Protest and property crime:

political use of police resources and the deterrence of crime

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Abstract

This article investigates the claim that the political use of police resources promotes crime. Using a panel of South Korean metropolitan regions, we show that (1) the reallocation of police resources toward the control of political protests reduces arrest rates for crime and (2) this trade-off effect becomes insignificant at the end of the government, potentially because police bureaucrats strategically defect against the outgoing government. The resulting change in deterrence critically influences the incidence of crime. Overall, the impact of the reallocation of police on crimes mainly works through its trade-off effect on the arrest rate. Our findings imply that it is not the size of the police per se, but the allocation of police resources toward crime control that deters crime. The use of police resources for protest control is explained by bureaucratic self-interest, rather than by public interest.

Keywords: police resource allocation, protest control, strategic defection, probability of arrest, deterrence of crime
JEL classification: K42, H39

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1. Introduction

Since Becker (1968), the economics of crime literature has examined the deterrence effects of the police (Levitt 1997; Lin 2009; Chandrasekher 2016), prosecutors (Dušek 2012; Entorf and Spengler 2015; Kim and Kim 2015), and courts (Drago et al. 2009; Almer and Goeschl 2011; Johnson and Raphael 2012). In particular, the allocation of police resources is said to critically influence crime by altering the probability of arrest (Benson et al. 1992, 1994, 1998; Resignato 2000; Benson 2010; Machin and Marie 2011).

This study investigates the claim that the reallocation of police resources toward (non-crime) political activities reduces the deterrence of crime. Although public policing is essentially a resource allocation problem, previous research has been relatively silent on the allocation of police resources (Benson 2010, p. 184). Existing studies have focused on the nexus between drug crimes and (non-drug) Index I crimes. For instance, a number of empirical studies have found that shifting police resources toward drug enforcement effectively reduces the deterrence of property crime by, for instance, reducing the number of police on patrol (Benson and Rasmussen 1991; Sollars et al. 1994; Benson et al. 1998; Mast et al. 2000; Shepard and Blackley 2005). Indeed, the reduction in deterrence led to a significant increase in property crime during the drug war in the 1980s (Benson et al. 1995, 1998).[1]

Drug crimes, however, are related to non-drug crimes, potentially causing an endogeneity problem (Goldstein et al. 1992). For instance, Kuziemko and Levitt (2004) found that locking up drug offenders reduces violent and property crime, potentially because drug offenders commit other crimes (at rates comparable to those of other types of criminals). Using a panel

[1] The tradeoff in the allocation of police resources between drug enforcement and non-drug crime is not unique to the U.S. See, for instance, Mendes (2000) and Miron (2001).

of German states, Entorf and Winker (2008) found that drug offenses have a significant impact on property crime.[2]

This paper builds on the literature by examining the tradeoff in the allocation of police resources between crime and political protests.[3] The central findings of this paper are that (1) a reallocation of police resources toward the control of political protests reduces arrest rates for crime (in particular, property crime) and (2) this trade-off effect is significantly reduced at the end of the government—potentially because police bureaucrats strategically defect against the outgoing government. The logic of strategic defection follows the separation-of-powers approach in the context of judicial rulings (Helmke 2002). Police bureaucrats, who lack independence, engage in strategic defection to distant themselves from a weakening government.

We are unaware of any study that has examined the effect of shifting police resources between protest control and crime control. By focusing on the political use of the police, we can determine whether the reallocation of police resources is motivated by bureaucratic self-interest or public interest. In support of the bureaucratic self-interest explanation, Benson et al. (1995) noted that the Comprehensive Crime Act of 1984 (that allowed local police

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[2] Some research, however, has maintained that drug users are no more likely to commit non-drug crime than are non-drug users (e.g., Benson et al. 1992; Resignato 2000). Benson (2009) also suggested that drug arrests, a measure of drug use in Entorf and Winker (2008), could reflect police resource allocations.

[3] Note that political protests could also be endogenous to Index I crimes. In the U.S., for instance, political protests are often accompanied by thefts, arson, and even vandalism. In Korean culture, however, these kinds of behaviors are not significant because those engaging in political protests are not generally crime-prone groups. If political protests are indeed positively associated with Index I crimes in South Korea, then the tradeoff effect may be even larger than the results of our study.

agencies to keep seized assets) significantly increased drug arrests.[4] Drug enforcement, however, also serves public interest to the extent that drug use poses public health risk. On the contrary, the control of political protests is more likely to serve the regime—and police bureaucrats' career potential. Our finding suggests that the use of the police for protest control serves bureaucratic self-interest rather than public interest.

Using a panel of 13 metropolitan regions in South Korea over 16 years (2000–2015), we test the hypotheses suggested by the bureaucratic approach to the allocation of police resources. The 13 metropolitan regions cover all the major cities and provinces in South Korea. The empirical methodology used in this paper inspects the causal effect of police forces deployed for protest control on the probability of arrest under different periods of the government. This means adding to the standard production equation of arrests *interactions* between the deployment of the police for protest control and a dummy variable indicating the early period of the government (e.g., the first two years of the five-year term). As robustness check, we estimate a simultaneous equations model in order to examine the causal relationships among the allocation of police resources, the probability of arrest, and the crime rate.

The empirical results of this paper show that the shift of police resources toward protests has a negative effect on arrest rates, but that the trade-off effect becomes insignificant at the end of the government. The resulting change in deterrence critically influences the incidence of crime. Overall, the impact of the reallocation of police resources on crimes mainly works through its trade-off effect on the arrest rate.

