively. In other words, if they can identify characteristics of OPC frequently committed in their jurisdictions (e.g., whether the majority are people-related OPC or technology-oriented OPC), it will be useful for them to determine priorities for more effective policies for responding to OPC. For instance, OPC using advanced and sophisticated hacking and crimeware tools (Type I cybercrime) might be prevalent in a region where a higher level of educational attainment or creativity appears. For a region economically deprived as well as anticipated to have a relatively high traditional crime rate, by contrast, less technology-oriented OPC or more people-related OPC such as spamming and online scam (Type II cybercrime) are a more prevalent form since these types of crime do not require advanced technological skills and knowledge. Thus, if future OPC data provides information about relationships between regional attributes and types of OPC, it would enable local policy makers to design more effective OPC policies including the aspects of social support and enforcement, as it allows them to consider their regional contexts.

Limitations of the Current Study

Some limitations related to data and methodology employed in the current study should be noted and considered when the research findings are discussed. Limitations of data measured OPC need to come foremost. The IC3's state-level OPC data employed in this study are collected and published if OPC victims report their victimization to the IC3 and information about an offender's location is identified after the investigation. Therefore, OPC represented by the data is highly likely to be only a small portion of actual OPC. As is widely known, underreporting crime makes it difficult to identify overall scales and characteristics of crime. According to the recent report of the National Criminal Victimization Survey (Truman & Langton, 2015), less than 40% of property crimes were reported to law enforcement agencies, while approximately 50 to 60% of violent crimes were. For traditional property crimes, it is particularly less likely to be reported compared to violent crimes since victims do not notice their victimization or do not want to report even though they are aware of their victimization when financial losses are relatively minor or they do not believe that they can be helped by law enforcement officers (Mosher, Miethe, & Hart, 2010; Skogan, 1984). Furthermore, individuals' reporting practices can be dependent on their diverse socio-demographic attributes such as economic status, unemployment, and ethnicity, and even macro-level economic cycles as well (MacDonald, 2001, 2002; Reyns & Randa, 2017). OPC data employed in this study might also have these issues of underreporting. The scale of underreported OPC may vary across states depending on their macro-social characteristics and socio-demographic structure, and this, in turn, may lead to biased results.

The limitations of the analytic strategy applied in this study, PLSR, should be noted as well. As mentioned previously, using the PLSR approach can be a good strategy to identify significant predictors of a research interest under the circumstance that relevant theories are rarely developed or do not exist. For the current study, specifically, OLS does not work efficiently because it has a relatively small sample size but many possible predictors, which lead to the issues of low statistical power and multicollinearity. Nonetheless, since the PLSR approach does not consider measurement error of variables when it extracts latent components from the variables for modeling, disregarding measurement error can be a weakness of the PLSR model. Some scholars, as mentioned earlier, argue that covariance-based modeling (e.g., CFA, LISREL) is superior to the PLS-based modeling (Rönkkö et al., 2015), one of the reasons is that the former estimates parameters considering measurement error of variables (Goodhue et al., 2012). Thus, the possible bias derived from the issue of measurement error should be considered when the results of the current study are discussed.

Conclusions

The present study attempted to explore macro-social predictors of OPC and to examine how effectively the model, which is constructed by multiple macro-social indicators based on the PLSR approach, predicts actual OPC rates across fifty states in the U.S. According to the results discussed above, 19 macro-social indicators out of 41 were found to have a significant association with OPC. Specifically, it should be noted that predictors related to macro-level economic conditions such as poverty, inequality, economic social support, and unemployment were a majority of the significant predictors of OPC. Some online opportunity predictors were also significantly and positively associated with OPC as expected.

On the other hand, the current study also examined what macro-social indicators were significantly related to online opportunity. Through this examination, this study also attempted to explore the possibility that macro-social conditions indirectly affect OPC mediated (or moderated) by online opportunity. Among 37 macro-social indicators, 9 were significantly associated with online opportunity. It should be noted that all three predictors in the domain of poverty/absolute deprivation had a highly inverse relationship to online opportunity, suggesting that absolute economic deprivation might have not only a direct effect on OPC but also an indirect effect via online opportunity. In addition, other indicators such as female labor force participation, age structure, cultural tightness/looseness index, education, political participation, and economic inequality were also found to have potential indirect effects on OPC through online opportunity.

Drawing on these findings, the present study pointed out that there are still many unidentified macro-social predictors of OPC and suggested that future studies focus on exploring the unidentified predictors. It is also suggested that future studies explore more diverse types of online opportunity predictors of OPC including not only the quantitative aspect (e.g., frequency of Internet access) but the qualitative one (e.g., types of location, time, and online activity) as well. Due to the lack of relevant theories and empirical studies in regard to OPC, the current study concentrated on providing preliminary information about relationships between macro-social conditions and OPC. One reason for the absence might be significantly attributable to critical limitations of OPC data. For a better understanding of OPC, therefore, more sophisticated OPC data collection to provide more reliable data was also suggested in this study. With this reliable data, it is expected that future studies can apply more advanced and inclusive analyses to examine structural relationships among macro-social conditions, online opportunity, and OPC, and this, in turn, may contribute to the development of theories explaining OPC.

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