ESSAYS IN APPLIED MICROECONOMICS

BY
ALAN SEALS

A DISSERTATION SUBMITTED TO THE GRADUATE SCHOOL
AT MIDDLE TENNESSEE STATE UNIVERSITY IN PARTIAL
FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE

DOCTOR OF PHILOSOPHY/ECONOMICS

MURFREESBORO, TN

MAY 2008

APPROVAL PAGE

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To My Wife Olivia

ACKNOWLEDGEMENTS

I would like to thank my dissertation committee members: Charles Baum (chair), Anthon Eff, Mark Owens and Joachim Zietz. I would also like to thank John Nunley for many helpful comments.

ABSTRACT

This dissertation consists of three essays on the effects that macroeconomic variables have on the microeconomic behavior of impoverished peoples. The first essay, "Are Gangs a Substitute for Legitimate Employment? Investigating the Impact of Labor Market Effects on Gang Affiliation," considers the relationship of gang participation to local economic conditions. The purpose of the study is to ascertain whether gang participation is the product of rational decision making. There is a statistically significant and positive relationship between gang participation and the local unemployment rate. These results indicate that potential gang members consider labor market opportunities when making the gang participation decision. The second essay entitled, "The Effects of Inflation and Demographic Change on Property Crime: A Structural Time-Series Approach," primarily considers the effect of inflation on property crime rates. Previous literature has focused on the relationship between unemployment rates and aggregate crime rates. The principal finding of the essay is that inflation has a statistically significant, positive, and persistent effect on property crime in the United States. The concluding essay "Declining Maize Prices, Biodiversity, and Subsistence Farming in Mexico," investigates the behavioral response of subsistence farmers in Mexico to fluctuations in the market price for maize. The principal finding is that since subsistence farmers purchase goods in the market place decreases in the price of maize will generate an increase in their maize production. A theoretical model, which makes use of a Stone-Geary utility function, is developed to explain the dominant income effect.

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INTRODUCTION

The first essay, "Are Gangs a Substitute for Legitimate Employment? Investigating the Impact of Labor Market Effects on Gang Affiliation," examines the economic determinants of street gang participation. The sociology literature has viewed gang participation as an outcome of greater social upheaval, rather than one of individual choice. I present empirical evidence that gang participation, while controlling for prevailing social conditions, is the product of individual economic decision making. I use data from the 1997 cohort of the National Longitudinal Survey of Youth to estimate the probability of gang membership in a given survey year. Exogenous variation in annual county unemployment rates is exploited to identify the effect of legitimate economic opportunity on gang participation, where the county unemployment rate proxies for the relative availability of employment. I find that the county unemployment rate is statistically significant and positively related to gang participation. To my knowledge, this is the first paper to use a nationally representative data set to examine the effect of economic opportunity on individual gang participation.

In another paper, "The Effects of Inflation and Demographic Change on Property Crime: A Structural Time-Series Approach," aggregate crime rates in the United States are examined. The structural time-series model essentially captures the systematic influence of unobservable variables, such as criminal deterrence, in a stochastic trend component. By using the structural time-series model, which is new to this literature, it is possible to consistently estimate the effects of macroeconomic variables on aggregate property crime rates. A statistically significant and positive relationship between inflation and property crime is found, which indicates that monetary policy meant to stabilize prices could also lower crime rates.

The third essay entitled "Declining Maize Prices, Biodiversity, and Subsistence Farming in Mexico" attempts to show the economic conditions under which the indigenous farmers of Mexico will continue to propagate genetic diversity in maize. While this topic is somewhat of a departure from the previous two essays, the paper addresses the effects of macroeconomic fluctuations on impoverished peoples and also has policy relevance for illegal immigration. Unlike modern industrial farmers who grow a few commercial corn varieties, the subsistence farmers of Mexico grow thousands of different varieties of maize. As a result, Mexico is the world's largest genetic repository of maize. There are approximately two million subsistence farmers in Mexico who cultivate the majority of the country's maize output. Since maize is the number crop in the world, in terms of caloric intake, the threat of disastrous crop failures, which is a concern due to the modern implementation of monoculture in farming, makes the economic behavior of the subsistence farmers in Mexico an important economic topic. The significant increase in Mexico's corn production, following the dramatic price decreases resulting from the North American Free Trade Agreement (NAFTA), offer a good starting point for the analysis. The dominant income effect associated with the decrease in the price of maize indicates that subsistence farmers are not autarchic and are therefore responsive to changes in the terms of trade between market goods and maize.

ARE GANGS A SUBSTITUTE FOR LEGITIMATE EMPLOYMENT? INVESTIGATING THE IMPACT OF LABOR MARKET EFFECTS ON GANG AFFILIATION

Street gangs are a common element of the urban landscape. The U.S. Department of Justice estimates there are 21,500 gangs, with 731,500 members, currently operating in the United States.[1] Gangs are thought to be the leading distributors of illegal drugs and to account for approximately six percent of all violent crime in the United States.[2] Deterrence of gang activity through policing is often ineffective because law enforcement officials can not control the factors generally attributed to gang participation, such as poor economic opportunity, inadequate family structure, and cultural isolation (Jankowski 1991; Padilla 1992; Klein 1995; Hagedorn 1998).[3]

A key empirical question yet to be answered is whether gang participation depends on economic incentives. Members of the crack-selling gang that Levitt and Venkatesh (2000) study faced life-threatening working conditions, but generally made little more than the minimum wage. The authors postulate that the possibility of future financial gain motivates gang members, but they also admit that, given their bizarre results, gang participation may be inconsistent with utility-maximizing behavior. With a few

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[1] Statistics from the Dept. of Justice (2005 National Gang Threat Assessment).
[2] Ibid.
[3] Los Angeles mayor Antonio Villaraigosa recently stated, "there is a connection between poverty, low education levels, lack of job opportunities and gang membership," and he went on to say that, "these root issues needed to be addressed as part of a solution to gang violence in the United States and elsewhere" (BBC News).

exceptions, sociology studies have completely rejected a rational-agent framework to explain gang participation.[4]

Sociological research has shown that gang activity is most common among young males (e.g., Thrasher 1927 and Hagedorn 1998). The literature shows a negative relationship between wage incentives and youth criminal behavior (Grogger 1998; Gould et al. 2002). However, it is difficult to separate the economic return of gang membership from the potential return to individual criminal activity, because many gangs may not be organized sufficiently to reduce transaction costs in an illicit market (Klein 1995; Hagedorn 1998). The local unemployment rate may be a better predictor of gang participation than prevailing market wages because young people are likely to be qualified only for low-paying jobs in the service economy, which generally are the least stable (Wilson 1987; Hagedorn 1998).

I assume individual gang members take local labor market conditions as given. I exploit exogenous variation in unemployment rates across time and counties to identify the effect of economic incentives on gang participation.[5] The local unemployment rate is a proxy for the availability of legitimate employment. I estimate the probability of gang involvement for males with data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97).[6] The NLSY97 is a unique data set for the study of youth

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[4] Jankowski (1991) insists that gang participation is the product of rational calculation. Padilla (1992) espouses a similar theoretical construction of gang participation. However, most gang researchers, such as Hagedorn (1998), have not adopted a rational agent theory of gang participation but rely on more traditional sociological theories.
[5] Gould et al. (2002) use average local wages of young men. However, this data is not collected annually.
[6] Much of the early literature on crime and economic conditions investigates the effect of unemployment on crime rates (e.g., Cantor and Land 1985).

gang activity in the United States because it annually collects detailed information on gang participation and is both nationally representative and current. The NLSY97 also collects extensive information on family, community, and individual characteristics (including detailed criminal activity for each year of the survey), which many other studies of youth criminal behavior lack (See Mocan and Rees 1999).

I also examine the effects of economic incentives on the gang participation of different age groups. The age profile of gang members in the NLSY97 suggests that individual gang careers are relatively short-lived, which is important, because it also implies that gangs require a steady supply of new recruits to remain extant. FIGURE 1A shows gang participation rises until age sixteen, which is also the minimum legal age required to work most jobs, and then gradually declines. It is possible that many individuals are unable to find legitimate employment before age sixteen, perhaps because of age requirements or transportation constraints, and join gangs to generate income (or pass the time). After age sixteen, the opportunity cost of gang participation may be higher because legitimate economic opportunities are more plentiful.

In an extension, I examine the relationship between economic opportunity and cognitive ability, as measured by ASVAB scores from the NLSY97, on gang participation. Disparity in cognitive ability, which has already been linked to criminal behavior (see Wilson and Hernstein 1985), provides a possible explanation for the variance in gang participation among individuals from similar socio-economic backgrounds.

The degree of diversity among both gangs and the communities in which gangs operate makes it difficult to construct generalizable public policies meant to deter gang activity. The analysis presented here advances the etiological discussion, as to the impact of economic opportunity on gang participation in the United States. Consistent with many earlier studies of economic incentives and criminal behavior, a statistically significant and positive relationship is found between gang participation and the local unemployment rate.[7] The most notable result in support of gang affiliation being a rational economic decision is that the local unemployment rate only affects individuals who are at least sixteen years old. I also find that gang participation among individuals with lower measured cognitive ability is particularly sensitive to local labor market conditions.

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework for gang participation. Section 3 describes the data and specific variables used in the analysis. The econometric strategy used to estimate the probability of gang membership is explained in Section 4. The results of the analysis are presented in Section 5. Section 6 provides an extension of the gang participation model to include a measure of cognitive ability. Section 7 concludes.

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[7] Among gang researchers, there is contention as to whether the definition of a gang should include criminal or deviant behavior. This is because all groups who engage in criminal activity (i.e. lynch mobs, unruly sports fans, etc.) should not necessarily be categorized as gangs. Furthermore, time spent committing crimes--assault, robbery, murder, rape, extortion, distributing illegal drugs, and burglary--generally associated with gangs and gang members, constitutes a relatively small fraction of gang activity (Klein 1995; Jankowski 1991; Hagedorn 1998). This presents an obstacle to the gang researcher, as well as agencies reporting crime statistics associated with gangs. Because this study is limited to the examination of existing survey data, I follow the survey's specific definition for a gang. I discuss the gang definition at length in Section 3. See Klein (1995, Ch. 2) for an overview of the debate on the definition of a gang.

2. Theoretical Background

For the past 80 years, ethnographic research has linked the behavioral patterns of the urban under-privileged to street gang formation and manifestation (e.g., Thrasher 1927; Short and Strodtbeck 1965; Moore 1978; Horowitz 1983; Padilla 1992; Klein 1995; Hagedorn 1998; Venkatesh 2000). With the aid of an extraordinary financial record, Levitt and Venkatesh (2000) present the only detailed economic analysis of a drug-selling street gang. The data set used by Levitt and Venkatesh (2000) also corresponds time-wise with the emergence of the "corporate-gang structure" in Chicago, where highly organized gangs marshaled to take advantage of the lucrative crack-cocaine trade. Levitt and Venkatesh (2000) find that the average wage (percentage of profits) for gang members is just above that of the legal market. Yet, income variation within the gang is "highly skewed", and similar in proportion to the wage disparity found in legal franchises, where the vast majority of gang members earn approximately the minimum wage (Levitt and Venkatesh 2000).[8] The authors also report an average annual mortality rate of seven percent for gang members during the sample period (Levitt and Venkatesh 2000).

The findings of Levitt and Venkatesh (2000) are peculiar, given the disparity between economic return and risk-of-death for gang members. It is important to note that residents of the gang's neighborhood during the sample period also report extreme levels of poverty and unemployment rates as high as 35 percent (Levitt and Venkatesh 2000). Approximately 40-50 percent of the "foot soldiers" in the gang are legally employed at

[8] Padilla (1992) and Bourgois (2003) report similar findings in their ethnographic studies.

any time during the sample period (Levitt and Venkatesh 2000).[9] Since so many gang members are simultaneously employed in the legal sector, the authors postulate that gang participation may be responsive to changes in legitimate labor market opportunities (Levitt and Venkatesh 2000). Levitt and Venkatesh (2000) conclude that the potential for future financial gain provides the economic impetus to join and stay in the gang. However, the authors' results are limited to a single entrepreneurial gang, which may not be an accurate representation of gang activity across the United States.[10]

Labor Market Effects on Criminal Participation

According to the economic model of crime, rational agents commit crimes when the expected benefits of doing so outweigh the expected costs (Becker 1968).[11] Grogger (1998) estimates a structural model of the economic return to crime (compared to legitimate employment), using data from the 1979 cohort of the NLSY (NLSY79), for young males and concludes that a rise in youth crime rates could be attributable to a decrease in earnings of male youths. Grogger (1998) shows that poor youth labor market conditions may account for the hump-shaped relationship between crime and age.[12] Grogger (1998) also concludes that the high incidence of black criminal offenders may be a result of the black/white earnings gap. Williams and Sickles (2002), with data from a

[9] The term "foot soldiers" refers to average street-level-drug dealers for the gang.
[10] In another article, Venkatesh and Levitt (2000) chronicle the history of a Chicago gang from one centered on fictive kinship to a full-fledged illicit enterprise during the crack epidemic of the 1990's.
[11] See Ehrlich (1973, 1975, 1996) and Levitt (1996, 1997, 1998a) for studies that estimate the impact of deterrence measures on criminal activity.
[12] Criminal behavior has been observed, in a wide range of environments, to rapidly increase in adolescence and gradually decline\ in adulthood (Hirschi and Gottfredson 1983).

1968 Philadelphia birth cohort, extend Grogger's (1998) framework to include proxy measures of social capital, and report a negative relationship between individual earnings capacity and criminal activity.

In both Grogger (1998) and Williams and Sickles (2002), crime is modeled as "work" and therefore is associated with disutility through reduction of leisure time. The "crime-as-work model" best predicts criminal behavior that generates economic return (i.e. drug-dealing, burglary, robbery).[13] However, gang participation does not always imply the gang member receives remuneration from gang crimes (in fact, it does not necessarily imply criminality of the individual), because many gangs may not be well enough organized to offer members economic rents.[14] It is possible that gang participation is a more subtle economic decision, which also is influenced by the utility from social interactions with friends (other gang members) and/or an ethnic bond with a certain group.[15] Hence, gang participation could be both "work" and leisure (taking drugs and hanging out with other gang members). Nevertheless, the decision to spend one's time hanging out with gangsters and/or "working" at criminal enterprise is to eschew legitimate employment.

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[13] See Block and Heineke (1975). Kelly (2000) gives an empirical test of several criminological theories and finds that the economic model crime is a good predictor of property crime rates.

[14] Institutionalized or culturally entrenched gangs often become criminal business enterprises, which provide economic opportunity for gang members (Hagedorn 2006). Hagedorn (1998) in a 2nd edition to a study from the 1980's in Milwaukee finds crack-cocaine very quickly became an enterprise in which gang members profited greatly. This is a relatively recent trend, as many studies in the gang literature assert that most street gangs are not entrepreneurial, and less still are organized sufficiently to sustain a profitable drug business (e.g., Decker and Van Winkle 1994; Klein 1995).

[15] Padilla (1992) notes how cultural kinships can promote the cohesiveness necessary to maintain successful illicit enterprises, such as drug trafficking and distribution.

In contrast with Grogger (1998) and Williams and Sickles' (2002) studies of crime, I examine the effect of local unemployment on gang participation. My hypothesis is that the local unemployment rate is positively related to male gang participation, as the availability of legitimate jobs is a key indicator of economic prospects for low-skilled workers. I take advantage of exogenous variation in annual county unemployment rates to capture this effect.[16] To lend more credence to the estimates I also include other variables suggested by the gang literature that theoretically influence the gang participation decision.

3 Data

I use data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97), which is collected annually to document the educational and labor market experiences of a cohort of youths who were born between 1980 and 1984. The NLSY97 also collects information on a wide array of demographic, family, and personal characteristics. The survey is designed to be representative of the population aged 12-16 living in the United States in 1997. There were 8,984 individuals in the initial sample of the NLSY97, composed of 6,748 respondents reflecting the overall racial/ethnic makeup of the population in 1997, with an over-sample of 2,236 Black and Hispanic respondents.

The NLSY97 offers a rich set of variables related to criminal activity for each year of the survey. Few studies of youth crime have used data as comprehensive as the

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[16] Levitt (2001) recommends a similar strategy to identify the unemployment/crime relationship.

NLSY97.[17] For example, Grogger (1998) uses nationally representative data from the NLSY79, but only has one year of data on criminal activity.