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[4] Similarly, prosecutors pursue (bureaucratic) self-interest in prosecuting cases. For instance, they may prefer the cases that either require less time to prepare for trial or benefit their future career (e.g., Boylan 2005; Gordon and Huber 2009).

Thus, it is not the size of the police force per se, but the allocation of police resources toward crime prevention and control that deters crime (Sherman and Weisburd 1995; Sherman 2004). In spirit, our findings are related to the economic model of crime that predicts that a policy that decreases the deterrence of certain crimes will cause offenders to substitute into these very crimes (e.g., Shepherd 2002).[5]

This paper is organized as follows. Section 2 explains political protests in Korea and police bureaucrats' incentives to reallocate resources between protests and crimes. Section 3 describes the data and variables used in this study. Section 4 presents the empirical models and discusses the findings. Section 5 concludes our paper.

2. Bureaucratic incentive and police resource allocation

Korean society is characterized by the frequent use of political protests and mass rallies as a means of expressing disagreements with government policy. This tendency is deeply rooted in the experience with military governments in the 1960–1980s. Decades after the end of military governments (and democratization), political protests are still common in Korea. During 2000–2015, for instance, there were about 11,000 annual cases of protests and rallies

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[5] As an anecdote, the Seoul Metropolitan Police Agency temporarily reassigned police forces from public security (e.g., protest control) to public safety (e.g., patrolling and criminal investigation) between December 2014 and January 2015. As a consequence, incidences of five types of serious crimes (homicide, robbery, rape and sexual harassment, theft, and violence) decreased by 34.4% compared with the same period in the previous year. In particular, the reduction in property crimes such as larceny-theft and burglary was substantial, for instance, owing to reinforcing patrol in residential areas. This anecdote suggests that even the temporary reallocation of police forces does appear to influence the deterrence of crime, potentially because police forces are effective across different functions (e.g., across public security and public safety).

to which police forces were deployed.[6] The average number of deployed police was about 262 officers per case of protest, which is substantial given that the overall average number of police is about 200 per 100,000 residents. Figure 1 shows the total number of protests and total number of deployed police forces in the capital city of *Seoul* during 2000–2015. The figure clearly indicates that (1) the number of protests tends to increase toward the end of the government and (2) more protests require more deployment of police forces (although this does not necessarily mean that more police forces will be deployed per case of protest).

Most political protests in Korea are organized by interest groups such as labor unions and citizen groups that oppose major government policies (Korea Development Institute 2006).[7] Because the protests can undermine the stability of the regime, the government in office routinely deploys the police so as to contain the anti-government protests.

Police agencies in Korea, whether central or local, are influenced by the Ministry of the Interior (an executive arm of the government) that determines the budgets for the police.[8] Thus, police bureaucrats, who lack independence, respond to the political pressure from the ministry to the extent that their career potential depends on their level of cooperation. The police agencies would reallocate more police resources toward protest control and away from

[6] These police forces typically belong to the public security bureau (located in each metropolitan or local police agency). Data were obtained from the *Police Statistical Yearbook* published by the Korean National Police Agency.

[7] The policies range from the decision to send troops to Iraq (2004) and the importation of U.S. beef (2008) to the *Miryang* transmission tower projects (2014). Other major incidences include the *Yangju* highway incident (2002) in which a United States military armored vehicle struck and killed two teenage schoolgirls; impeachment of President Roh Moo-hyun (2004); *Yongsan* incident (2009); meddling in the presidential election by the National Intelligence Service (2012); *Seoul* City Employee Spy case (2013); *Sewol* ferry disaster (2014); and impeachment of President Park Geun-hye (2016-2017).

[8] Both the Korea National Police Agency (central agency) and the 17 local agencies are subordinate to the Minister of the Interior.

other functions.[9] For instance, the shift of police resources can reduce patrolling that both deters and responds to crimes after they have been committed (Benson et al. 1998).[10]

This shifting of police resources could be less evident at the end of the government, however, because police bureaucrats strategically defect against the outgoing government. One reason for the defection is that the opposition political party, a potential incoming government, often supports the protests, with its members even participating in the rallies themselves. This strategic behavior is similar to the separation-of-powers theory in which judges are rational decision-makers constrained by the government in office (Ferejohn and Weingast 1992; Epstein and Knight 1996). Judges, if they lack independence, would increase antigovernment rulings, "*once the government in office begins to lose power*" (Helmke 2002, p. 293). Similarly, when police bureaucrats are constrained by incoming governments that oppose the incumbent government, the best response is to engage in strategic defection to "*distance themselves from a weakening government*" (Helmke 2002, p. 291). Police bureaucrats would then focus more on crime control, which is also important for their future career.

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[9] This sometimes results in disproportionately large police forces mobilized for certain protests. For instance, Arnold Fang of Amnesty International said, "The force used by police at the *Miryang* protest was disproportionate and in breach of international standards." Note that the *Miryang* protest (2014) took place in the second year of President Park's administration.

[10] The share of police officers in security control relative to police officers in crime investigation increased from 45.2% in 2001 to 54.1% in 2015. In the same period, the probability of arrest for conventional crimes (including property and violent crime) decreased from 78.2% to 74.9%. The decrease in arrest rates may explain the fact that conventional crimes increased at a rate of 1.9% during the same period. (Note that violent crime increased at a rate of 4.9% during 2000–2015.) These data were obtained from the *Police Statistical Yearbook* published by the Korean National Police Agency and the *Annual Crime Reports* published by the Supreme Prosecutors' Office of Korea.

Note that the alternative model of public interest cannot predict that the reallocation of police resources depends on government periods. According to the public interest model, a government would allocate police resources to protest control regardless of the election cycle (i.e., whether the government is weakening or not).[11] As we show in the next section, however, bureaucratic self-interest is more consistent with the empirical results.

3. Data and variables

To examine the tradeoff in the allocation of police resources between crime and protests, we estimate both police production and crime supply function. We use a panel of data collected over 16 years (2000–2015) in 13 metropolitan regions in Korea. These metropolitan regions cover all the major cities and nine provinces, which form the political, cultural, and commercial centers of the country. The 2000–2015 period overlaps four governments led by Presidents Kim Dae-jung (1998–2002), Roh Moo-hyun (2003–2007), Lee Myung-bak (2008–2012), and Park Geun-hye (2013–2017), each serving a five-year term.[12] We use a dummy variable (*EARLY*) that is 1 for the first 2 years of the five-year term and 0 otherwise.[13] This assumes that the third year marks the point at which the government begins to lose power. As an alternative measure, we also used the dummy variable (*EARLY1*) indicating the first 3 years of the five-year term.

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[11] For instance, the government would shift more resources to protest control at the end of the government if protests tend to increase due to the lame duck syndrome.

[12] President Park Geun-hye was impeached on March 10, 2017.

[13] Since the data are not available for the first 2 years of the Kim's administration (1998 and 1999), *EARLY* is 1 for 2003–2004, 2008–2009, and 2013–2014, and 0 otherwise. We do not include pre-2000 data because crime statistics before and after 2000 are not consistent because of major changes in data compiling and crime categorization.

For the police production function, the main dependent variable is the probability of arrest for theft (defined as the number of arrests divided by the number of reported thefts). The probability of arrest represents the police production of crime deterrence, which negatively affects crime rates (Benson 2010). Note that theft crime in Korea is approximately equal to the property crime component of Index I offenses (i.e., burglary, larceny-theft, and motor-vehicle theft).[14] We focus on theft because property crime is more relevant for the tradeoff effect (e.g., the reallocation of police toward protest control reduces patrolling) and because consistent time-series data on the other categories of property crimes are not available.[15] In addition, we include conventional crimes (i.e., property and violent crimes combined) as an alternative dependent variable.

We use two proxy variables to capture the reallocation of police resources toward (non-crime) political activities away from crime control: the average number of deployed police officers per case of protest control (*POLIT1*) and the average number of deployed police officers per case of protest control and guard/security service (*POLIT2*).[16] Note that these

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[14] First, theft in Korea includes larceny and motor-vehicle theft, which constitute about 80% of property crimes in the United States (*Uniform Crime Reports 2013*). Second, theft also includes a proportion of the burglary category in the United States.

[15] Other categories of property crimes include fraud, embezzlement, and vandalism. According to the *Annual Crime Reports* published by the Supreme Prosecutors' Office of Korea, total crimes consist of conventional crimes (including property crimes and violent crimes) and regulatory crimes (i.e., violation of numerous administrative regulations). See Kim and Kim (2015) for detailed accounts of these two subcategories.

[16] All the data on protests and police deployment were obtained from the *Police Statistical Yearbook* by the National Police Agency. Some of the missing values were obtained through the Open Information System (www.open.co.kr) and interviews with the local police agencies. The Korean National Police Agency classifies six types of police mobilization for security purposes: protests, guard/security, emergency guard, congestion, disasters, and elections. We focus on protests and guard/security because these two types are most likely to be politically relevant in Korea. For instance,

police officers are members of the public security department (located in each local police agency).[17] Importantly for our purpose, a higher number of *POLIT* presumably implies a shift of police forces from crime control to protest control because (1) policy agencies often reinforce protest control by temporarily assigning officers from other departments (e.g., public safety and crime investigation) and (2) the agencies now have less capacity to assign public security police to other functions. For instance, between 2010 and 2014, about 20,000 crime investigation officers (or about 24% of the crime investigation departments) were deployed to control night protests (National Assembly 2014).[18]

Control variables include police, non-theft crime, protest (or protest and guard/security services), population, and the share of single households. The number of police officers per 100,000 residents (*POLICE*) is included because the level of police has a positive effect on the probability of arrest (e.g., a greater number of police officers allow each officer to devote more efforts to the cases). A high level of non-theft crime ($CR^{NON\text{-}THEFT}$) could reduce the likelihood of solving theft crime due to competing demands for police resources. We use the number of reported conventional crimes excluding theft per 100,000 residents. We control for the number of protest (*PROTEST1*) or the number of protest and guard/security services

we do not include police security for elections because major elections take place only every 2 to 4 years, and elections in Korea are usually peaceful events that require a limited police presence.

[17] A local police agency consists of various departments working in cooperation, including the public security, criminal and special investigation, national security, and narcotics departments.

[18] Although the decision to reallocate police resources is made at the local level, the central agency has some influence on the actions of local police agencies. This opens up the possibility that the central agency may allocate more police resources to areas where political opposition is greater if protests are frequent. Another possibility is that more police resources could be allocated to locations where the regime is strongly supported (to strengthen the support). If this is the case, the tradeoff effect will not be exclusively local because the other areas from which police are drawn should have less crime control regardless of political protests in those areas. However, reallocation of police resources across cities and regions is not a common practice.

(*PROTEST2*) because these variables can influence the allocation of police resources (*POLIT1* and *POLIT2*) and may also affect the dependent variable (probability of arrest for theft). In areas with a large population (*POP*), criminals are less likely to stand out and be recognized because neighborhood ties are weak (Benson and Rasmussen 1991; Sollars et al. 1994).[19] The share of single households (*Single*) is included because the police tend to allocate more resources (e.g., patrol) to areas with more single populations.[20] All variables are in natural logs except for the share of single households and a dummy variable indicating the early period of the government.