The NLSY97 defines a gang as the following:

> By gangs, we mean a group that hangs out together, wears gang colors or clothes, has set clear boundaries of its territory or turf, protects its members and turf against other rival gangs through fighting or threats.

Using this definition of a gang, respondents provide information on gangs for each year of the survey including gang activity in the respondent's neighborhood or school and whether the respondent has ever been in a gang. If respondents answered yes to the latter, then they were asked the age they first joined a gang and whether they had been in a gang in the last twelve months. From this information, I created the key outcome variable, a dummy variable for respondents who admit ever being in a gang and also admit gang activity in the last twelve months. So, a person who admits gang activity, but not in the last twelve months, will receive a zero for that observation-year, the same as a person who never admits gang activity. This specification measures only current gang participation and incorporates the behavior of individuals who sporadically participate in gangs.[18]

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[17] A notable exception is Mocan and Rees (1999).

[18] This type of behavior has been documented by Jankowski (1991) and Bourgois (2003).

Respondents who admit gang activity, at some point in their lives, constitute 12.24 percent of the initial sample of 8,984. Of these 12.24 percent who report gang activity, 71.7 percent are male, 24.7 percent are Hispanic, and 34.7 percent are Black.[19] After deleting observations with missing values, 55.9 percent of the sub-sample who ever report gang membership also report gang activity within the last 12 months of completing a survey.[20] Males reporting current gang membership account for 5.28 percent of the initial sample of 8,984 respondents in the NLSY97.[21] The sample retention rate for male gang members in the NLSY97 (95.99 percent as of the 2003 survey) is higher than the rest of the NLSY97 sample (86.33 percent as of the 2003 survey).

Although the definition of a gang in the NLSY97 does mention fighting and intimidation, it does not specifically address the criminal nature of the gang. Unfortunately, the NLSY97 does not supply information on crimes directly attributable to gang activity (i.e. those activities directed by the gang). However, TABLE 1 shows that the self-reported incidence of drug-dealing among male gang members is over five-times greater than the rest of the sample and that the incidence of theft is almost ten-times greater. According to TABLE 1, gang members also appear to be considerably more violent than the population of people not currently in a gang.

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[19] The average age reported for first joining a gang was thirteen.

[20] There were 641 (58.3 percent of the sub-sample of respondents who had ever reported gang activity) respondents who admitted gang participation in the last twelve months. List-wise deletion left 455 (out of 474) male respondents or 70.9 percent of those who had admitted gang activity in the last twelve months.

[21] For the rest of the paper, I will refer to persons admitting gang membership in the last twelve months of a survey simply as gang members. TABLE 2 shows that gang members constitute 2.9 percent of the sample in a given year.

TABLE 2 displays sample means. Because ethnic minority groups are the primary progenitors of gangs in the United States (Thrasher 1927; Horowitz 1983; Jankowski 1991; Padilla 1992; Klein 1995; Venkatesh 2000; Hagedorn ed. 2006), I control for the race of respondents with the dummy variables *black* and *hispanic*. The *age* of respondents is a control for the potential biological effects of age on gang participation (Hirschi and Gottfredson 1983).[22] FIGURE 1A shows that gang participation rapidly increases in early adolescence and gradually declines in early adulthood. It is likely that gangs experience high member-turnover rates as a result of relatively short individual gang careers. Public policies that inhibit individual gang participation (particularly initial gang participation) are likely to generate positive results because gangs need new members to remain viable. FIGURE 1B depicts a steady decline of male gang activity as the survey progresses, which is probably due to the aging of respondents but could also be attributable to the increasing economic well-being that often accompanies getting older. However, the decline of gang members in the sample does not appear to be a result of more rapid attrition from the sample, as evidenced by the high retention rate among male gang members.

I use the continuous annual county *unemployment rate* as a proxy for the relative scarcity of legitimate employment. Wilson's (1987) influential study cites a lack of opportunity for low-skilled workers in the post-industrial economy and the resulting unemployment (or underemployment) of those workers as the fundamental cause of

[22] According to Thrasher (1927) most young gang members would mature out of the gang and either move on to organized crime or to legitimate work.

urban poverty in the United States.[23] FIGURE 1A shows gang participation peaks for NLSY97 respondents at age sixteen, the minimum legal working age for all non-hazardous occupations, and then begins to decline. The rise in gang participation until age sixteen could be the result of economic opportunity provided by gangs to those unable to find legitimate employment. The decline in gang participation after age sixteen could be due to the increased availability of legitimate employment for that age group.

A relative scarcity of public resources such as community centers, youth counseling services, police protection, and even churches and schools necessary to service large populations is endemic to urban ghettos where street gangs flourish (Jacobs 1961; Jankowski 1991; Anderson 1999; Venkatesh 2000; Bourgois 2003). I account for available community resources with the variable *doctors*--the number of doctors per 100,000 county residents. The neighborhoods where gang activity is prominent are also crime ridden, which I control for with the variable *crime rate*--serious crimes per 100,000 residents of the respondent's county of residence.

To control for the potential effect of not having a male figure present in the household, the variable *father* is included which is a dummy for whether the respondent was living with his father (or father figure) at the time of the first survey-year. I also use self-reported measures of the respondent's exposure to violent situations before entering

[23] Wilson (1987, 1996) and Freeman (1991, 1996) also illustrate that unemployment (or underemployment) of young adult males in the service economy is the primary contributor to many of the problems endemic to poor neighborhoods such as high crime rates, disproportionate numbers of unwed mothers (i.e. female-headed households), abnormally high incidence of drug and alcohol addiction, inadequate schools, and persistent welfare dependency of the population.

the NLSY97 survey with the variables *shot* and *bully*.[24] Similarly, Williams and Sickles (2002) use youth arrests and family criminal history to predict adult criminal involvement. TABLE 1 illustrates the differences in home and neighborhood environment for gang members and non-gang members. Gang members report an astonishingly high rate of gun violence (34.9 percent) in their childhood environment compared with non-gang members.[25] The rate of fatherless homes is also much higher among gang members than for non-gang members.

TABLE 1 indicates neither school enrollment nor labor force participation is mutually exclusive of gang participation, which is consistent with the findings of Levitt and Venkatesh (2000). The frequencies for school participation and labor force participation are also much lower for gang members than non-gang members. I include school *enrollment* to control for social access to gang activity: gangs could be operating in schools or high school drop-outs could be more exposed to gang activity.[26] The

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[24] *shot* is a dummy variable for whether the respondent had witnessed someone being shot before the respondent was 12 years of age. The variable *bully* is a dummy for whether or not age the respondent had been bullied by someone in his neighborhood before the he was twelve-years-old. The NLSY97 provides information on each of these two occurrences for all survey years. However, to minimize problems with endogeneity, I have included only the occurrences which pre-date the first survey.

[25] This statistic may seem unreasonably high. However, Katz et al. (2005) in an analysis of the Moving to Opportunity (MTO) Experiment in Boston report approximately 25 percent of households they study contained a member who had been "assaulted, beaten, or shot within the past six months."

[26] The NLSY97 does ask respondents if gangs are present in their neighborhood or school. Whether or not gangs are in a respondent's neighborhood could represent a resource constraint for gang participation. However, the question was not answered by a large segment of the respondents for the years 1998 and 1999. I employed a model-based univariate imputation technique using the statistical package STATA to account for the missing observations. I then estimated a selection equation based upon the assumption that the sample was selected on whether or not a gang was present in the respondent's

respondent's *highest-grade-completed* is a control for human capital acquisition. Gang members report an average of 9.5 for *highest-grade-completed*, while non-gang members report an average of 10.5 for *highest-grade-completed*.[27] There is a potential for omitted variable bias with the education variables, because ability is possibly correlated with educational attainment and delinquency is perhaps correlated with enrollment. It could be that gang members, on average, are less employable than the rest of the population and sort into gangs because they have a lower opportunity cost for committing crimes. I address this potential issue in section 6.

4 Econometric Method

I use a logit specification to estimate the probability of gang participation in a given year. The equation below characterizes the basic econometric model of gang participation:

$$Gang_{i,t} = \beta_1 + \beta_2 X_{i,t} + \beta_3 \Gamma_i + \beta_4 \Phi_i + \beta_5 unemployment_{i,t} + \beta_6 D_t + \beta_7 state_{i,t} + \beta_8 D_t * state_{i,t} + e_{i,t}.$$

$Gang_{i,t}$ is a (0,1) indicator for current gang participation; X is a vector of respondent *i's* individual characteristics in time *t*; Γ is a vector of characteristics which indicate family composition; Φ is a vector of variables which measure the level of crime and violence in

neighborhood. However, the final results were not significantly different from the ones I report later in the paper; so, I have omitted these estimates.

[27] This could also be attributable to gang members being, on average, half a year younger than non-gang members.

the individual's childhood environment; *unemployment*$_{i,t}$ is a continuous unemployment rate for person *i's* county of residence; D_t is a vector of time dummies; *e* captures the idiosyncratic utility attributable to gang participation and is assumed to follow a standard logistic distribution. I cluster the standard errors at the county level. I also include state dummy variables and state-time interactions because some states have a long history of gang problems (e.g., California, Illinois, and New York) and over time have developed their own strategies to combat gang crime.[28]

5 Results

TABLE 3 presents estimation results for gang participation. Models 1, 2, and 3 are the most parsimonious and do not contain likely endogenous regressors. In Models 1 and 5, dummy variables for the respondent's region of residence are included in lieu of state dummies.

The local *unemployment rate* has a positive coefficient and is statistically significant for Models 1, 4, and 6 in TABLE 3. Adding the state-time interaction terms increases the size of the coefficients for the *unemployment rate* in both Models 3 and 6. In Model 6, at the bottom of TABLE 3, when the *unemployment rate* changes from five to ten percent the predicted probability of gang participation changes from 0.033 to 0.042 (a 27.2 percent increase).

[28] For instance, Grogger (2002) studies the effects of civil gang injunctions, a new anti-gang tactic, implemented in Los Angeles. Civil gang injunctions are meant to "prohibit specifically named individuals from engaging in particular activities within a clearly defined target area" (Grogger 2002). Also see Decker et al. (1998) for the differences in gangs between established and emerging gang cities.

The two indicators for race are positive and statistically significant for all models. Having a *father* (or father figure) present in the child's household in pre-adolescence has a statistically significant and negative effect on gang involvement, which is contrary to Jankowski's (1991) finding that gang members are just as likely to come from stable two-parent homes. The county characteristics *doctors* and *crime rate* are statistically significant with negative and positive coefficients respectively, indicating that gang members are more likely to come from high-crime areas with fewer public resources. The coefficients for the violence indicators *shot* and *bully* are both positive and statistically significant in Models 4, 5, and 6, which suggests that living in a physically threatening environment during pre-adolescence increases the probability of future gang membership considerably. The variables *highest-grade-completed* and *enrolled* are likely endogenous. Limiting the interpretation to the signs on the coefficients of *highest-grade-completed* in Models 4, 5, and 6 indicates that the opportunity cost of gang involvement increases with each year of education. Being *enrolled* in school has a negative effect on the probability of gang participation.

I square the *age* variable in each model to test for a non-linear relationship with gang participation. The *age* variable is positive and statistically significant for all models, while the variable *age-squared* is negative and statistically significant for all models indicating that gang participation displays the same hump-shaped relationship with age as regular criminal activity.

Juveniles have a lower opportunity cost for committing crimes because criminal punishment in the United States is more severe for the adult population (Levitt 1998b). Gangs often require participation in activities which impose high costs (e.g., fights with other gangs, drive-by shootings, and meetings) that may not directly benefit individual members (Jankowski 1991). Even though members can reap financial gains from gang crimes, those who are old enough to have more economic opportunity outside the gang may weigh the costs of gang membership differently. The average *age* of those who admit gang participation in the last twelve months is 17.2; however, 35.8 percent of this sub-sample is also below the age of sixteen at some point during the survey.[29] If gang members respond to economic incentives, the *unemployment rate* should have a greater effect on the gang participation decision for those who are legally eligible to work most jobs.

TABLE 4 presents estimates for gang participation by *age* of respondent. The *unemployment rate* is statistically significant for all six models where $age \geq 18$. In Model 6 of TABLE 4, when the *unemployment rate* changes from five to ten percent the predicted probability of gang membership changes from 0.029 to 0.039 (a 34.4 percent increase), which indicates the sub-sample where $age \geq 18$ are affected more by the local labor market. I also estimate a model where $age < 16$ and find no statistically significant effect for the *unemployment rate* in any of the six models.[30] Although estimates of the *unemployment rate* where $16 \leq age < 18$ are only statistically significant in four of the

[29] Levitt and Venkatesh (2000) argue that gang participation can be explained in context of a tournament, where individual gang members compete for large shares of the gang's revenue. Early entry to the gang could increase the chances of future leadership positions within the gang, which could lead to greater share of the wealth generated through the gang. Additionally, some of the current sociology literature on gangs is concerned with gang members who are unable to mature out of the gang (see Moore 1991 and Venkatesh and Levitt 2000).

[30] The sample size for these estimates was smaller than for the sample $age \geq 18$. However, the variables *black, hispanic, shot,* and *bully* were all statistically significant and positive in the corresponding models to the reported sample.

six models (and the other two models are marginally statistically insignificant), all of the coefficients are positive.

My results indicate juveniles most eligible for legitimate employment take into account outside opportunities when deciding to participate in gang activities. The statistical insignificance of the *unemployment rate* where *age* < 16 and the statistically significant and positive effect on gang participation for individuals who are sixteen and seventeen is compelling evidence of rational decision-making among gang members.

6 Analyzing the Effects of Cognitive Ability on Gang Participation

An extensive literature investigates the effect of cognitive ability on individual social and economic outcomes (Hernstein and Murray 1994; Heckman 1995). Wilson and Hernstein (1985) and Levitt and Lochner (2000) report a negative relationship between cognitive ability and criminal behavior. In this section, I investigate the relationship between economic opportunity and cognitive ability, as measured by Armed Services Vocational Aptitude Battery (ASVAB) scores from the NLSY97, on gang participation.

I use a percentile score for specific age cohorts, within the sample, based upon four components of the ASVAB which attempt to measure mathematical and verbal ability.[31] This percentile score is similar to the Armed Forces Qualification Test (AFQT) scores produced by the U.S. Department of Defense. 7,093 respondents, or 78.9 percent of the initial sample, had taken all four parts of the ASVAB used to calculate the percentile

[31] See the NLSY97 User's Guide (4.1.2 Administration of the *CAT-ASVAB*) for information regarding the calculation of the percentile score.

score. Of the 455 individuals who report gang activity within the past twelve months of the survey, 340 (74.7 percent) of this sub-sample have reported ASVAB scores. The mean score (on a scale of 0-100) for individuals reporting gang activity in the past twelve months is 27.66, while the mean score for those reporting no gang activity in the past twelve months is 45.68. The mean score of a respondent who admits joining a gang at some point but reports no gang activity in the last twelve months is 30.67. FIGURE 2 shows that the ASVAB scores for gang members are concentrated in the lower-percentile ranges, as compared with a relatively even distribution of scores for non-gang members. If the NLSY97 is an accurate depiction of the population of gang members in the United States, individuals with lower cognitive ability are disproportionately represented in gangs.

TABLE 5 displays estimation results with *asvab* scores and the interaction of *asvab* with *unemployment rate* as additional regressors in the gang participation equation. The coefficient of *unemployment rate* is positive, statistically significant and also larger in models accounting for cognitive ability.[32] The interaction term *asvab***unemployment rate* is negative and statistically significant, except for Model 3 where it is not statistically significant.[33] Based upon the predicted probabilities at the bottom of TABLE 5, gang participation of persons with lower measured cognitive ability is much more sensitive to the local *unemployment rate*. For example in Model 6 of TABLE 5, moving from an *unemployment rate* of five to ten percent for a person scoring twenty on the

[32] I also find that *unemployment rate* is statistically significant and positive for all models in this sample when I do not include *asvab* scores.
[33] The sign and statistical significance of the interaction term was also confirmed using the method developed in Ai and Norton (2003).

ASVAB (i.e. the twentieth percentile) corresponds to a 1.4 percentage point change (a 40 percent increase). The same change in the *unemployment rate* for a person scoring in the eightieth percentile on the ASVAB corresponds to a 0.2 percentage point change (a 10.5 percent decrease).

It could be that individuals with lower cognitive ability sort into gangs because they face a lower opportunity cost for criminal behavior. Lower levels of labor force participation, lower educational attainment, and higher levels of criminal activity observed in the data among gang members could be correlated with cognitive ability.

7 Conclusion

Empirical research on street gangs is sparse. This paper adds to the literature estimates of local labor market effects on gang participation. The local unemployment rate's effect is statistically significant and positive in a wide range of model specifications for gang participation. However, robustness checks reveal gang participation of individuals less than sixteen years old (the legal minimum age for most jobs) is not responsive to the local unemployment rate. For individuals eighteen and older, a change from five to ten percent in the local unemployment rate corresponds to a 34.4 percent increase in the predicted probability of gang participation. The effect of the local unemployment rate on sixteen and seventeen year olds is also statistically significant and positive, which suggests juvenile gang participation depends on economic incentives.

Gang participation of individuals with lower measured cognitive ability is more sensitive to the local unemployment rate. The predicted probability of gang participation increases by 40 percent for persons with ASVAB scores in the twentieth percentile when the local unemployment rate increases from five to ten percent. If ASVAB scores are good predictors of aptitude for skill acquisition, individuals with lower ability (and one could argue lower opportunity cost of time) are more likely to participate in gangs.

Because individual gang careers are relatively short, street gangs are heavily dependent on new recruits. Programs designed to increase economic opportunity among disadvantaged youth could greatly reduce gang participation and, as a result, gang-related crime.

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TABLE 1: FREQUENCY OF CRIMINAL BEHAVIOR, LABOR FORCE PARTICIPATION, AND SCHOOL ENROLLMENT BY GANG AFFILIATION

Percent	Currently in a Gang	Not Currently in a Gang
Sell Drugs?	39.54	7.01
Steal Property > $50?	30.69	4.05
Attack Someone?	56.28	10.96
Carry A Gun?	45.43	8.95
Work?	33.16	46.07
Enrolled in School?	57.4	67.11

Notes: Frequencies are derived from the sample used in estimation, which contains 27,186 observations for males with 455 current gang members. The heading "Currently in a Gang" represents males who admit gang participation in the last twelve months of the survey date. All frequencies are tabulated across time and each variable, except for the first survey year, is representative of behavior since the date of their last interview (i.e. "Sell drugs since date of last interview?"). Tabulations for "Carry A Gun?" are computed from a slightly smaller sample of 27,135 observations and 453 current gang members.

TABLE 2: SAMPLE MEANS BY GANG PARTICIPATION (STANDARD DEVIATION)

	Full Sample	Gang Members	Non-Gang Members
gang	0.029 (0.167)	--	--
black	0.253 (0.435)	0.422 (0.494)	0.248 (0.432)
hispanic	0.207 (0.405)	0.300 (0.458)	0.204 (0.403)
highest-grade-completed	10.44 (2.222)	9.499 (1.867)	10.468 (2.226)
age	17.684 (2.596)	17.219 (2.408)	17.698 (2.600)
enrolled	0.668 (0.471)	0.574 (0.495)	0.671 (0.470)
father	0.742 (0.470)	0.615 (0.487)	0.746 (0.435)
shot	0.131 (0.337)	0.349 (0.477)	0.124 (0.330)
bully	0.219 (0.414)	0.341 (0.474)	0.215 (0.411)
crime rate	5762.593 (2899.822)	6272.835 (2897.438)	5747.441 (2898.575)
doctors	210.13 (141.255)	214.943 (127.647)	209.987 (141.639)
unemployment rate	5.131 (2.234)	5.365 (2.566)	5.124 (2.223)

Note: The sample contains only males with 27,186 observations for all variables. The sub-sample of gang members contains 784 observations. The sub-sample for non-gang members contains 26,402 observations. The variables *crime rate* and *doctors* are collected by the Census Bureau and are supplied with the Geocode supplement of the NLSY97.

TABLE 3: ESTIMATION RESULTS FOR GANG PARTICIPATION

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6

black	1.223*** (0.124)	1.208*** (0.138)	1.232*** (0.138)	0.811*** (0.136)	0.795*** (0.148)	0.800*** (0.149)
hispanic	1.006*** (0.141)	1.048*** (0.147)	1.057*** (0.146)	0.770*** (0.132)	0.778*** (0.145)	0.779*** (0.147)
age	0.679*** (0.210)	0.667*** (0.215)	0.715*** (0.206)	1.545*** (0.236)	1.550*** (0.242)	2.017*** (0.249)
age-squared	-0.020*** (0.006)	-0.020*** (0.006)	-0.021*** (0.006)	-0.041*** (0.007)	-0.041*** (0.007)	-0.054*** (0.007)
highest-grade-completed	.	.	.	-0.327*** (0.050)	-0.333*** (0.051)	-0.351*** (0.053)
enrolled	.	.	.	-0.579*** (0.092)	-0.586*** (0.089)	-0.547*** (0.093)
father	.	.	.	-0.216** (0.110)	-0.243** (0.115)	-0.243** (0.119)
shot	.	.	.	0.862*** (0.107)	0.863*** (0.111)	0.898*** (0.113)
bully	.	.	.	0.612*** (0.101)	0.601*** (0.105)	0.624*** (0.105)
crime	.	.	.	0.003 (0.003)	0.006** (0.003)	0.005** (0.003)
doctors	.	.	.	-0.055 (0.048)	-0.117** (0.005)	-0.106** (0.005)
unemployment rate	0.043* (0.024)	0.030 (0.029)	0.051 (0.030)	0.048** (0.023)	0.030 (0.027)	0.055** (0.027)
time dummies	yes	yes	yes	yes	yes	yes
region dummies	yes	no	no	yes	no	no
state dummies	no	yes	yes	no	yes	yes
state time-trends	no	no	yes	no	no	yes
pseudo R-square	0.041	0.054	0.053	0.099	0.112	0.112
predicted probabilities						
unemployment rate = 5%	0.028	.	.	0.028	.	0.033
unemployment rate = 10%	0.035	.	.	0.036	.	0.042
unemployment rate = 15%	0.043	.	.	0.044	.	0.054

Note: *indicates significance at the 10% level; **indicates significance at the 5% level; *** indicates significance at the 1% level. Standard errors, in parentheses, are clustered at the county level. Gang participation within last twelve months of a survey is the dependent variable for all models. All models are estimated using logistic regression. Model 1 and Model 4 each have 27,175 obs. Model 2 and Model 5 have 27,080 obs. Model 3 and Model 6 have 25,525 obs.

TABLE 4: EFFECTS OF LOCAL UNEMPLOYMENT ON GANG PARTICIPATION BY AGE OF RESPONDENTS

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
unemployment rate	0.090***	0.074**	0.082**	0.086***	0.059*	0.064*
(age ≥ 18)	(0.033)	(0.035)	(0.039)	(0.030)	(0.031)	(0.035)
unemployment rate	-0.003	-0.025	-0.004	0.0028	-0.020	0.008
(age < 16)	(0.030)	(0.040)	(0.044)	(0.033)	(0.045)	(.053)
unemployment rate	0.043*	0.041	0.050*	0.059**	0.049	0.067**
(16 ≤ age < 18)	(0.024)	(0.028)	(0.029)	(0.027)	(0.031)	(0.033)
social variables	No	No	No	Yes	Yes	Yes
time dummies	Yes	Yes	Yes	Yes	Yes	Yes
region dummies	Yes	No	No	Yes	No	No
state dummies	No	Yes	Yes	No	Yes	Yes
state time-trends	No	No	Yes	No	No	Yes
pseudo R-square	0.059	0.076	0.084	0.117	0.136	0.150
Predicted Probabilities						
unemployment rate = 5%	0.022	0.023	0.029	0.022	0.023	0.029
unemployment rate = 10%	0.034	0.033	0.042	0.033	0.030	0.039
unemployment rate = 15%	0.051	0.046	0.061	0.048	0.040	0.052

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. Standard errors, in parentheses, clustered at the county level. Pseudo R-square and predicted probabilities are from the *unemployment rate (age ≥ 18)* models. Predicted probabilities are calculated from the models where *unemployment rate (age ≥ 18)*. Gang participation in the last twelve months of a survey is the dependent variable for all models. All models are estimated using logistic regression. The Model specifications are the same as in Table 3, where social variables represent: *highest-grade completed, enrolled, father, shot, bully, crime, doctors*. For age ≥ 18, Models 1 and 4 each have 14,517 observations; Models 2 and 5 have 13,924 observations; Models 3 and 6 have 11,042 observations. For age < 16, Models 1 and 4 each have 5,855 observations; Models 2 and 5 have 5,425 observations; Models 3 and 6 have 4,705 observations. For 16 ≤ age < 18, Models 1 and 4 each have 6,776 observations; Models 2 and 5 have 6,609 observations; Models 3 and 6 have 5,372 observations.

TABLE 5: ESTIMATION RESULTS FOR ASVAB SCORES

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
unemployment rate	0.100***	0.091**	0.091**	0.116***	0.095***	0.104***
	(0.038)	(0.040)	(0.041)	(0.032)	(0.034)	(0.034)
asvab	-0.008	-0.009	-0.010	0.001	-0.001	-0.003
	(0.004)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
*unemployment rate*asvab*	-0.002*	-0.002*	-0.002	-0.002**	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
social variables	No	No	No	Yes	Yes	Yes
time dummies	Yes	Yes	Yes	Yes	Yes	Yes
region dummies	Yes	No	No	Yes	No	No
state dummies	No	Yes	Yes	No	Yes	Yes
state time-trends	No	No	Yes	No	No	Yes
pseudo R-square	0.066	0.083	0.085	0.113	0.130	0.126
Predicted Probabilities where *asvab* = 20						
unemployment rate = 5%	0.034	0.034	.	0.029	0.030	0.035
unemployment rate = 10%	0.044	0.044	.	0.041	0.039	0.049
unemployment rate = 15%	0.058	0.056	.	0.057	0.050	0.067
Predicted Probabilities where *asvab* = 80						
unemployment rate = 5%	0.012	0.012	.	0.016	0.016	0.019
unemployment rate = 10%	0.008	0.009	.	0.012	0.013	0.017
unemployment rate = 15%	0.006	0.006	.	0.009	0.010	0.015

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. Standard errors, in parentheses, clustered at the county level. Gang participation in the last twelve months of a survey is the dependent variable for all models. All models are estimated using logistic regression. The Model specifications are the same as in Table 3, where social variables represent: *highest-grade completed, enrolled, father, shot, bully, crime, doctors*. Models 1 and 4 each have 21,859 obs. Models 2 and 5 have 21,710 obs. Models 3 and 6 have 18,387 obs.

Figure 1a: Gang Participation by Age

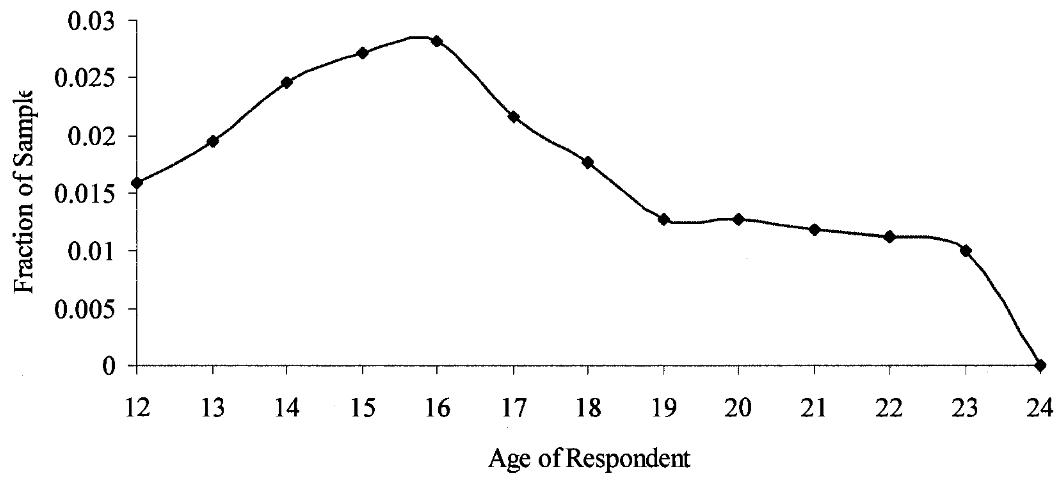


Figure 1b: Gang Participation by Year

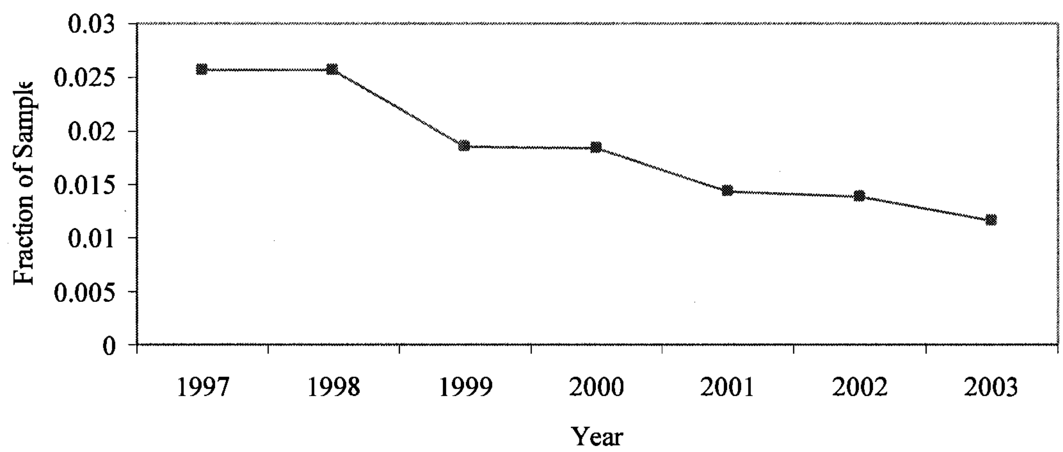
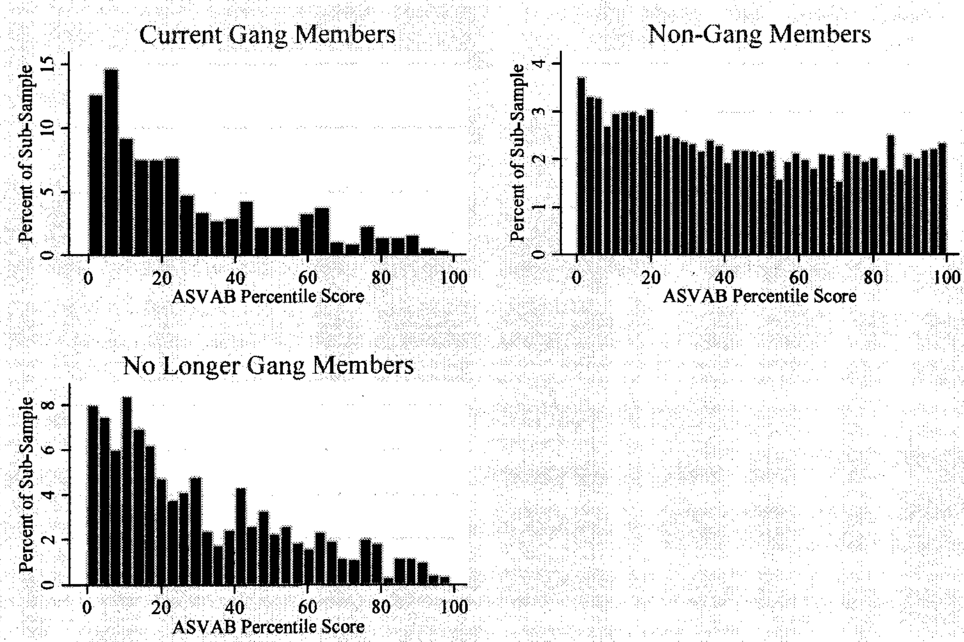


Figure 2: Distribution of ASVAB Scores by Gang Participation



THE EFFECTS OF INFLATION AND DEMOGRAPHIC CHANGE ON PROPERTY CRIME: A STRUCTURAL TIME-SERIES APPROACH

I. INTRODUCTION

Crime is a chronic and costly ailment of society. In 2005, over ten million property crimes were reported to law enforcement agencies in the United States.[34] Anderson (1999) estimates the total cost of property crimes to victims in the United States to be $603 billion per annum.

A large empirical literature investigating the link between macroeconomic conditions and aggregate crime rates has developed over the last thirty years. The majority of these studies focus on the relationship between unemployment rates and crime incidence (Cantor and Land, 1985; Kapuscinski et al., 1998; Chamlin and Cochran, 2000; Paternoster and Bushway, 2001; Greenberg, 2001a, 2001b). However, a great deal of debate persists concerning the appropriate data and empirical methodology necessary to analyse a society's changing propensity for crime (Greenberg, 2001a, 2001b; Britt, 2001; O'Brien, 2001; Levitt, 2001).