For the crime supply function, the dependent variable is crime rates defined as the number of reported crimes per 100,000 residents.[21] We examine both theft and conventional crimes.

As the explanatory variables, we first include two deterrence variables: the probability of arrest (*PA*) and the probability of prosecution (*PP*).[22] Both these deterrence variables are expected to have a negative effect on crime rates. We also include the number of protest (or the number of protest and guard/security services) and a proxy variable for the allocation of police resources toward political protests (*POLIT1* or *POLIT2*). The *POLIT* variable can influence crime rates indirectly through its effect on the probability of arrest but may also directly affect crime rates (if protests increase the incidences of crime).

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[19] In addition, residents in a smaller, more homogenous community are more likely to report criminal activity (Benson et al. 1991, 1992).

[20] Living alone increases the risk of crime victimization because single households engage in more public activity (Hindelang et al. 1978; Sampson and Wooldredge 1987; and Meier and Miethe 1993).

[21] All the crime data and deterrence variables were obtained from the *Annual Crime Reports*. The demographic and socioeconomic variables were obtained from *Statistics Korea* (http://kosis.kr).

[22] We first collected the number of prosecutors from all 58 district prosecutors' offices. We then grouped them into 13 metropolitan areas to calculate the probability of prosecution.

Among the socioeconomic control variables, we include the male population aged 30 to 44 (*Male30-44*) because this crime-prone group dominates participation in crime in Korea (*Annual Crime Reports* 2015).[23] Following Buonanno and Montolio (2008) and Fougère et al. (2009), we include the unemployment rates among young people aged 15 to 29 (*Unemp_Young*).[24] We also include the female unemployment rate (*Unemp_Female*) because unemployed women are less attractive targets of crime (Ochsen 2010; Saridakis and Spengler 2012). The wage is another popular proxy for labor market outcomes. We use monthly wages in the construction industry (*Wage*) because such disaggregated statistics are widely used (Cornwell and Trumbull 1994; Doyle et al. 1999). We control for the GRDP growth rate because crime rates tend to increase during recessionary periods (Laspa 2015). The number of female heads (aged 45 to 69) per 1,000 households (*Female_HH*) reflects a family environment that is associated with a higher crime rate (Levitt 1998). Finally, we control for alcohol expenditure per capita (*Alcohol*) because the consumption of alcohol is highly associated with crime incidence (Cook and Moore 1993; Raphael and Winter-Ebmer 2001; Kim et al. 2017).[25] Table 1 presents the definitions and descriptive statistics of all the variables used in this study.

[Table 1 here]

[23] Since the early 1970s, many studies have found a positive effect on crimes of certain age groups of a predominantly male population (Freeman 1996).

[24] The recent literature has focused on the unemployment rates among certain crime-prone groups such as the young population because the aggregate unemployment rate may not identify the marginal criminal (Raphael and Winter-Ebmer 2001; Gould et al. 2002; Lin 2008; Mustard 2010; Tauchen 2010).

[25] Previous literature emphasized that alcohol consumption is an important predictor of violent crimes (Saridakis 2004).

4. Empirical model and results

This section provides an empirical analysis of our main hypotheses: (1) the shift of police resources toward protest control and away from crime control negatively affects the probability of arrest, and (2) this trade-off effect would be less evident at the end of the government. The resulting change in the police production of arrest critically influences the incidence of crime. Thus, we examine both the production function of the police (by estimating the probability of arrest) and the crime supply function (by estimating crime rates).

4.1 Police production function

The police production of arrests is estimated as follows:

$$PA_{it} = \beta_0 + \beta_1 POLIT_{it} + \beta_2 POLIT_{it} \times EARLY_{it} + \beta_3 X_{it} + \delta_i + \lambda_t + u_{it}. \quad (1)$$

In (1), PA_{it} is the probability of arrest for crime in city i at time t, $POLIT_{it}$ is the police forces deployed for protest control (and guard/security service), and $EARLY_{it}$ is a dummy variable indicating the early period of the government (i.e., the first 2 years of the five-year term). X_{it} is a vector of the control variables, including police, non-theft crime, protest, population, the share of single households, and $EARLY$. Vectors δ_i and λ_t are the set of city-specific effects and time effects, and u_{it} is the error term.

The coefficient on the interaction term $POLIT \times EARLY$ measures how the effect of police reallocation on the arrest rate varies with government periods. If $EARLY = 1$, $\beta_1 + \beta_2$ measures the relationship between the police deployed for protest control ($POLIT$) and the probability of arrest (PA) during the early period of the government. Similarly, β_1 measures the marginal effect of $POLIT$ on PA at the end of the government (i.e., when $EARLY = 0$). Comparing ($\beta_1 + \beta_2$) with β_1 thus gives the full picture of the marginal effects of $POLIT$

before and at the end of the government. Our theoretical discussion implies that ($\beta_1 + \beta_2$) is significantly larger in magnitude than β_1 (i.e., $\beta_1 + \beta_2 < \beta_1 \leq 0$).

In this specification, we include *EARLY* as a separate regressor because the period of the government could directly affect the probability of arrest. For instance, police bureaucrats may produce more arrests at the end of the government to improve their future career (Excluding a simple *EARLY* term does not affect the main results, however.)

Table 2 shows the results of estimating the police production of arrests for theft, in which the dependent variables are the probability of arrest. As benchmark models, columns 1 and 2 take a basic equation that includes the number of police force deployed per case of protest control (*POLIT1* in column 1), the number of police force deployed per case of protest control and guard/security service (*POLIT2* in column 2), and control variables (in both columns). Columns 3 and 4 add interaction terms ($POLIT1 \times EARLY$ and $POLIT2 \times EARLY$) that allow the impact of the trade-off effect to vary according to whether the government is in the early period.