In the United States, the low-income segment of the population commits a disproportionate amount of crime. Numerous studies report a high incidence of non-participation in the legal labour market among criminals (Wilson and Herrnstein, 1985,

[34] Statistics are referenced from the 2005 Uniform Crime Report. Arson is not included in the estimates of property crime in the Uniform Crime Report.

ch. 12; Grogger, 1992). Research ranging from anthropological ethnographies to micro-level econometric studies cite lack of education and job skills, poor economic opportunity, and social isolation as key explanations for criminal motivation (Wilson, 1987; Grogger, 1998; Kelly, 2000; Bourgois, 2003). For those with low levels of marketable skills the economic return to crime is often greater than that of legal employment (Freeman, 1996; E. Anderson, 1999; Grogger, 1998; Williams and Sickles, 2002). Since the unemployment rate only measures persons actively seeking jobs, the aggregate unemployment rate may not be an ideal predictor of crime rate fluctuations.

In this paper, we investigate the effects of inflation and labour market dynamics on property crime rates, using data from the Federal Bureau of Investigation's Uniform Crime Report (UCR) for the years 1959 to 2005.[35] We hypothesize that in an economic environment with unstable prices individuals have additional incentive to bypass legal exchange and obtain material goods by illicit means. Periods of rising prices erode the value of money, which should make property crime more economically attractive, particularly for the lower income segment of society. We contend that inflation accounts for a significant portion of the steady increase in crime through the 1960s and 1970s, along with the dramatic decrease in crime in the mid- 1990s.[36]

Previous studies of unemployment's effect on crime rates do not consider variables capturing the changing demographic composition of the post-World War II United States

[35] According to the F.B.I., property crime is composed of larceny, burglary, and motor vehicle theft. We omit motor vehicle theft from our analysis, because only a single type of good is involved in the crime and would require the inclusion of covariates specific to the market for transportation. We also analyse robbery, because it contains a property component. Our analysis begins in the year 1959 due to the change in crime reporting by the F.B.I.

[36] See FIGURE 1 for graphs of the larceny, robbery, and burglary rates. FIGURE 2 shows graphs of the variables used in predicting property crime rates.

labour market.[37] In our analysis, we include the rate of female labour force participation and the ratio of manufacturing employment to total employment, as the rise of female labour force participation and the decline in the manufacturing sector represent the most significant transformations of the U.S. labour market.

Most studies in the economics of crime literature focus on the link between deterrence and crime rates. Identifying the parameters of an empirical model of aggregate crime, in which deterrence is included as a right-hand-side variable, is a major obstacle for researchers.[38] Likewise, omitting such a theoretically relevant variable can introduce bias to the estimates. To circumvent the identification problems associated with measures of deterrence, an alternative econometric strategy is used to model aggregate property crime rates. We implement a structural time-series model to allow for a stochastic trend in the data for property crime rates (Harvey, 1989, 1997; Koopman et al., 1995).[39] The unobserved components model captures the systematic influence of variables that we omit by choice or necessity through a stochastic trend. By moving the effects of omitted variables, such as deterrence, out of the residuals into a stochastic component, we can consistently estimate the effects of macroeconomic conditions on aggregate property crime rates.

We find that inflation is statistically significant, positive, and persistent for all property crime rates examined. The unemployment rate does not appear to play as large

[37] An exception is Witt and Witte (2000). They consider the effects of female labour-force participation on aggregate crime rates.

[38] Levitt (1996, 1997, 1998a) specifically addresses the issue of endogenous deterrence in a model of crime.

[39] For the remainder of the paper, we will use the terms structural time series and unobserved component modeling interchangeably.

a role as previously thought, once female labour force participation, the decline in manufacturing employment, and inflation are also considered.

II. Theoretical Background

Becker's (1968) economic model of crime suggests that individuals commit crimes based not upon genetic disposition or world-weariness, but rather in response to differences in costs and benefits. The behaviour of criminals in response to changes in the probability of apprehension and expected punishment for offenses is the traditional object of study in the economics of crime literature.[40] However, much of this literature is also devoted to studying the effect of economic conditions and individual earnings potential on criminal activity.[41]

The primary macroeconomic variable considered in previous studies of aggregate crime rates has been the unemployment rate. Higher unemployment rates could induce a transition from legal employment to illegal employment, as the returns to crime are greater when unemployment is higher and job seekers are accepting lower wages.[42] Recent economic studies do report anomalies with respect to economic factors and their effect on violent crimes, such as rape and murder (Kelly, 2000). However, most studies report results consistent with economic theory concerning the effect of economic well-being on property crimes (Myers, 1983; Grogger, 1998; Kelly, 2000; Gould et al., 2002).

[40] For example, see Sjoquist (1973), Wolpin (1980), Viscusi (1986), Corman et al. (1987), Trumbull (1989), Tauchen et al. (1994), Ehrlich (1996), Levitt (1996, 1997, 1998a, 1998b), and Corman and Mocan (2000).

[41] For example, see Myers (1983), Grogger (1998), Kelly (2000), Williams and Sickles (2002), and Gould et al. (2002).

[42] Grogger (1998) points out that many criminals are simultaneously employed in the legitimate sector. In Grogger's framework, the benefits associated with the first hour of criminal participation must exceed the return to an hour worked in licit employment.

The downward pressure on purchasing power associated with periods of rising inflation affect low-income households more adversely (Wilson, 1987). Since low-income groups commit a high proportion of crimes in the United States, one would expect periods of higher inflation to be concomitant with higher rates of crime. The low-income segment of society should find crime more attractive during inflationary periods, as wages generally do not adjust as freely as other prices. A positive effect on the rate of crime, attributable to higher inflation, should be observed in crimes with a property component. In periods of high inflation, one would expect society's propensity for property crime to increase because of the reduced purchasing power of the currency. Despite the significant macroeconomic implications of monetary policy, most studies neglect the role of inflation on the aggregate level of property crime.[43]

It has been well documented that the real wage-earnings of low-skilled workers in the United States have fallen since the 1970s (Burtless, 1990a, 1990b; Blackburn et al., 1990; Blank, 1990; Moffitt, 1990; Katz and Murphy, 1992). A disproportionate amount of these low-skilled workers are young minority males in the age group 18-25, the group most likely to commit crimes (Wilson, 1987, 1996; Freeman, 1996). The decline in the percentage of the workforce in the manufacturing industry has been cited as a primary contributor to the high rates of unemployment and non-participation in the labour market among urban male youth because larger additions of human capital are required to

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[43] Devine et al. (1988) is a notable exception. The authors estimate a first-differenced model of macroeconomic (i.e. inflation and unemployment) and social control (i.e. imprisonment and relief programs) factors and find a positive effect of inflation on homicide, robbery and burglary. However, the theoretical basis for the inclusion of inflation in a model of crime is not the actual effect of price volatility but rather that the "perception of inflation" motivates behavioral change (See Footnote 1). Additionally, the authors use 2SLS to estimate the effect of imprisonment on crime, yet provide no discussion of the variable(s) which generates the exogenous variation necessary for identification.

compete effectively for high-wage jobs (Wilson, 1986, 1996). Gould et al. (2002) use both county-level crime data and individual-level panel data from 1979-1997 to examine the relationship between the labour market opportunities for unskilled male workers and crime rates. The authors find that movements in wage compensation for unskilled workers account for 50 percent in the rise of both violent and property crime rates for the sample period.

Another key economic development of the 20th century was the dramatic increase in female labour force participation which restructured the United States' economy (Goldin, 2006). The decline in the manufacturing sector was roughly concurrent with a sharp rise in the female labour force participation rate.[44] Attendant movements in these two variables indicate that men, who have historically held manufacturing jobs, exited the field to enter a more competitive market for service jobs where women held a comparative advantage (Welch, 2000). During this reorganization of the labour market women gained access to affordable contraceptives, which granted women greater control over fertility decisions and reduced the costs of long-term investments in human capital (Goldin and Katz, 2000). Remarkable improvements in the economic well-being of women (particularly single women) and the overall prospects for high-wage employment increased the bargaining power of women in the home (Costa, 2000).

The female labour force participation rate and the decline in the manufacturing sector can be seen as proxy measures of rapid socioeconomic change which drastically altered the composition of the American family and redefined the division of labour between the

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[44] See FIGURE 2.

sexes.[45] We hypothesize that female labour force participation should be positively related to property crime because increases in the female workforce have decreased the relative earnings of men (Katz and Murphy, 1992). A decline in the manufacturing sector should make it more difficult for males with low levels of human capital to obtain high-wage jobs (Wilson, 1987; Katz and Murphy, 1992). As a result, we expect manufacturing employment to be negatively related to property crime.

Because the crime rates we examine differ in their degrees of violence and audacity, we might expect to find anomalies with respect to female labour force participation and employment in the manufacturing sector. However, we expect the effects of inflation and unemployment to be consistent across different property crime rates. The economic return to property crime and, as a result, the aggregate rate of property crime should be greater during periods of high unemployment. Inflation should also generate a positive response of property crime because the relative purchasing power of money is diminished and individuals have additional incentive to bypass the licit terms of trade.

III. DATA

We use data on the unemployment rate, inflation rate, percentage of manufacturing employment relative to total employment, and female labour force participation rate as predictors of various property crime rates. All data series span from 1959 to 2005, giving 47 total years of data. Data on property crime rates are collected from the Uniform Crime Report (UCR), and are represented by three different headings: (*i*) larceny, (*ii*)

[45] Witt and Witte (2000) also use the female labour force participation rate as a proxy measure of social change in a model of the aggregate crime rate.

burglary, and (*iii*) robbery (which is classified as a violent crime, but has a property component).[46]

Begun in 1929, the UCR is a national record of crimes reported to state and local law enforcement agencies in the United States. While homicide is the most accurately measured, all other crimes in the UCR suffer from underreporting bias (DiIulio, 1996). While the UCR has its limitations, no other time series with as many observations of aggregate crime rates is available.[47] The sample period we study captures the dramatic upsurge in crime during the 1960s and 1970s, along with the rapid decrease of the 1990s.

TABLE 1 displays variable names, definitions, and data sources. TABLE 2 presents summary statistics. We employ a test for stationarity to determine if any of the data series follow a unit root.[48] The test statistics with and without a trend are presented in TABLE 3. The variables *unrt* and *infl* appear stationary. However, the variables *manu* and *flfpr* appear non-stationary and enter the model in first differenced form. As a result, all explanatory variables are stationary.

[46] Levitt (2001) criticises the use of national-level crime data to examine the unemployment/crime relationship, because there is local variation in both crime rates and unemployment rates that could be exploited. Levitt (2001, pp. 380) states that criminological explanations for the unemployment/crime relationship found in aggregate national crime data are at best "subtle predictions." Although inflation is calculated at the regional-level and at the local-level for a select number of large cities, the most accurate measure of inflation is at the national-level (See the Bureau of Labor Statistics, http://www.bls.gov/cpi/.). As a result, investigating the role of inflation in an economic model of crime should use national-level crime data.

[47] The long time-span of the UCR accounts for its popularity in the crime literature. The second longest running aggregate crime record is the National Crime Victimization Survey (NCVS) annually conducted since 1973 by the Bureau of Justice Statistics (BJS).

[48] We test all variables, excluding various property crime rates for stationarity, employing the test outlined by Kwiatkowski et al. (1992).

IV. ECONOMETRIC METHODOLOGY

We use a structural time-series framework to analyse property crime rates.[49] Harvey (1989, 1997) and Koopman et al. (1995) advocate the use of structural time series, especially when there is a clear trend in the series. Since all dependent variables are non-stationary, it is necessary to include a trend for each in order to avoid spurious results. Because a deterministic time trend is too restrictive for most time series data, allowing the slope and level components to vary over time is the preferred specification (Harvey, 1997). The general form of the structural time-series model can be written as

$$y_t = \mu_t + \sum_i \sum_j \alpha_{ij}\, x_{i,t-j} + \varepsilon_t \qquad for\ t = 1,2,.,T. \tag{1}$$

The term y_t is the dependent variable; μ_t is a time-varying intercept term; $x_{i,t-j}$ is regressor i subject to time lag j; α_{ij} represents the coefficient associated with variable $x_{i,t-j}$; and ε_t is a zero mean constant variance disturbance term. The term μ_t enables the researcher to capture unobservable influences that drive the dependent variable.[50] The μ_t process takes the form

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta \sim NID\left(0, \sigma_\eta^2\right) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi \sim NID\left(0, \sigma_\xi^2\right). \tag{3}$$

μ_t is interpreted as the "level component" of a stochastic trend. β_t represents the drift parameter, which is the "slope" of the level component. The level component is assumed

[49] Structural time series is an outgrowth of the General-to-Specific empirical methodology advocated by the London School of Economics (LSE). We begin with a general model, and test the model down to a more parsimonious form. Each time a restriction is made the validity of the restrictions in terms of the model are tested. in order to find the best statistical fit for the data generating process. All models within the LSE tradition are believed to be false. Therefore, the objective is to find a statistically adequate and parsimonious model that outperforms all other known models.

[50] Since criminal deterrence is largely unobservable and has no ideal proxies, μ_t should capture criminal deterrence efforts.

to follow a random walk with drift and the slope component is assumed to follow a random walk. Both level and slope components have white noise disturbances represented by η_t and ξ_t, respectively. The white noise disturbances η_t and ξ_t are assumed to be independent of each other and of ε_t. After estimation of the model's parameters a Kalman filter is applied in order to recover the state vectors, μ_t and β_t.[51]

Equations (1) through (3) present the model in its most general form. Nothing is lost by starting with a general stochastic specification because the model can be tested down to only contain a fixed level, a fixed slope, and/or some combination of both. For example, if the model has a fixed level and stochastic slope, the level and slope components take the following form

$$\mu_t = \mu_{t-1} + \beta_{t-1} \quad (4)$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi \sim NID\left(0, \sigma_\xi^2\right). \quad (5)$$

With this specification, the component μ_t is fixed (or constant) when $\sigma_\eta^2 = 0$. Equation (5) implies that the slope component, β_t, remains unchanged. This specification is also referred to as a "smooth trend."[52] A smooth trend model implies the dependent variable is $I(2)$.

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[51] All models are estimated using the program Structural Time Series Analyser, Modeller, and Predictor 6.30 (STAMP). STAMP has a built-in procedure for the Kalman filter.

[52] If the variances of the disturbance terms in both the level and slope components are zero (i.e. σ_η^2 = σ_ξ^2 = 0), then the structural time-series model collapses to a deterministic trend model (Harvey, 1997). However, when the unobserved component is constant (i.e. $\beta_t = \sigma_\eta^2$ = 0), the structural time-series model collapses to an OLS specification.

As noted earlier, three different types of property crimes are investigated. Numerous models are estimated for each of the dependent variables. The models' respective components and parameters are tested using standard methods outlined in Harvey (1989).

Previous studies that analyse aggregate crime rates use a variety of econometric techniques: (*i*) ordinary least squares (OLS), (*ii*) vector autoregressions (VARs), and (*iii*) cointegration. In what follows, we discuss each of these empirical methodologies and how the structural time- series approach addresses potential problems associated with these techniques.

Visual inspection of a plot of crime rates over time suggests the presence of a trend.[53] As a result, estimating crime rates with OLS can produce spurious results, unexplainable lags on the variables, and residual series that indicate a misspecification.[54] Cantor and Land's (1985) seminal paper, from the sociology literature, examining the effects of unemployment on aggregate crime rates has come under criticism because of the paper's empirical technique, which is an OLS model in first differenced form (Greenberg, 2001a, 2001b; Britt, 2001; O'Brien, 2001). The most notable problem with differencing is that the trend in the series is eliminated, and emphasis is on changes from period to period. To warrant elimination of the trend, the researcher must assume the short-run dynamics are theoretically different from the long-run dynamics in the estimation (Harvey, 1997).[55] One other problem with estimating the effect of changes in the unemployment rate on

[53] See Figure 1.

[54] If the model takes the smooth trend specification, the dependent variable would need to be differenced twice in order to make it stationary. Failure to do so can result in spurious estimates. This applies to other specifications as well, not only OLS.

[55] Detrending implicitly assumes that the variable follows a stochastic trend without corroborating evidence.

changes in the crime rate is that the variables may be of different order.[56] In response to Cantor and Land (1985), a number of alternative estimation techniques are used to investigate the relationship between crime and unemployment in the short-run and long-run.