In columns 1 and 2, *POLIT1* and *POLIT2* have a robust and negative impact on the probability of arrest. These results simply show that a shift of police force away from crime control toward protest control reduces the police production of arrests, but do not account for the election cycle that alters the bureaucratic incentive.

When the interaction terms in *EARLY*, $POLIT \times EARLY$, are included in columns 3 and 4, the coefficients of the simple *POLIT1* and *POLIT2* become statistically insignificant. On the contrary, the interaction effects are negative and significant at the 10 percent level.

When interaction terms are added to a regression, the marginal effects provide more meaningful results (Brambor et al. 2006). The bottom panel of Table 2 presents the marginal effects of *POLIT* on *PA*, conditional on whether the government is in the early period (i.e., $\beta_1 + \beta_2 EARLY$ in Equation (1)). Note that all the marginal effects of *POLIT* are negative and larger in magnitude when the government is in the early period. For instance, when $EARLY = 1$, expanding the police deployed for protest control by 10% reduces the arrest rate by about 1.7% (in column 4). Thus, evaluated at the mean, adding 21 police officers per case of protest would be associated with a reduction of about 8,318 arrests across the regions. This is a substantial effect given that 21 police officers account for only 0.3% of the average police force across metropolitan regions while 8,318 arrests account for nearly 37% of all theft arrests made in *Seoul* in 2015.

If $EARLY = 0$ (i.e., at the end of the government), however, the marginal effects of $POLIT$ become statistically insignificant. These results indicate that the trade-off effect disappears toward the end of the government. One potential explanation is that the police agency strategically defects against the outgoing government by systematically undersupplying protest control by, for instance, deploying little or no police resources from public safety departments (e.g., patrolling and criminal investigation). An increase in $POLIT$ now reflects the greater deployment of police from public security departments only.[26] Thus, an additional force deployed for protest control leads to an insignificant reduction in crime prevention (e.g., street patrol).

Among the control variables, $POLICE$ has a robust, positive impact on the probability of arrest (PA), in line with common expectations. $CR^{NON\text{-}THEFT}$ is negatively associated with PA, but is not significant.[27] Both $PROTEST1$ (number of protests) and $PROTEST2$ (number of

[26] Another possibility is that the agencies deploy more nonessential forces such as temporary conscripted police. In Korea, some young males (mostly college students) volunteer to serve as temporary policemen in lieu of mandatory military service. Their functions include general patrol, protest control, and traffic control.

[27] We also used violent crime rate (the number of reported violent crimes per 100,000 residents), and the results remained qualitatively similar.

protest and security services) have a negative and significant relationship with PA.[28] POP and $Single$ have a positive association with the arrest probability, but the results are statistically insignificant.

[Table 2 here]

Police bureaucrats might be less willing to shift police resources away from the control of more serious crimes—for instance, violent crimes attract more media attentions than theft. Table 3 estimates the police production of arrest (i.e., the probability of arrest) for conventional crimes that include violent crimes and other types of property crimes (e.g., fraud).

In columns 1 and 2, $POLIT$ has a robust, negative impact on the probability of arrest for conventional crimes. In the bottom panel of Table 3, the marginal effects of $POLIT$ on PA are negative and significant when $EARLY = 1$. On the contrary, the marginal effects of $POLIT$ become insignificant when $EARLY = 0$. This finding confirms that police bureaucrats do not respond to the political incentive of shifting resources away from crimes at the end of the government.

[Table 3 here]

In Tables 2 and 3, we assume that a government begins to lose control of police bureaucrats in the third year of the five-year term—a point that may be considered arbitrary. Table 4 presents the marginal effects of $POLIT$ using alternative measures of $EARLY$. In Panels A and B, $EARLY1 = 1$ if the government is in the first 3 years of the five-year term (i.e., the fourth year marks the point at which the government begins to lose power). Note that the basic results remain similar in that the marginal effect of $POLIT$ on PA is negative and

[28] The impact of $PROTEST$ on PA is potentially endogenous, however. For instance, a lack of crime control (i.e., lower PA) and more political protests may both reflect social instability. In any case, excluding $PROTEST1$ and $PROTEST2$ did not change the main results (not reported).

significant only if $EARLY = 1$. We also used a different definition of $EARLY$ that is 1 for the first 4 years of the five-year term (not reported). The main results did not change qualitatively.

[Table 4 here]

4.2 Crime supply function

Our account of the trade-off effects suggests that any effect of the political use of police forces $POLIT$ on crime rates CR must be only through an effect of $POLIT$ on arrest rates PA. This argument is consistent with the deterrence hypothesis that a decrease in arrest rates (due to the shift of police resources away from crime control) increases crime rates. Section 4.1 showed that the trade-off effects hold for theft and conventional crimes.

To test this conjecture, we estimate the following crime supply function:

$$CR_{it} = \gamma_0 + \gamma_1 PA_{it} + \gamma_2 POLIT_{it} + \gamma_3 X_{it} + \theta_i + \pi_t + \zeta_{it}, \quad (2)$$

where CR_{it} is the annual number of crimes per 100,000 residents. X_{it} is a vector of the control variables, including the probability of prosecution (PP), protest, share of the male population aged 30 to 44, unemployment rates among young people aged 15 to 29, female unemployment rates, monthly wages in the construction industry, GRDP growth rate, the number of female heads aged 45 to 69 per 1,000 households, and alcohol spending per capita.