VARs are reduced-form models, in which all variables are considered jointly endogenous (Enders, 2004). Corman et al. (1987) use a VAR approach to estimate the interrelationship between the supply of crime in New York City and variables meant to capture changes in the business cycle, demographic composition, and criminal deterrence. While VARs are useful for uncovering dynamic relationships (i.e. crime and criminal deterrence) without imposing ad hoc identification restrictions, VARs are not a substitute for structural modeling where more clearly defined causal relationships can be determined (Corman et al., 1987). VARs make restrictive assumptions requiring the number of lags to be limited, the number of lag lengths to be the same for all variables, and that no structural breaks occur during the sample period (Corman et al., 1987). VARs also require strong assumptions regarding the ordering of the equations in the system to identify impulse response functions (Enders, 2004).[57]

Greenberg (2001a, 2001b) advocates using cointegration techniques to identify the long-run relationship between the unemployment rate and the crime rate. One well-

[56] If the crime rate is an $I(1)$ variable, differencing the crime rate would make it an $I(0)$ variable. Assuming also that the unemployment rate is stationary over time, differencing the unemployment rate, as in Cantor and Land (1985), would result in an $I(-1)$ variable. Such improper ordering of the variables could result in spurious results.

[57] As Harvey (1997) notes, VARs become more meaningful when altered in a way that allows for detection of long-run relationships. One example is the vector error correction model (VECM), which allows for one to test for the number of cointegrating vectors by employing the Johansen (1988) test. Harvey (1997) also suggests that VAR-based cointegration techniques have poor statistical properties and problems arise when one relies on unit-root tests to determine the order of integration in a series. The use of unit-root tests may result in one concluding that a series is $I(1)$ when in fact it is $I(2)$.

known problem with cointegration analysis is its sensitivity to structural change over time. As a consequence, the absence of cointegration between variables does not necessarily imply that they are truly unrelated. This problem may arise in the case of Greenberg (2001a, 2001b). Greenberg interprets the lack of a cointegrating relationship to mean there is no stable long-run relationship between the unemployment rate and crime rates.

When compared with other empirical strategies previously mentioned, structural time-series models have several advantages. They (*i*) model the trend in the data for property crime rates as an unobserved component, (*ii*) allow for trend changes through time-varying parameters, and they (*iii*) attribute omitted right-hand side variables to the unobserved component.[58] Also, the unobserved component methodology does not rely on unit root tests to specify the dependent variable.[59]

Naturally, one would prefer to have a model with no unobserved component, as this model would completely capture the data generating process. However, in some (if not most) cases, the elimination of an unobserved component may not be possible or desirable because of data limitations. An unobserved component can also provide insight with respect to the underlying developments not explained by included explanatory variables.

V. RESULTS

[58] This allows for consistent estimation of the model's parameters.

[59] Most unit root tests rely on autoregressive models which may have poor statistical properties (Harvey, 1997). Harvey and Jaeger (1993) show that unit root tests are unlikely to detect integration of order two in a time series, which can result in model misspecification.

Each of the property crime rates are estimated with identical right-hand side variables and an equal number of lags for each. First, all models are estimated with a stochastic slope and level. These general models are tested down to a more parsimonious form. The variance of the disturbance in the level component for both larceny and burglary rates is zero. Therefore, the unobserved component for larceny and burglary rates takes the form of equations (4) and (5). This is not the case for the robbery rate, which takes the general stochastic form shown in equations (2) and (3).

The model results for larceny, burglary, and robbery rates are presented in TABLES 4, 5, and 6, respectively. Tests are employed to check for non-normality, higher-order autocorrelation, heteroskedasticity, and the models' out-of-sample performance. We rely on the out-of-sample forecasting properties to justify any further parameter restrictions.[60]

The models for the larceny rate do not indicate statistical adequacy problems. There are statistical adequacy problems detected in the estimation of both burglary and robbery rates. The model for the burglary rate appears to have a problem with higher-order autocorrelation, as indicated by the Box-Ljung statistic provided in Model 2 of TABLE 5. Inspection of the residual series indicates a large value for one observation, the year 1977. To correct for autocorrelation, an observation-specific dummy variable is included for the year 1977. The robbery rate has a non-normality problem (see TABLE 6). The residual series indicates large values for the years 1986 and 1987. To address the non-normality problem, we include observation-specific dummy variables for the years 1986 and 1987.

[60] More detail regarding the statistical adequacy tests are presented in the *Notes* section at the bottom of TABLES 4, 5, and 6.

The residual graphics for the final models of the property crime rates are displayed in FIGURES 3, 4, and 5. As indicated by the residual graphics, the models fit the data relatively well. FIGURES 6, 7, and 8 display the remaining slope and level components of larceny, burglary, and robbery rates not explained by the included explanatory variables. The remaining components imply that the included explanatory variables alone do not fully capture the data generating process for the various property crime rates. A large portion of the remaining trend components may be attributable to criminal deterrence efforts.

Consistent with our theory, inflation is statistically significant, positive, and persistent for all property crime rates considered. The change in manufacturing employment is statistically significant and negative for all property crime rates, which is also consistent with our hypotheses. There are results unsupported by the theory of this paper. The model results for burglary indicate female labour force participation has no statistically significant effect. A possible explanation is that burglary requires a greater investment of criminal human capital than other crimes, which makes it less sensitive to long-run demographic changes. For the robbery rate, unemployment is statistically insignificant, and the female labour force participation rate is statistically significant but has a negative coefficient. Robbery is a violent crime. As a result, an increase or decrease of the robbery rate may be more a response to institutional change than a response to temporary shocks in the labour market. The negative sign of female labour force participation could be attributable to the rising affluence of women, corresponding to the increase in female labour force participation. Robbery is most common in less affluent neighborhoods (E. Anderson, 1999). As women become more prosperous they are able to afford additional security measures (e.g., living in safer neighborhoods).

We find that the unemployment rate does not provide consistent predictive power across property crime rates. However, the percentage of total employment in the manufacturing sector is a reliable predictor of property crime rates. As TABLE 7 reveals, the long-run effect of manufacturing employment is greater than all other explanatory variables. TABLE 7 also shows inflation has a greater long-run effect than that of unemployment.

VI. CONCLUSIONS

Unobserved component models of various property crime rates are constructed using annual data for the unemployment rate, inflation rate, percentage of total employment in the manufacturing sector, and the female labour force participation rate. The structural time-series approach is the preferred empirical specification, as it models the trend in the dependent variable as an unobserved component.

Because trend components remain in each model we estimate, the included explanatory variables do not completely capture the data generating process. The theoretical relevance of deterrence efforts may suggest a large portion of the remaining trends could be attributable to these measures. However, our focus is the impact of inflation and other labour market dynamics on property crime. Hence, the inclusion of a stochastic trend, which captures unobservable and omitted variables, provides an attractive alternative to obtain consistent estimates for included covariates.

The unemployment rate does not appear to play a consistently significant role in the determination of property crime rates. The variables used to proxy for the dramatic change in the U.S. labour market, particularly the decline in manufacturing employment, have considerable explanatory power with respect to property crime. The sizeable long-run effects of manufacturing employment suggest that larger additions of human capital investment, particularly for low-income males, could greatly reduce property crime. Public policies that encourage human capital accumulation could decrease the economic incentive to commit property crime through increases in earnings potential in the service economy.

Our results are robust with respect to inflation; inflation is positive, statistically significant, and persistent for all property crime rates considered. Both the short-run and long-run effects of inflation on property crime rates are considerable. Thus, a monetary policy regime meant to stabilize prices may indirectly reduce property crime.

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TABLE 1
VARIABLE NAMES AND VARIABLE DEFINITIONS

Variable	Variable Definition
burglary	Burglary rate of the population per 100,000
larceny	Larceny rate of the population per 100,000
robbery	Robbery rate of the population per 100,000
unrt	Percentage of workforce who is unemployed but is actively pursuing employment
manu	Ratio of manufacturing to total payroll employment
infl	Log of the ratio of the Consumer Price Index (CPI) at time *t* relative to the log of the CPI at time *t*-1
flfpr	Percentage of females participating in the workforce

Notes: All property crime rates come from the FBI's Uniformed Crime Report. The other variables all come from the Bureau of Labor Statistics (BLS).

TABLE 2

SUMMARY STATISTICS

Variable	Mean	Std. Deviation	Minimum	Maximum
burglary	1.0522	0.3369	0.4881	1.6841
larceny	2.4380	0.6917	1.0347	3.2288
robbery	0.1745	0.0636	0.0583	0.2727
unrt	5.8901	1.4169	3.4917	9.7083
infl	4.2122	3.0103	0.6710	13.2550
manu	19.9642	5.6833	10.6657	28.7141
flfpr	50.7222	8.0622	37.1333	60.0417

Note: All data relate to United States for the years 1959 to 2005 (obs. = 47).

TABLE 3
TEST FOR STATIONARITY

Variable	KPSS Test	
	Trend {H0 = *I*(0)}	**No-trend {H0 = *I*(0)}**
unrt	0.1641	0.1699
infl	0.1896	0.2115
manu	0.1002	1.0425*
flfpr	0.2278	1.0066*

Notes: * indicates significance at the one percent level. Details of the KPSS test are outlined in Kwiatkowski et al. (1992). The KPSS uses stationarity as the null and tests against the alternate hypothesis of a unit root. We do not test the property crime rates for stationarity because of our modeling approach. Structural time series models allow for a unit root process to be present in the dependent variable.

TABLE 4
MODEL RESULTS FOR THE LARCENY RATE

Variable	Model 1 coeff.	Model 1 p-val.	Model 2 coeff.	Model 2 p-val.
μ	1.3091	0.000	1.4247	0.000
β_t (for last year)	-0.0420	0.055	-0.0448	0.043
$larcenyy_{t-1}$	0.7430	0.000	0.6601	0.000
$larceny_{t-2}$	-0.4118	0.000	-0.3922	0.000
$infl_t$	0.0119	0.029	0.0121	0.009
$infl_{t-1}$	0.0257	0.000	0.0279	0.000
$infl_{t-2}$	-0.0028	0.710		
$unrt_t$	0.0041	0.749		
$unrt_{t-1}$	0.0247	0.089	0.0256	0.028
$unrt_{t-2}$	-0.0039	0.773		
$\Delta\ manu_t$	-0.0570	0.014	-0.0685	0.001
$\Delta\ manu_{t-1}$	0.0254	0.322		
$\Delta\ flfpr_t$	0.0431	0.133	0.0480	0.041
$\Delta\ flfpr_{t-1}$	0.0805	0.003	0.0819	0.001
R^2	0.9946		0.9944	
AIC	5.4489		5.5937	
SIC	4.8467		5.1521	
Heterosk. $F(14,14)$	1.1751		1.4821	
Cusum $t(6)$	0.4432		0.5228	
Cusum $t(10)$	-1.1168		-1.0267	
p-values:				
Normality $\chi^2(2)$	0.9540		0.9849	
Box-Ljung $\chi^2(6)$	0.3750		0.4448	
Forecast $\chi^2(6)$	0.9257		0.8965	
Forecast $\chi^2(10)$	0.7880		0.7318	

Notes: AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last *h* residuals to the first *h* residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests *h* observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests *h* observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

TABLE 5
MODEL RESULTS FOR THE BURGLARY RATE

Variable	Model 1		Model 2		Model 3	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
μ	0.2919	0.001	0.3188	0.000	0.3784	0.000
β_t (for last year)	-0.0106	0.364	-0.0103	0.355	-0.0098	0.393
$burglarly_{t-1}$	0.7877	0.000	0.7772	0.000	0.7489	0.000
$burglarly_{t-2}$	-0.4302	0.000	-0.4062	0.000	-0.4727	0.000
$infl_t$	0.0107	0.002	0.0102	0.002	0.0110	0.000
$infl_{t-1}$	0.0138	0.001	0.0135	0.000	0.0141	0.000
$infl_{t-2}$	-0.0080	0.115	-0.0094	0.039	-0.0077	0.061
$unrt_t$	0.0133	0.096	0.0140	0.039	0.0145	0.021
$unrt_{t-1}$	-0.0016	0.864				
$unrt_{t-2}$	0.0071	0.419				
$\Delta\ manu_t$	-0.0226	0.098	-0.0192	0.102	-0.0233	0.029
$\Delta\ manu_{t-1}$	-0.0144	0.286				
$\Delta\ flfpr_t$	-0.0084	0.647				
$\Delta\ flfpr_{t-1}$	0.0179	0.247				
D_1977					0.0769	0.004
R^2	0.9920		0.9912		0.9929	
AIC	6.4510		6.5696		6.7459	
SIC	5.8488		6.1681		6.3042	
Heterosk. F(14,14)	0.8479		0.9702		0.8535	
Cusum $t(6)$	1.2531		1.3437		1.5450	
Cusum $t(10)$	0.6978		0.7110		0.8221	
p-values:						
Normality $\chi^2(2)$	0.6530		0.4813		0.4679	
Box-Ljung $\chi^2(6)$	0.0971		0.0149*		0.3743	
Forecast $\chi^2(6)$	0.8158		0.8051		0.7330	
Forecast $\chi^2(10)$	0.8605		0.7852		0.6187	

Notes: AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last h residuals to the first h residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests h observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests h observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

TABLE 6
MODEL RESULTS FOR THE ROBBERY RATE

Variable	Model 1		Model 2		Model 3		Model 4	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
μ_t (for last year)	0.0632	0.002	0.0624	0.001	0.0565	0.001	0.0598	0.000
β_t (for last year)	-0.0010	0.751	0.0019	0.608	0.0016	0.731	0.0017	0.715
$robbery_{t-1}$	0.6824	0.000	0.7278	0.000	0.4656	0.000	0.4405	0.000
$robbery_{t-2}$	-0.0424	0.762	-0.0895	0.387				
$infl_t$	0.0010	0.178	0.0017	0.004	0.0019	0.000	0.0019	0.000
$infl_{t-1}$	0.0036	0.000	0.0029	0.000	0.0039	0.000	0.0039	0.000
$infl_{t-2}$	-0.0017	0.088	-0.0147	0.073	-0.0002	0.805		
$unrt_t$	-0.0007	0.727	-0.0003	0.837				
$unrt_{t-1}$	-0.0014	0.429	-0.0020	0.172				
$unrt_{t-2}$	-0.0018	0.324	-0.0015	0.345				
$\Delta\, manu_t$	-0.0422	0.140	-0.0033	0.096	-0.0039	0.037	-0.0038	0.032
$\Delta\, manu_{t-1}$	-0.0446	0.114	-0.0033	0.102	-0.0042	0.024	-0.0043	0.021
$\Delta\, flfpr_t$	-0.0046	0.193	-0.0069	0.009	-0.0063	0.003	-0.0062	0.003
$\Delta\, flfpr_{t-1}$	0.0028	0.435	0.0016	0.560				
D_1986			0.0081	0.223				
D_1987			-0.0192	0.067	-0.0249	0.000	-0.0245	0.000
R^2	0.9895		0.9943		0.9922		0.9922	
AIC	9.5010		10.007		9.9682		10.014	
SIC	8.8586		9.2838		9.4864		9.5721	
Heterosk. F(14,14)	1.9092		1.8447		1.4491		1.4545	
Cusum $t(6)$	1.6079		1.6324		1.1143		1.1384	
Cusum $t(10)$	0.0065		1.0167		0.9637		0.9996	
p-values:								
Normality $\chi^2(2)$	0.0433*		0.1089		0.6909		0.6758	
Box-Ljung $\chi^2(6)$	0.7856		0.1079		0.3395		0.3362	
Forecast $\chi^2(6)$	0.6069		0.1822		0.2169		0.5650	
Forecast $\chi^2(10)$	0.7993		0.4081		0.5384		0.8231	