Table 5 presents the results of estimating crime rates, in which the dependent variables are the rates of theft (in columns 1 and 2) and conventional crimes (in columns 3 and 4). Throughout the columns, the probability of arrest PA has a robust, negative impact on both crime rates, while the effect of the allocation of police $POLIT$ is statistically insignificant. These results indicate that the impact of $POLIT$ on theft and conventional crimes mainly works through its trade-off effect on the arrest rate (PA). Our results are thus in line with the deterrence hypothesis that is well established in the economics of crime literature (Becker

1968; Ehrlich 1996). Note that if *POLIT* were to directly affect crime, this would imply that political protest itself influences the incidences of crime.

[Table 5 here]

4.3 Simultaneous-equations model

In Table 2, models of the probability of arrest (*PA*) include variables measuring the allocation of police (*POLIT*). The allocations of police are, however, potentially determined by the probability of arrest (*PA*) through its impact on crime supply (*CR*)—a higher crime rate might force the agencies to allocate less police resources to protest control. In Table 5, models of crime supply show that the effect of the allocation of police resources (*POLIT*) on crime supply (*CR*) mainly works through the probability of arrest (*PA*)—because the allocation of police itself has no direct impact on crime supply. These considerations imply that simultaneous-equations estimation is required to clean up the results.

Following Benson et al. (1992) and Shepherd (2002), we estimate the following simultaneous-equations model.

$$POLIT_{it} = \tau_0 + \tau_1 CR_{it} + \tau_2 X_{it} + \sigma_i + o_t + \omega_{it}, \quad (3)$$

$$PA_{it} = \kappa_0 + \kappa_1 POLIT_{it} + \kappa_2 X_{it} + \chi_i + \phi_t + \varepsilon_{it}, \quad (4)$$

$$CR_{it} = \nu_0 + \nu_1 PA_{it} + \nu_2 X_{it} + \vartheta_i + \rho_t + \varphi_{it}. \quad (5)$$

In Equation (5), the crime supply (*CR*) is a function of the probability of arrest (*PA*); in Equation (4), the probability of arrest (*PA*) is a function of the allocation of police resources (*POLIT*); and in Equation (3), the allocation of police resources (*POLIT*) is a function of the crime supply (*CR*).

Table 6 shows the empirical results of estimating (3) through (5). For brevity, we only report the results for the police deployed for protest control (*POLIT1*) and the probability of arrest for theft (PA^{THEFT}) and crime supply for theft (CR^{THEFT}). Note in column 1 (i.e., estimation of Equation (3)) that the allocation of police ($POLIT1$) is not significantly associated with the crime supply (CR^{THEFT}). This shows that our results in Tables 2 and 5 are not affected by the endogeneity of the allocation of police. In columns 2 and 3 (i.e., estimation of Equations (4) and (5)), all of the main hypothesized relationships are supported by the data. That is, allocating more police resources to protests reduces the probability of arrest, and the lower probability of arrest, in turn, increases the crime rates. This validates our approach of estimating Equations (4) and (5) separately.

[Table 6 here]

5. Concluding remarks

The conclusion of this paper is in line with the bureaucracy literature, which claims that career bureaucrats maximize the objective function that depends on their career potential and the public reputation of their bureau (Niskanen 1971; Breton and Wintrobe 1982; Le Maux 2009).

This paper examined the effect of shifting police resources between crime control and protest control. The empirical evidence indicates that the allocation of police resources between crime and political protests critically influences the deterrence of crime. While a larger number of police officers mobilized for protest control does reduce arrest rates, the effect is conditional on the government period. Indeed, the trade-off effect is significantly reduced at the end of the government—potentially because police bureaucrats strategically defect against the weakening government. The resulting change in deterrence critically influences the incidence of crime. Our findings indicate that it is not the size of the police force per se, but the shifting of police resources toward crime prevention and control that deters crime.

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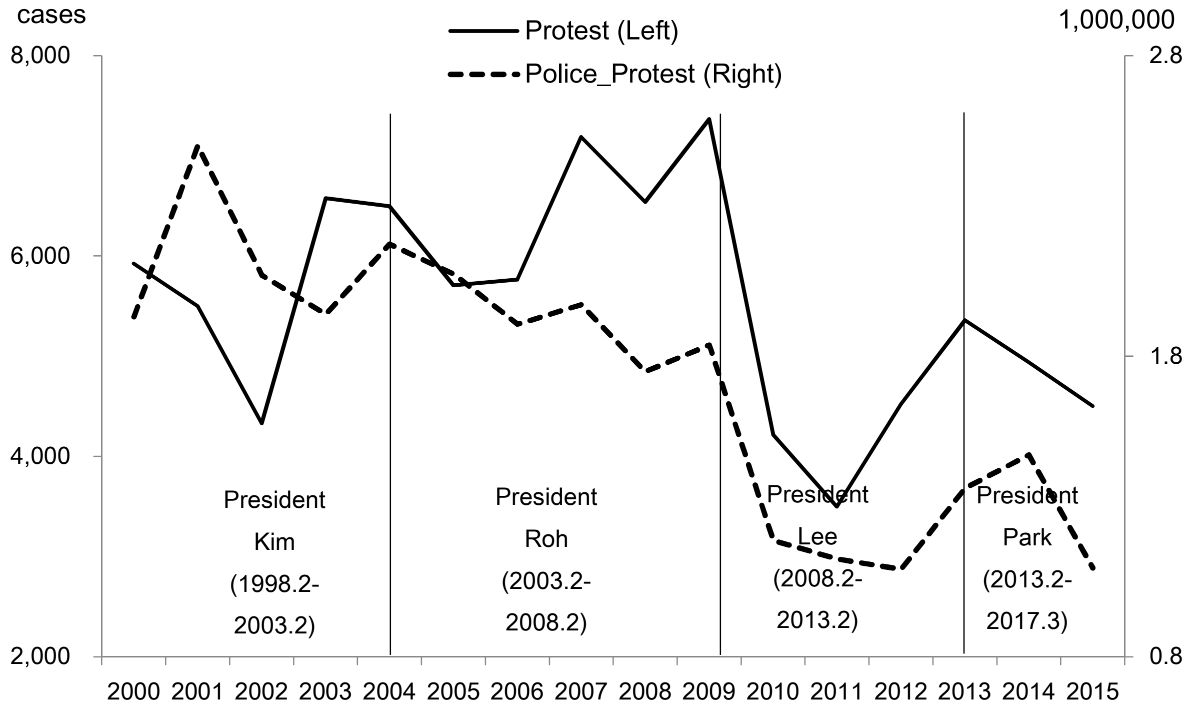
Figure 1. Protests and deployed police forces (Seoul)



Source: The *Police Statistical Yearbook*, by the Korean National Police Agency.

Notes: Protest indicates the total number of protests in *Seoul* (in which police forces were deployed). Police_Protest represents the total number of police forces deployed for protest control in *Seoul*. Note that the early period of the Lee administration (2008–2009) covers major protests and rallies against important government policies (e.g., the importation of U.S. beef).

Table 1. Definition of the variables and descriptive statistics

Variables	Description	Mean (S.D.)
CR^{C}	Number of reported conventional crimes per 100,000 residents	1,828.2 (332.7)
PA^{C}	Probability of arrest for conventional crimes	0.762 (0.073)
PP^{C}	Probability of prosecution for conventional crimes	0.341 (0.043)
CR^{THEFT}	Number of reported thefts per 100,000 residents	466.3 (144.8)
PA^{THEFT}	Probability of arrest for theft	0.498 (0.146)
PP^{THEFT}	Probability of prosecution for theft	0.319 (0.037)
$CR^{NON\text{-}THEFT}$	Number of reported non-theft in convention crimes per 100,000 residents	1,361.9 (250.8)
POP	Population	3,814,943 (3,180,114)
Single	Share of single households (%)	22.3 (4.4)
Male30-44	Percentage of the male population aged 30 to 44 (%)	12.9 (1.1)
Unemp_Young	Unemployment rate among young people aged 15 to 29 (%)	7.6 (1.6)
Unemp_Female	Female unemployment rate (%)	2.8 (0.9)
Wage	Monthly wages in the construction industry (KRW in 2010)	2,358.7 (1,028.6)
GRDP growth	GRDP growth rate (%)	3.9 (2.7)
Female_HH	Number of female heads aged 45 to 69 per 1,000 households	74.9 (10.9)
Alcohol	Alcohol and tobacco expenditure per capita (KRW in 2010)	261.1 (26.3)
POLICE	Number of police officers per 100,000 residents	201.8 (34.0)
PROTEST1	Number of protests (that mobilized police resources)	850.9 (1,447.3)
PROTEST2	Number of protests and guarding security services (that mobilized police resources)	1,049.6 (1,933.8)
POLIT1	Average number of deployed police officers per case of protest control	218.2 (169.9)
POLIT2	Average number of deployed police officers per case of protest or guarding security control	206.7 (160.4)
EARLY	Early = 1 for the first 2 years of the five-year term of the government	0.4 (0.5)

Table 2. Trade-off effects: political use of police resources

	1	2	3	4
ln(POLICE)	1.3972***	1.4291***	1.4138***	1.4345***
	(0.3647)	(0.3699)	(0.3499)	(0.3398)
ln($CR^{NON\text{-}THEFT}$)	-0.3022	-0.3040	-0.3050	-0.3086
	(0.2539)	(0.2567)	(0.2476)	(0.2479)
ln(PROTEST1)	-0.0676***		-0.0749***	
	(0.0213)		(0.0240)	
ln(PROTEST2)		-0.0664*		-0.0738*
		(0.0315)		(0.0344)
ln(POP)	0.2034	0.2271	0.1998	0.2349
	(1.1331)	(1.1345)	(1.1274)	(1.1280)
Single	0.0194	0.0237	0.0113	0.0155
	(0.0510)	(0.0515)	(0.0515)	(0.0522)
EARLY	-0.0652	-0.1101	0.5839	0.5825
	(0.6100)	(0.6113)	(0.7635)	(0.7467)
ln(POLIT1)	-0.0931***		-0.0449	
	(0.0297)		(0.0361)	
ln(POLIT2)		-0.0965**		-0.0478
		(0.0346)		(0.0386)
EARLY × ln(POLIT1)			-0.1085*	
			(0.0579)	
EARLY × ln(POLIT2)				-0.1174*
				(0.0596)
Constant	-8.633	-9.194	-8.733	-9.386
	(15.672)	(15.810)	(15.471)	(15.682)
Obs.	208	208	208	208
R^2	0.614	0.611	0.621	0.619
Marginal effects of POLIT				
EARLY = 1			-0.1533***	-0.1651***
			(0.0394)	(0.0431)
EARLY = 0			-0.0449	-0.0478
			(0.0361)	(0.0386)

Notes: The dependent variable is the probability of arrest for theft (in natural logs). All columns include fixed effects and time dummies. Estimation method: fixed effects. Cluster-robust standard errors are reported in parentheses. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$.