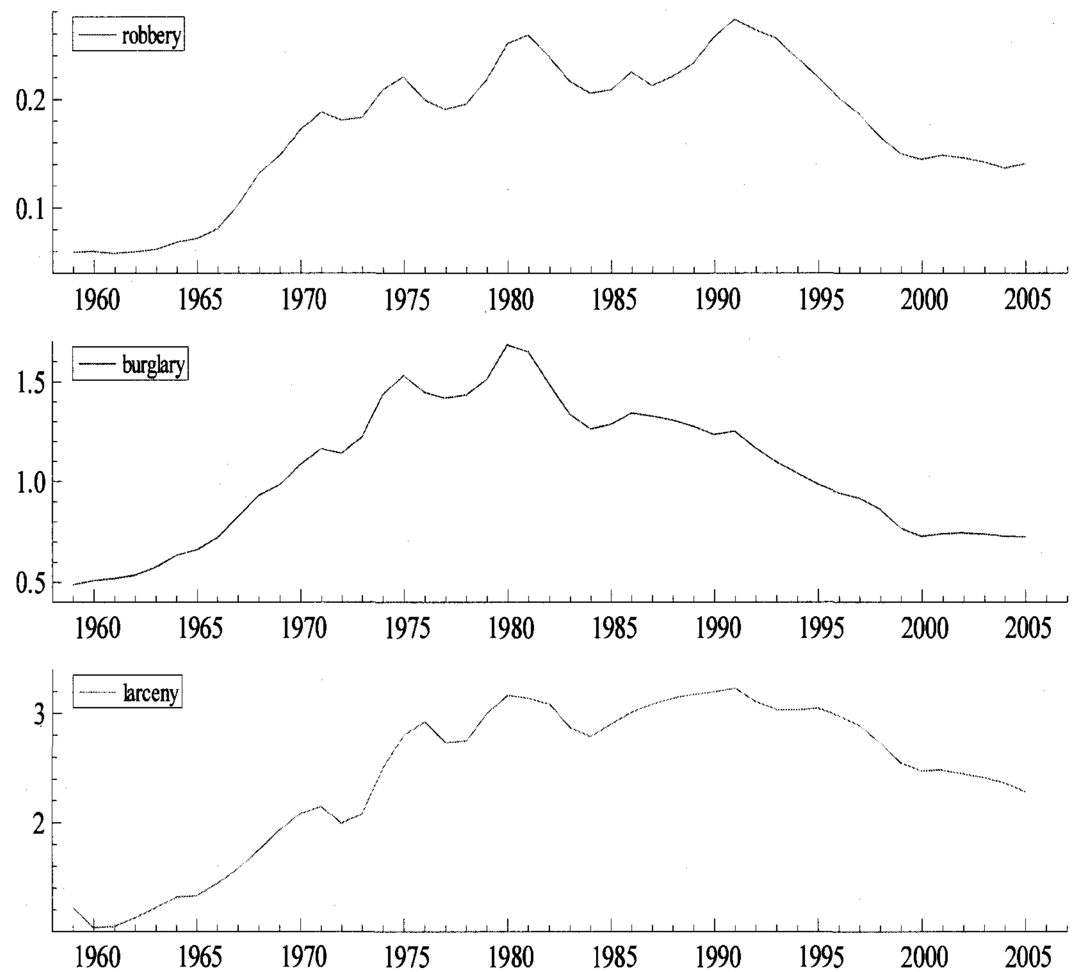
Notes: AIC represents the Akaike Information Criterion developed by Akaike (1974). SIC is the Schwarz Information Criterion. The SIC is sometimes referred to the Bayesian Information Criterion (BIC). Heterosk. is a test for heteroskedasticity, which has homoskedasticity as the null. The Heteroskedasticity test is the ratio of the squares of the last *h* residuals to the first *h* residuals (See Koopman et al., 2000). The critical value for the Heterosk. at the five percent level is 2.48. The Doornik and Hansen (1994) test is employed to check for normality; normality is the null hypothesis. The test Box-Ljung represents the Ljung and Box (1978) test for higher-order autocorrelation, which has a null of no-autocorrelation. The test Forecast $\chi^2(h)$ are one-step-ahead predictive tests *h* observations into the future. Cusum $t(h)$ are one-step-ahead predictive tests *h* observations into the future for the residuals. Model 1 represents the general specification of the model. Subsequent models successively restrict parameter values, while checking the validity of each set of restrictions with the statistics mentioned above.

TABLE 7
LONG-RUN MULTIPLIERS FOR PROPERTY CRIME RATES

Variable	Larceny	Burglary	Robbery
infl	0.0544	0.0240	0.0104
unrt	0.0350	0.0200	
Δ *manu*	-0.0936	-0.0322	-0.0145
Δ *flfpr*	0.1774		-0.0111

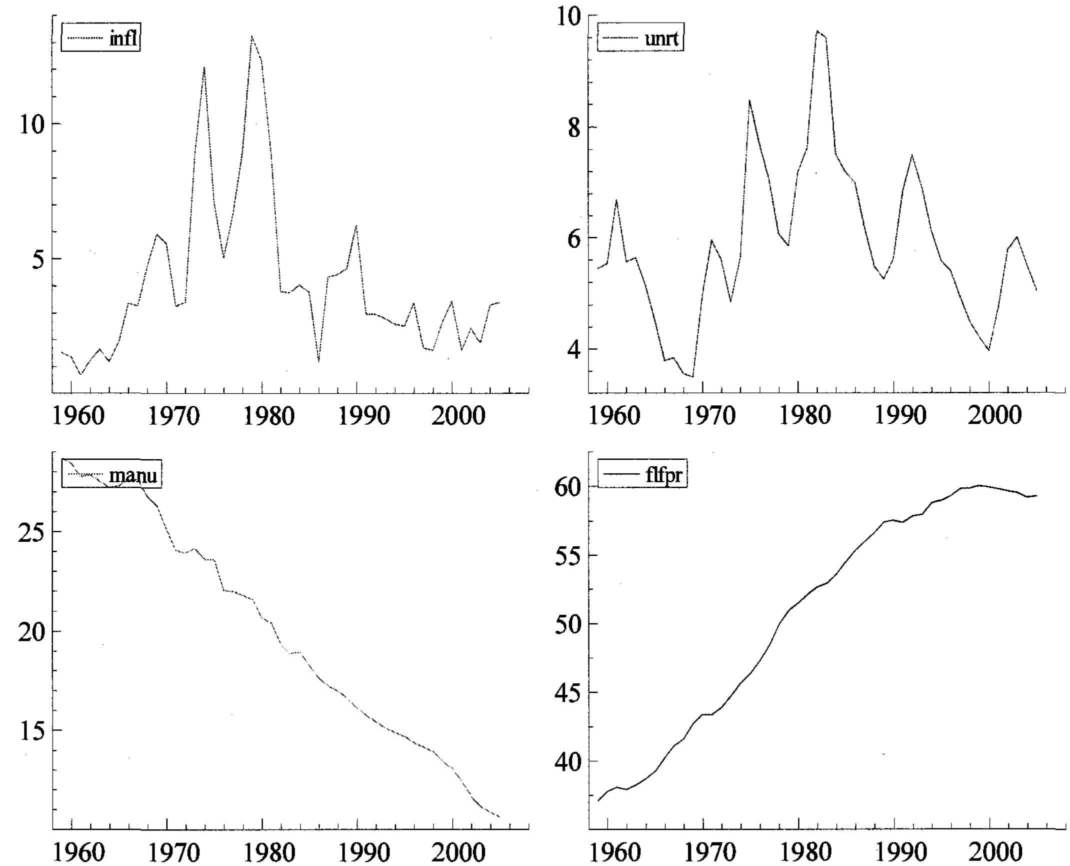
Notes: Long-run multipliers are calculated by dropping the time subscripts in each of the final models and solving for the dependent variable. Note that some of the long-run multipliers are equal to the impact multipliers. Recall that the variable *unrt* is not significant in the estimates for robbery and Δ *flfpr* is not significant in the estimation of the burglary rate.

FIGURE 1: PLOTS OF THE ROBBERY, BURGLARY, AND LARCENY RATES OVER TIME



Note: The *y-axis* measures the various property crime rates per 100,000 persons.

FIGURE 2: THE INFLATION RATE, UNEMPLOYMENT RATE, RATIO OF MANUFACTURING EMPLOYMENT TO TOTALEMPLOYMENT, AND FEMALE LABOUR FORCEPARTICIPATION RATE OVER TIME



Note: The upper-left graph shows the inflation rate over time and the upper-right graphs shows the unemployment rate over time. The bottom-left graph shows the decline in manufacturing employment and lower-right graph shows the increase in female labour force participation over time. The *y-axes* measure the rate of the explanatory variable.

FIGURE 3: RESIDUAL GRAPHICS FOR THE LARCENY RATE

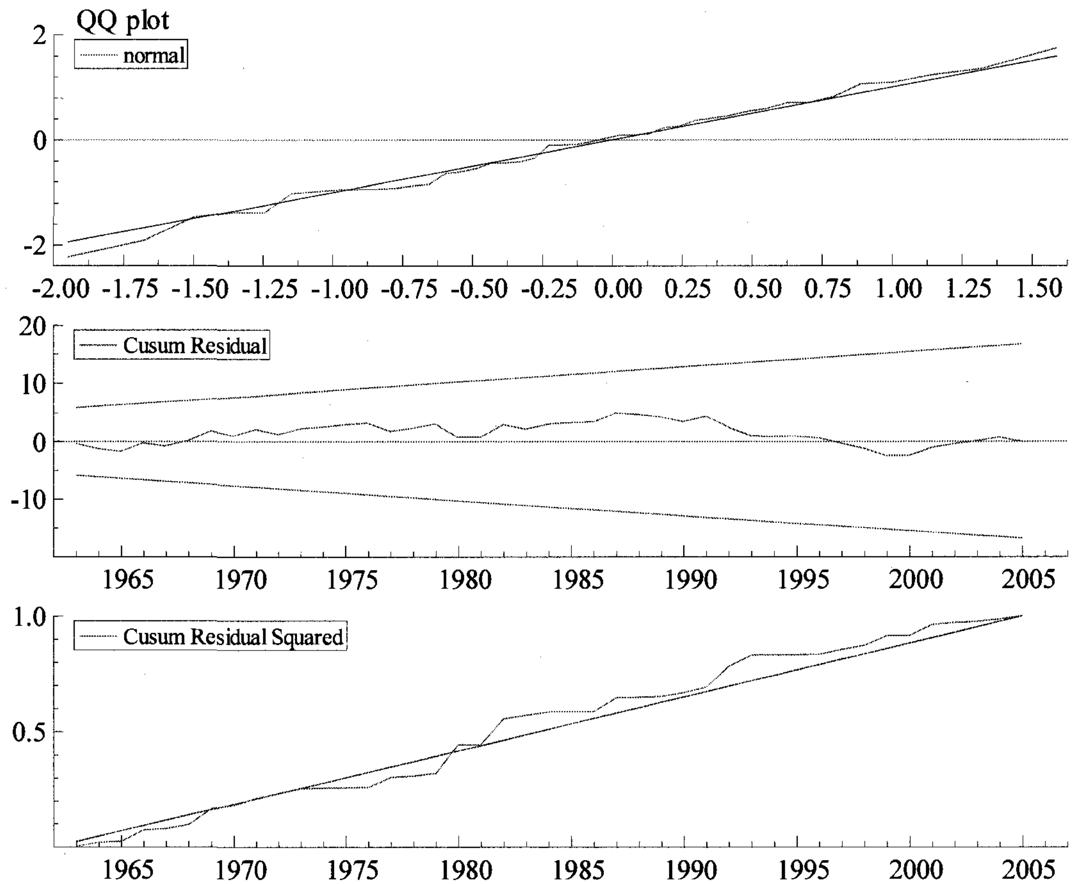


FIGURE 4: RESIDUAL GRAPHICS FOR THE BURGLARY RATE

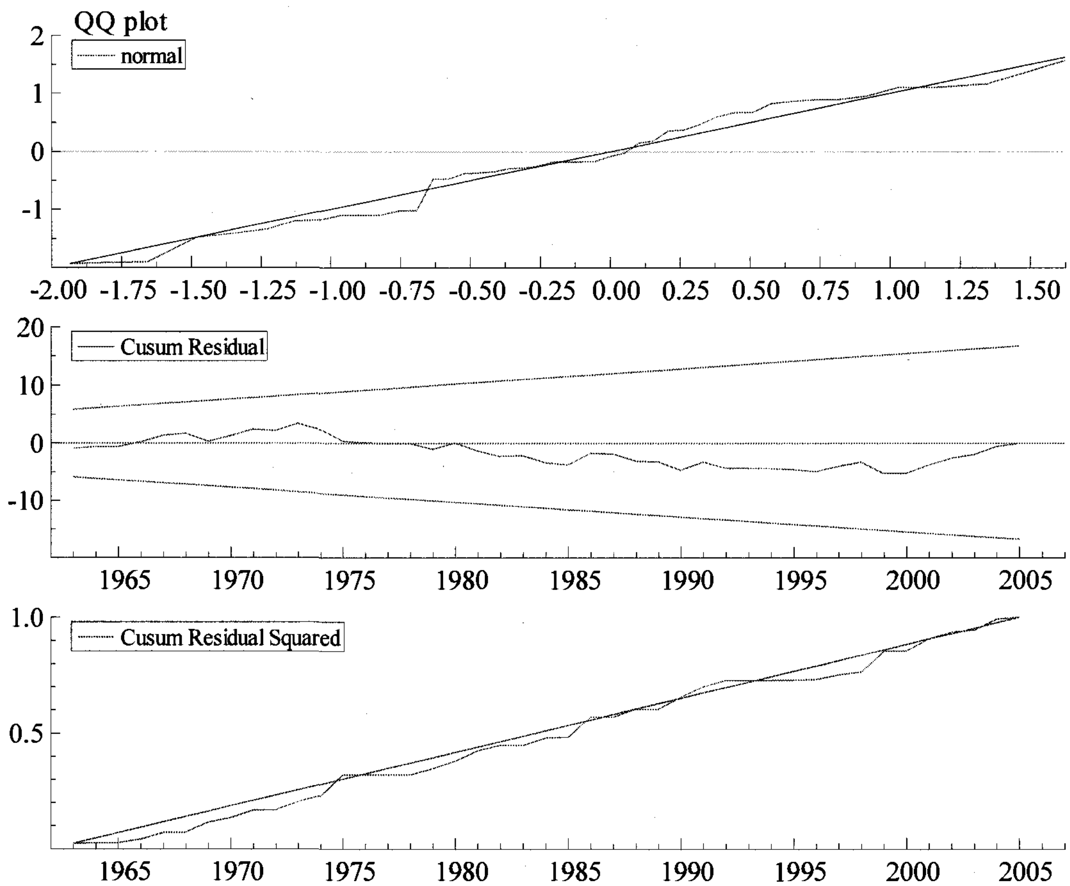


FIGURE 5: RESIDUAL GRAPHICS FOR THE ROBBERY RATE

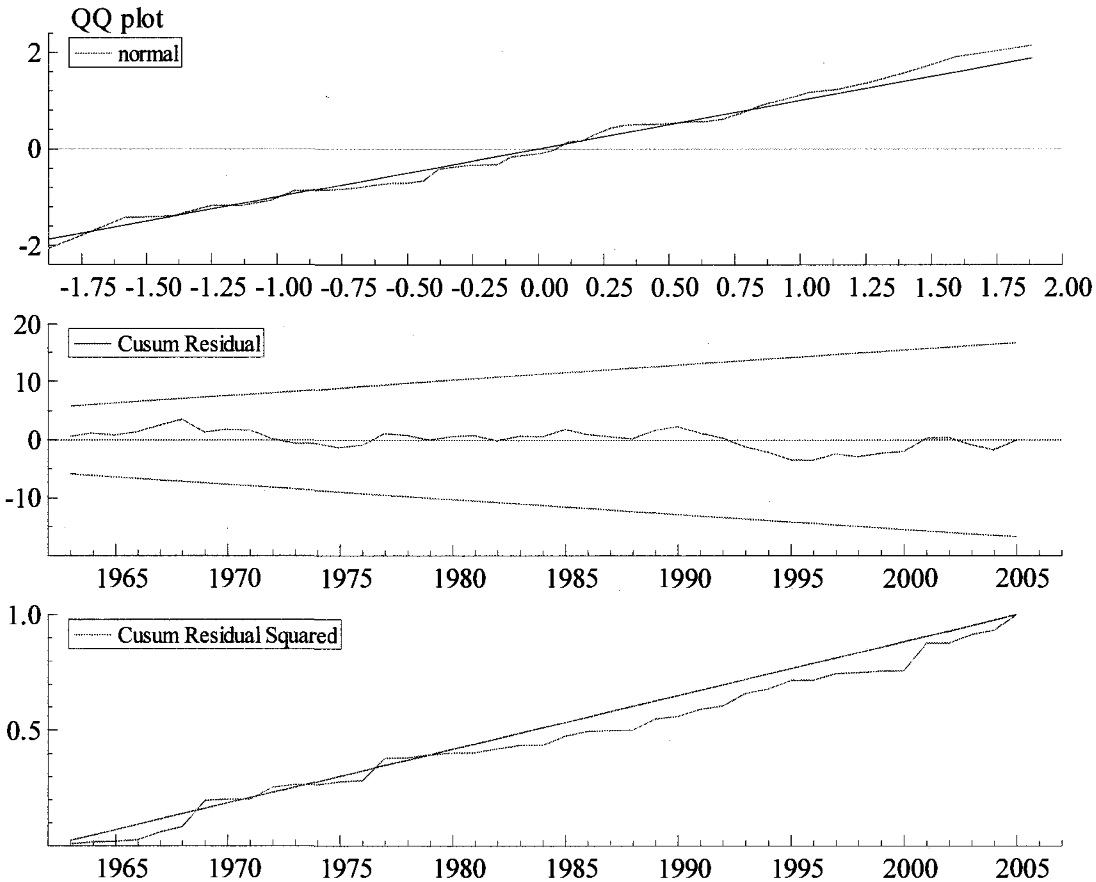
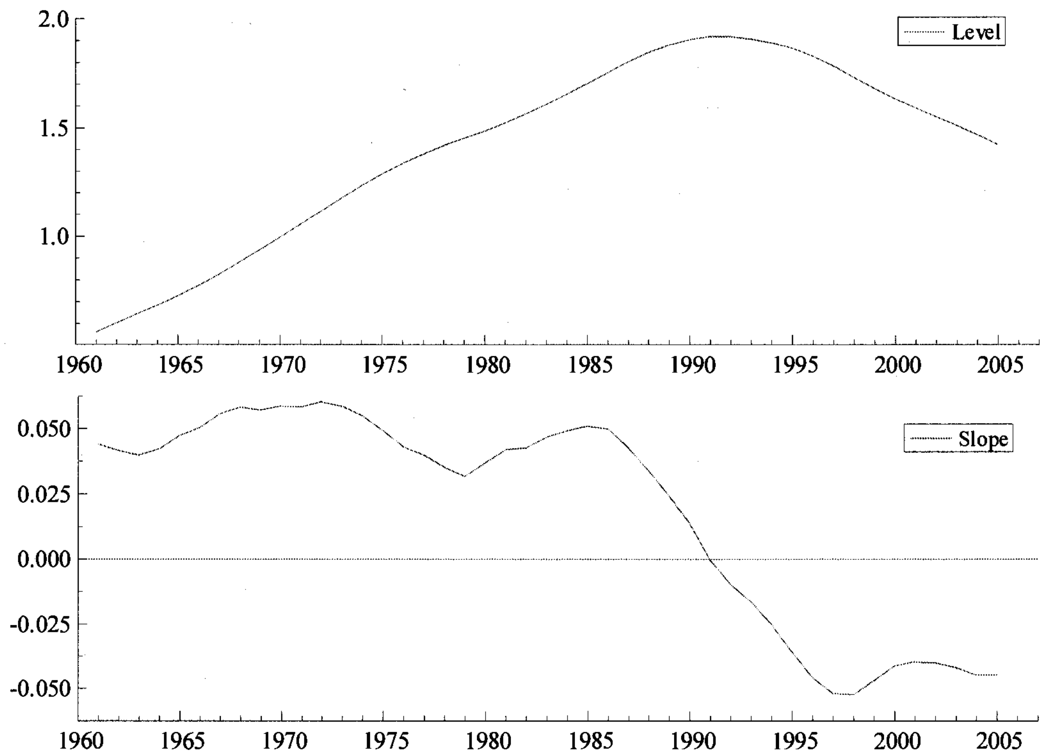
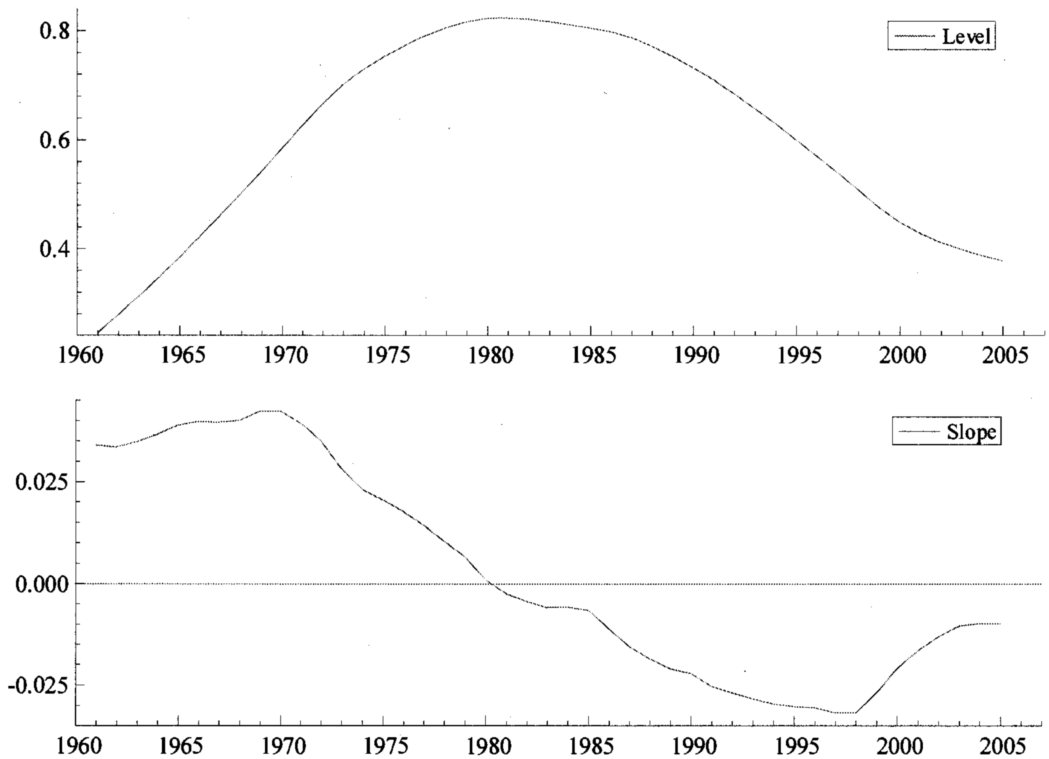


FIGURE 6: REMAINING COMPONENTS OF THE LARCENY RATE



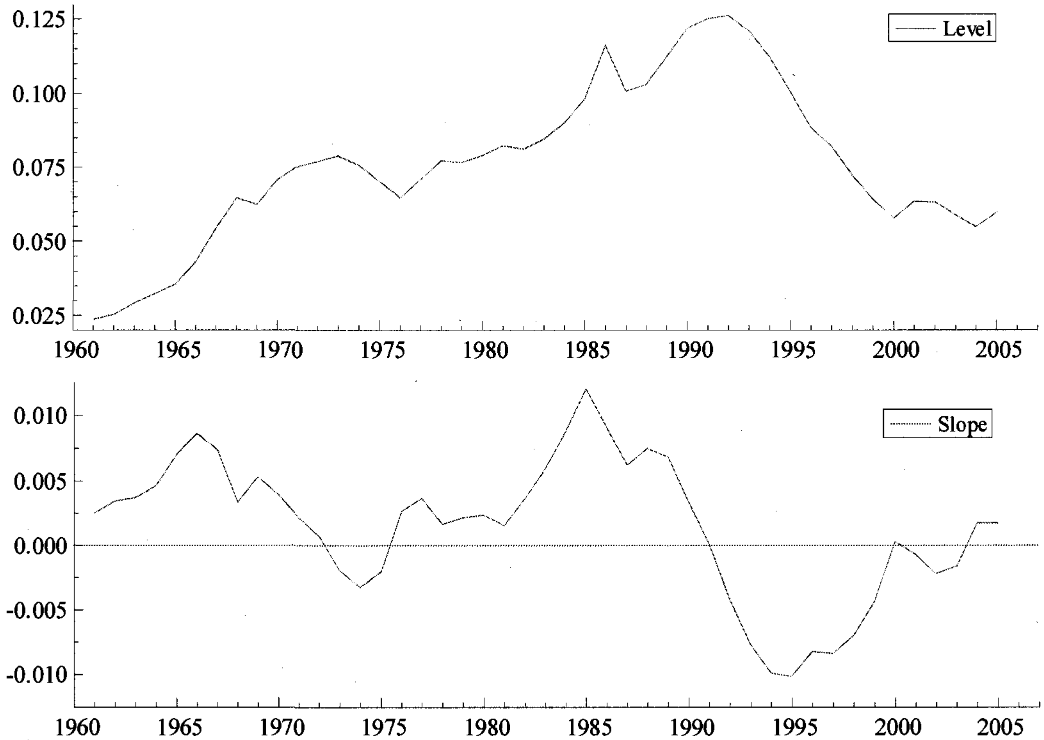
Note: The y-axis for both graphs represents the larceny rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.

FIGURE 7: REMAINING COMPONENTS OF THE BURGLARY RATE



Note: The y-axis for both graphs represents the burglary rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.

FIGURE 8: REMAINING COMPONENTS OF THE ROBBERY RATE



Note: The y-axis for both graphs represents the burglary rate per 100,000 persons. The upper graph is the remainder of the level component and the lower graph is the remaining portion of the slope.

THE DECLINE IN MAIZE PRICES, BIODIVERSITY, AND SUBSISTENCE FARMING IN MEXICO

I INTRODUCTION

In terms of caloric intake, maize is the number one crop in the world according to the statistics of the Food and Agriculture Organization (FAOSTAT). The issue of preserving the plant's genetic diversity is thus of significant policy importance. Even though several scientific studies have been conducted by now, the latest one being the European Commission report by Messean et al. (2006), a resolution of the issue of *transgenic*[1] contamination of Mexico's native maize varieties is not likely to occur in the near future.[2]

As the debate on genetically modified (GM) maize is ongoing, not only in Mexico following the 1998 moratorium on growing GM maize,[3] but also elsewhere, such as in Europe, this paper will add some fundamentally economic arguments to the debate as it pertains to Mexico.[4] In particular, we examine how the current biodiversity of maize in Mexico may be endangered as subsistence farmers, who maintain and propagate the biodiversity, are faced with declining market prices for their produce as a consequence of the large and rapidly rising maize imports from the U.S. These imports not only worsen the terms of trade of subsistence farmers, but, as much of the imported maize is of the GM variety (such as *Bt corn*[5]), they also raise the risk of lower yields as indigenous varieties of maize may lose their resilience to environmental stress through contamination with GM maize.

The paper is organized as follows. The subsequent section will provide some institutional background on the connection between biodiversity and maize farming in Mexico. This is followed by a section that examines empirically the impact on the behavior of Mexican maize farmers of arguably the most important economic event that has affected them since the mid 1990s: the very large increase in maize imports from the U.S. This is done for two reasons. First, there is not much point in arguing about the loss in biodiversity through the impact of GM maize if one cannot predict that enough subsistence farmers with an interest in indigenous maize varieties will be left a decade from now to take on the job of preserving the biodiversity of maize. Second, by observing farmers' reactions to a major change in their economic environment, it may be possible to distill what drives farmers' behavior. That, in turn, will help predict how farmers may react to the lower yields that may arise from a contamination of their indigenous maize varieties with GM maize.

The section following the empirical analysis discusses to what extent the observed empirical regularities are consistent with a model of rational behavior of farmers. The model provides, among other things, an explanation of the puzzling fact that output of maize has reacted very little to the sharp decrease in the price of maize since NAFTA was enacted in 1994 (Ackerman et al. 2003; Nadal 2000 and 2002). Based on this model, some tentative policy recommendations can be formulated on what set of economic policies and incentives may support the objective of preserving the current biodiversity of maize in Mexico.

II INSTITUTIONAL BACKGROUND

Since the beginning of the Green Revolution in the 1940's, modernization of agricultural practices in the developing world has attracted the attention of policy makers. Increasing the scale of farm production through technological innovation has regularly been promoted as a substitute for low-output indigenous agriculture. Subsistence farming is often viewed by governments as an indication of economic inefficiency, and its eradication is perceived as a harbinger for a modern economy.[6] However, such views ignore that subsistence farmers, throughout the world, promote and protect the genetic diversity of native crop species and thus provide a significant public service to all of humanity. Due to their diversity, traditional varieties generally outperform modern varieties in the adverse conditions that the indigenous farmers face. The rich diversity of domestic varieties[7] not only meets local consumption requirements, which may be very specific,[8] but it also minimizes the agronomic risks posed by drought, climatic change, soil degradation, and insect infestation (Perales et al. 2003).

The genetic diversity that subsistence farmers propagate is also valuable to modernized agricultural nations, such as the United States. Capital-intensive farming in the industrialized world has created an increasing demand for genetically modified seeds that are resistant to pests or certain chemical applications. Industrial agriculturalists, due to the restrictions of mechanical farm production, can not promote genetic diversity and are not yet required to fully internalize the environmental degradation attributable to commercial fertilizers and pesticides. Thus, mechanized agriculture necessarily renders high levels of crop diversity economically infeasible. Potential pitfalls that attend low levels of crop diversity become evident when severe crop damage occurs due to disease or pest infestation, as happened in the United States in 1970 when approximately 25 percent of the U.S. maize crop was destroyed by the southern leaf blight (Boyce 1996; Nadal 2000).[9] Due to the ecological pressure of pests and disease, the average commercial life of a modified seed is only about seven years (Boyce 1996). Commercial plant breeders must continually use the genetic material from different varieties of a crop to obtain the desired pest and disease resistant qualities. Off-farm[10] conservation methods, such as germ plasm banks, preserve the native varieties only at a specific moment in time and can not capture the evolutionary changes of the crop. Thus, off-farm conservation is only a complement, not a substitute to the on-farm conservation performed by the farmers.

The incentive structure, which motivates the production process of the subsistence farmer, is markedly dissimilar to that of the conventional cash-crop farmer. This fact is clearly evident when one considers that U.S. producers do not face the same environmental and financial constraints as Mexican subsistence farmers, who are generally relegated to isolated lands marginally unfit for industrial agriculture, with no access to credit. A farmer who employs large amounts of physical capital expects to make a profit, while the expectation of the peasant farmer is to sell the surplus crop (if any), after own-consumption needs and seed requirements are met. Ashraf et al. (2005) contend that the agricultural provisions of the North American Free Trade Agreement (NAFTA) have had no discernible effect on the Mexican subsistence farmer. The initial fear that NAFTA would destroy the indigenous farmers of Mexico by forcing them to compete with the heavily subsidized farmers of the United States appears unfounded, as Mexican subsistence farmers have shown no significant agricultural diversification away from maize during a period in which the average price of maize in Mexico fell by 50 percent. Ashraf et al. (2005) also show that 75 percent of all the farmers surveyed report growing maize as their principal means of subsistence, while only 12-22 percent reported maize as the primary cash-crop. Of the poorest farmers surveyed from 1991-2000, 89-92 percent reported that maize was their primary crop for subsistence and 56-57 percent reported they did not produce maize to sell in the market. A survey of peasant farmers in the Guanajuato region of Mexico by Smale et al. (2001) reveals that farmers unanimously recognize maize as a critical component of their livelihood and grow maize even when it is unprofitable to do so.

Mexican subsistence farmers use labor-intensive methods to cultivate several varieties of maize,[11] with different planting and harvest times, to hedge against environmental risk.[12] Accordingly, indigenous farmers, with smaller plots of land, have a comparative advantage in labor-intensive farming over their larger and less diverse counterparts. Seed varieties favored by modern agriculture require large amounts of chemical inputs and are bred for low-stress environmental conditions not suitable for the small-scale farmers in Mexico (Soleri and Cleveland 2001). Most indigenous farmers raise their crops on peripheral lands that are primarily rain-fed, as opposed to the heavily irrigated farmland of industrial agriculturists. However, the cultivation of different varieties of maize is not only implemented to mitigate the environmental constraints of production, where irrigation and fertilizers are not readily available. Smale et al. (2001) find the determining factor in the allocation of maize varieties is the differential in consumption preferences for specific varieties. Subsistence farmers have also been found to cultivate crop varieties for the purpose of ensuring that the seeds from these crops remain available in their community. Perales et al. (2005), in a study of maize diversity between neighboring towns in the Chiapas highlands, find that maize varieties are cultivated *"distinctly"* according to *ethnolinguistic* groups. The authors show that farmers continue to use local maize varieties even when a superior and otherwise acceptable substitute is available from neighboring farmers. Knowledge of genetic resources[13] is generally well-defined among indigenous communities, due to the significance of securing reliable food supplies (Bellon 2001). Yet, diffusion of genetic knowledge between different *ethnolinguistic* groups is often costly due to language and ethnic barriers (Perales et al. 2005). Reluctance, on the part of indigenous farmers, to substitute away from their local maize varieties is cited as one possible explanation for the persistence of native varieties.