Table 3. Trade-off effects: conventional crimes

	1	2	3	4
EARLY	-0.1692	-0.1786	0.0048	0.0236
	(0.1976)	(0.2018)	(0.2648)	(0.2709)
ln(POLIT1)	-0.0251**		-0.0122	
	(0.0090)		(0.0136)	
ln(POLIT2)		-0.0261**		-0.0119
		(0.0112)		(0.0152)
EARLY × ln(POLIT1)			-0.0291	
			(0.0221)	
EARLY × ln(POLIT2)				-0.0343
				(0.0222)
Obs.	208	208	208	208
R^2	0.670	0.668	0.675	0.675
Marginal effects of POLIT				
EARLY = 1			-0.0413***	-0.0462***
			(0.0126)	(0.0131)
EARLY = 0			-0.0122	-0.0119
			(0.0136)	(0.0152)

Notes: The dependent variable is the probability of arrest for conventional crimes (in natural logs). Other independent variables are not reported. All columns include fixed effects and time dummies. Estimation method: fixed effects. Cluster-robust standard errors are reported in parentheses. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$.

Table 4. Marginal effects of POLIT, using an alternative definition of the early period of the government

Specifications from Tables 2 and 3	3	4
Panel A: Theft		
EARLY1 = 1	-0.1087**	-0.1081**
	(0.0380)	(0.0437)
EARLY1 = 0	-0.0714	-0.0825*
	(0.0397)	(0.0406)
Panel B: Conventional crimes		
EARLY1 = 1	-0.0283**	-0.0299*
	(0.0125)	(0.0143)
EARLY1 = 0	-0.0206	-0.0215
	(0.0130)	(0.0137)

Notes: EARLY1 = 1 for the first 3 years of the five-year term. The dependent variables are the probability of arrest (in natural logs) for theft (Panel A) and the probability of arrest (in natural logs) for conventional crimes (Panel B).

Table 5. Estimates of the crime supply function

	1	2	3	4
	Theft		Conventional crimes	
ln(PA)	-0.4290***	-0.4281***	-0.6170***	-0.6159***
	(0.0910)	(0.0890)	(0.1739)	(0.1694)
ln(PP)	-0.2771*	-0.2714*	-0.0430	-0.0487
	(0.1490)	(0.1513)	(0.2616)	(0.2605)
Male30-44	0.0387	0.0452	0.1153*	0.1198*
	(0.1404)	(0.1394)	(0.0642)	(0.0638)
Unemp_Young	0.0243	0.0244	0.0129	0.0129
	(0.0227)	(0.0226)	(0.0148)	(0.0147)
Unemp_Female	-0.0504**	-0.0504**	-0.0466*	-0.0472*
	(0.0224)	(0.0219)	(0.0230)	(0.0228)
ln(Wage)	-0.1219	-0.1344	-0.3138**	-0.3248**
	(0.2352)	(0.2305)	(0.1101)	(0.1119)
GRDP growth	-0.0136*	-0.0136*	-0.0055	-0.0055
	(0.0064)	(0.0064)	(0.0045)	(0.0044)
ln(Female_HH)	-0.6155	-0.5792	0.6693**	0.6855**
	(0.7025)	(0.6901)	(0.2428)	(0.2357)
ln(Alcohol)	-0.3008	-0.2942	-0.1695	-0.1510
	(0.5009)	(0.5019)	(0.2777)	(0.2726)
ln(PROTEST1)	-0.0022		0.0086	
	(0.0210)		(0.0089)	
ln(PROTEST2)		0.0050		0.0118
		(0.0213)		(0.0114)
ln(POLIT1)	-0.0188		-0.0158	
	(0.0308)		(0.0132)	
ln(POLIT2)		-0.0279		-0.0211
		(0.0338)		(0.0133)
Constant	9.842	9.660	6.050**	5.899**
	(5.068)	(4.987)	(2.622)	(2.552)
Obs.	208	208	208	208
R^2	0.709	0.710	0.659	0.661

Notes: In columns 1 and 2, the dependent variables are the theft crime rate in natural logs (i.e., the number of reported crimes of theft per 100,000 residents). In columns 3 and 4, the dependent variables are the conventional crime rate in natural logs. All columns include fixed effects and time dummies. Estimation method: fixed effects. Cluster-robust standard errors are reported in parentheses. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$.

Table 6. Simultaneous-equations estimation: Theft crime

	Dependent variables		
	ln (POLIT1)	ln (PA^{THEFT})	ln (CR^{THEFT})
	1	2	3
ln(CR^{THEFT})	0.3910 (0.2251)		
ln(PA^{THEFT})			-0.4298*** (0.0911)
ln(POLIT1)		-1.5063*** (0.1513)	
ln($CR^{NON\text{-}THEFT}$)		-0.2581* (0.1362)	
ln(POLICE)	-1.3227 (1.4095)	0.7725* (0.4101)	
ln(PP^{THEFT})			-0.2767 (0.1714)
ln(POP)	1.4835* (0.7764)	0.3238 (1.1292)	
Male30-44			0.0338 (0.0674)
Unemp_Young			0.0234 (0.0154)
Unemp_Female			-0.0513 (0.0384)
ln(Wage)			-0.1093 (0.1955)
GRDP growth			-0.0132** (0.0064)
ln(Female_HH)			-0.6297 (0.6673)
ln(Alcohol)			-0.3197 (0.3408)
Single		0.1020*** (0.0277)	
EARLY	-0.4878* (0.2721)		
ln(PROTEST1)	-0.0986 (0.0728)		
Constant	-11.363 (10.114)	-29.550*** (6.694)	9.917*** (1.912)
Obs.	208	208	208

Notes: Estimation methods: two-stage least squares (2SLS). All columns include fixed effects and time dummies. Cluster-robust standard errors are reported in parentheses. $*\,p < 0.1$, $**\,p < 0.05$, $***\,p < 0.01$.