III EMPIRICAL REGULARITIES

1 Data and Methodology

The empirical results make use of data published by the Food and Agriculture Organization (FAO). The FAO data set is rather limited and extends from 1991 to 2004 for most variables. There are no separate data on commercial and subsistence farmers available from FAO. The data used are defined in Table 1.

TABLE 1. VARIABLE DEFINITIONS

Variable	Definition
price	Producer price of maize (US $/ton)
imports	Import quantity of maize (1,000 tons)
area	Area harvested of maize (1,000 Ha)
yield	Yield per hectare of maize (tons/Ha)
cpi	Consumer price index, derived from the *cpi* inflation rate
mig	Off-farm migration, calculated as (population growth rate at *t* times agricultural population at *t* - 1) – agricultural population at *t*

Notes: All data relate to Mexico and cover the time period 1991-2004, except *price*, which ends in 2003. The data are taken from FAO, http://faostat.fao.org/default.aspx.

The estimates are based on the structural time series approach, which is also known as unobserved component modeling, as advocated by Harvey (1989, 1997) and as implemented, among others, by Koopman et al. (2000).[14] Univariate structural time series models can be expressed as

$$y_t = \mu_t + \sum_i \sum_j \alpha_{ij} x_{i,t-j} + \varepsilon_t \qquad \text{for } t = 1,\ldots,T,$$

where μ_t is a time-dependent intercept term, which is modeled as a stochastic process, and where the x_i are observed regressors as in ordinary least squares regression. The stochastic term μ_t captures unobserved influences driving the dependent variable. It is assumed to follow a random walk with time dependent drift (β_t). The drift parameter itself may follow a random walk,

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta \sim \text{NID}(0,\sigma_\eta^2)$$
$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi \sim \text{NID}(0,\sigma_\xi^2).$$

Both μ_t and β_t are driven by white-noise disturbances, η_t and ζ_t . These disturbances are assumed to be independent of each other and of ε_t.[15] The general trend model can be tested down to a simpler form, such as a model with no drift parameter, for which μ_t would be written as

$$\mu_t = \mu_{t-1} + \eta_t \qquad \eta \sim \text{NID}(0, \sigma_\eta^2),$$

or, for example, a model with deterministic trend, which arises when the disturbances η_t and ζ_t have zero variance. OLS is a limiting case of the structural time series model. It arises when β_t and the variance of the disturbance terms η_t are both zero.

The advantage of the structural time series model over OLS is that it can capture movements in the data that are not represented by the observed independent variables. This can play a significant role in applications such as the present one where the data set is rather limited in the sense that potentially relevant variables are missing because they are not measured or are not known theoretically. In the absence of allowing for unobserved components in these cases, the left-out variables will typically show up in OLS estimates as spurious trends, unexplained lags on variables, or residual statistics that suggest misspecification. It should be obvious that the inclusion of unobserved stochastic components is a second-best approach, like all black-box methods.[16] Ideally, one would want to replace unobserved components with observed variables. Oftentimes, the movement of the unobserved components over time will provide some hints as to what variables may be driving them. Hence, unobserved component modeling may help in the process of identifying the data generating process. In fact, if all relevant variables are being employed in a particular application of structural time series modeling, no unobserved components should be statistically significant any longer and the model collapses to OLS.

2 Estimation Results

A key element in understanding the behavior of Mexican maize farmers is the relationship between maize imports from the U.S. and the producer price of maize in Mexico. Anecdotal evidence (Lambrecht 2005; Campbell and Hendricks 2006) suggests that farmers find it difficult to survive when the output price of maize drops. Most commentators take it for granted that the massive influx of U.S. maize into Mexico following the implementation of NAFTA in 1994 is responsible for the decrease in the maize price. A recent study by the Word Bank (Fiess and Lederman 2004), however, appears to suggest that U.S. imports do not play much of a role for the price of maize.

Since there is little statistical evidence of a stochastic trend, the structural time series model that explains the maize price as a function of maize imports and maize yield collapses to OLS. A negative sign is expected for the explanatory variables *imports* and *yield.* The estimated equation in log-linear format for the time period 1991 to 2003 is given as

$$\ln price = \underset{(0.00)}{7.11} - \underset{(0.001)}{0.173} \ln imports - \underset{(0.072)}{0.582} \ln yield$$
$$R^2 = 0.8251, Auto = 0.53, LB = 0.40, JB = 0.81, Het = 0.54,$$

where p-values are provided in parenthesis underneath the estimated coefficients. P-values are also given for a test of first-order autocorrelation (*Auto*), the Ljung-Box test of autocorrelation up to lag order four (*LB*), the Jarque-Bera normality test (*JB*), and a test for heteroskedasticity (*Het*). None of the p-values suggest any statistical problem at conventional levels of statistical significance. The estimates suggest that a 10 percent rise in imports has lowered the maize price by 1.7 percent over the sample period.

Since imports tripled over the period from the pre-NAFTA average for the years 1991 to 1993 to the year 2004, this elasticity estimate suggests that imports are responsible for about a fifty percent drop in the price of maize.

Based on previous research (Fiess and Lederman 2004) and anecdotal evidence (Lambrecht 2005; Campbell and Hendricks 2006), the acreage cultivated of maize has reacted little to the dramatic change in the price of maize since the implementation of NAFTA. This observation is consistent with regressions on the FAO data. Similar to the price equation, no unobserved component appears significant for the regression of acreage on the price of maize (*price*$_{-1}$) and the consumer price index (*cpi*$_{-1}$), both lagged by one year,[17]

$$\ln area = \underset{(0.00)}{9.38} - \underset{(0.819)}{0.075} \ln price_{-1} - \underset{(0.647)}{0.044} \ln cpi_{-1}$$

$$R^2 = 0.0948, Auto = 0.83, LB = 0.61, JB = 0.54, Het = 0.23,$$

Although there is no statistical problem evident with the estimated equation, it clearly does not explain acreage. Neither the price of maize nor the consumer price appears to influence acreage.

It is often suggested that maize farmers may be forced to leave the agricultural sector and migrate to the cities as economic conditions worsen on the farm (Lambrecht 2005). A worsening of conditions could be associated with lower output prices, rising inflation, or lower yields associated with a contamination of the maize crop with GM maize. The migration data used in this study are derived from FAO data on total population growth and agricultural population figures (Table 1). Migration is explained as a function of the acreage and yield of maize. As more acreage is planted, one would expect more work opportunity for agricultural workers. This should reduce migration. Similarly, as yields go up, everything else constant, subsistence farmers are better off. Again, this should reduce off-farm migration. Over the time period 1991-2004, the structural time series model contains a smooth trend, which is brought about by the variance of η being zero in combination with the variance of ξ being positive. The estimated coefficients of the fixed regressors and some statistical adequacy tests are given as

$$\ln mig = \underset{(0.00)}{7.35} - \underset{(0.02)}{0.097} \ln area - \underset{(0.10)}{0.085} \ln yield$$
$$R^2 = 0.846, Auto = 0.20, LB = 0.90, JB = 0.98, Het = 0.29,$$

Starting the regression sample one year later in 1992 raises the parameter values of both *area* and *yield* considerably. At the same time, the unobserved trend becomes statistically insignificant. An OLS regression over the period 1992-2004 yields

$$\ln mig = \underset{(0.00)}{7.76} - \underset{(0.00)}{0.119} \ln area - \underset{(0.00)}{0.298} \ln yield$$
$$R^2 = 0.9137, Auto = 0.84, LB = 0.44, JB = 0.65, Het = 0.58,$$

where none of the statistical adequacy tests suggests a statistical problem.

The regressions explaining off-farm migration for Mexico for the 1990s and early 2000s suggest that increases in both acreage and yield have a retarding effect on migration. Given that maize acreage has changed little since the early 1990s, while yields have been rising somewhat, the results indicate that off-farm migration would have been higher in the absence of these two trends. They also reveal that a drop in yields that may be brought about by GM maize contaminating the traditional maize varieties may have significant consequences for off-farm migration.

IV A MODEL TO EXPLAIN THE OBSERVED BEHAVIOR

The purpose of this section is to check whether the empirical regularities described in the last section are consistent with common assumptions of maximizing behavior on the part of farmers. This is done by postulating a simple utility maximization problem for a maize farmer and checking whether the empirical findings can be encompassed by this model. An analysis of this type is useful for two reasons. First, there has been some suggestion (Fiess and Lederman 2004) that Mexican maize farmers have somehow behaved irrationally in response to the large decrease in the maize price by increasing production. Second, without an understanding of the core driving forces behind farmers' behavior, it is difficult to formulate economic policy prescriptions about preserving biodiversity.

Hymer and Resnick (1969) develop a theoretical model to explain the positive production response of subsistence farmers who are faced with price volatility. Barnum and Squire (1980) extend Hymer and Resnick's work to incorporate a number of different scenarios where farmers can choose among heterogeneous crops, the acreage they cultivate, and between farming and non-agricultural employment. However, neither Hymer and Resnick (1969) nor Barnum and Squire (1980) distinguish between tradable and non-tradable agricultural output. We extend Barnum and Squire's model to include the farmer's choice between consumption of market goods and the own-consumption of agricultural goods.

The farmer's decision problem is to maximize a utility function,

$$u = \theta^{\alpha} (m - \overline{m})^{\beta} l^{\delta},$$

where utility depends on consuming (a) a given fixed amount of maize that is taken from own production (θ), (b) household products that are purchased from outside the farm (m and $\bar{m}$), and (c) leisure (l). The parameters α, β, and δ identify weights. The preference for own consumption (θ) is discussed in a previous section, but it should again be stressed that θ is the farmer's preference for a specific maize variety which is endemic to the farmer's region or particular ethnicity. A key component of the farmer's utility function is its dependence on a certain minimum number of household products which need to be purchased off the farm ($\bar{m}$). Following the Stone-Geary utility function, household products purchased off-farm (m) raise utility only to the extent that their quantity exceeds this minimum requirement.

Utility is maximized subject to a time constraint and a budget constraint. According to the time constraint, total available time, which is set to unity for simplicity, has to be divided between leisure (l), and time spent working on the farm (n), $1 = n + l$. Maximization of the utility function is also subject to the budget constraint

$$p(y-\theta) = m,$$

where the left-hand side is the revenue from selling maize in the open market and where the right-hand side contains all expenditures on off-farm goods and services. Revenue from selling maize is the product of the price of maize relative to that of off-farm products (p)[18] and the quantity of production that is not destined for own consumption (y -θ). Production is assumed to be given by the function

$$y = z(1-l)^{\phi},$$

where z is a productivity parameter, perhaps representing the idiosyncratic genetic characteristics of the farmer's indigenous maize. There are two production factors: land or acreage planted and labor (n = 1 - l). Only labor is treated as a decision variable in production. The parameter ϕ is the corresponding weight of labor in the production function. Land is assumed constant and normalized to unity for simplicity. It is assumed that the farmer does not enter the credit market. Hence, all off-farm purchases have to be paid for from the market sale of maize.

The specification of the utility function with respect to market goods suggests consumption of market goods m exceeds the minimum $\overline{m}$, otherwise utility could be zero or negative. A Kuhn-Tucker formulation replaces strict equality measures and the farmer's optimization problem is therefore given by

$$\max \theta^{\alpha}(m-\overline{m})^{\beta} l^{\delta} \qquad s.t. \quad p[z(1-l)^{\phi}-\theta] \geq m, \quad m \geq \overline{m}, \quad l \geq 0,$$

where variable n has been substituted out by the time constraint. The variables for off-farm purchases of household items (m) and leisure (l) are the farmer's decision variables. The Lagrangean for the farmer's optimization problem can be written as,

$$\max_{l,m} \ \theta^{\alpha}(m-\overline{m})^{\beta} l^{\delta} - \lambda[m - p(z(1-l)^{\phi}-\theta)] - \psi(\overline{m}-m) - \xi(-l).$$

The Kuhn-Tucker conditions for a maximum are given by,

$$\frac{\partial L}{\partial m} = \frac{\beta\theta^{\alpha} l^{\delta}}{(m-\overline{m})^{\beta}} - \lambda + \psi = 0,$$

$$\frac{\partial L}{\partial l} = \frac{\theta^{\alpha}(m-\overline{m})^{\beta}\delta}{l^{\delta}} - \frac{\lambda p \phi z}{(1-l)^{\phi}} + \xi = 0,$$

$$p[z(1-l)-\theta] \geq m, \quad \lambda \geq 0, \quad \lambda\{p[z(1-l)-\theta]-m\} = 0,$$

$$m \geq \overline{m}, \qquad \psi \geq 0, \qquad \psi(m-\overline{m}) = 0,$$

$$l \geq 0, \qquad \xi \geq 0, \qquad \xi(l) = 0.$$

The sign of the bordered Hessian for $\lambda > 0$, $\psi = \xi = 0$ is positive which is necessary to establish a maximum. The key comparative static result $\frac{\partial l}{\partial p}$ is unambiguously positive (See Mathematical Appendix), which indicates that, as the relative price of maize decreases, leisure declines and, hence, farm labor increases, and with it output. As a result, the income effect of a price change dominates.

The theoretical specification is consistent with the fact that few subsistence farming households are completely autarchic. Subsistence farmers need to purchase market goods that they cannot produce at home (e.g., pharmaceuticals and professional medical care). It is easy to imagine that some of these market goods are also used as complementary goods to leisure, such as a television. Leisure is not worth as much without these complementary goods. As the output price of maize drops, fewer market goods would be available without a concurrent increase in agricultural work effort and additional market sales resulting from this increased work effort. Thus, the key contribution of the theoretical derivations is to show that when a farmer must consume a minimum amount of market goods and also has preference for own-consumption, the output response to a price decrease is positive.

The evidence provided by Ackerman et al. (2003), the empirical results of the last section, and the work of Fiess and Lederman (2004) suggest that the Mexican farming sector in total has not reacted to the price decrease in maize with a reduction in output. The fact output has not fallen in response to the sharp drop in the price of maize is fully consistent with the theoretical model. There is little irrational about this behavior when one considers the constraints maize farmers are likely to face.

It is interesting to postulate what may happen if the price of agricultural output were to fall to a point where farmers could no longer purchase a minimum quantity of market goods. Harris and Todaro (1970) argue that higher expected earnings in the non-agricultural sector will induce rural farmers to migrate to urban areas if those farmers are maximizers of expected utility. Our simple utility maximization model does not explicitly incorporate a stopping rule for agricultural production that is linked to deterioration in the terms of trade of subsistence farmers, although such an extension would be possible in principle. Barnum and Squire (1980) provide an example of a similar model which incorporates the basic Harris and Todaro (1970) predictions when time spent in non-agricultural employment is included as a choice variable.[19] Even without an explicit rule for farm out-migration, the model suggests an intuitively appealing explanation for out-migration. Given the lack of capital available to subsistence farmers and their positive output response to a price decrease, there must be some minimum threshold level of leisure and of utility that induces a farmer to leave the farm and to search for off-farm employment. One may speculate that the farm would be purchased and used by a more efficient farmer, which ensures that, across all farms, acreage does not fall but yields rise in the long run.

Given that the comparative static results are sufficiently consistent with the empirical evidence, it is interesting to hypothesize how subsistence maize farmers would react to the contamination of their fields with GM maize. Since GM maize is primarily used for feeding livestock, it is reasonable to assume that farmers would have trouble selling their crop in the market for domestic maize, and as a result would have to accept a lower market price. Thus, the reaction of the subsistence farmer to genetic contamination may be analogous to that of a decrease in the price of maize.

Given the difficulty of identifying infected maize, it would be almost impossible to stop the process of contamination. Most likely, contaminated maize would be reused as seed even if an infection is obvious if for no other reason than lack of funds on the part of subsistence farmers to root out the contamination and start with clean seed for several seasons. How a contamination is ultimately affecting the indigenous gene pool of maize and the properties of maize is an open question. However, it appears fairly certain that the total output of maize will be declining, at least for a short time, as farmers are unfamiliar with the agronomic properties of the new contaminated seed stock. In addition, the GM maize varieties are not intended for reuse as seed and GM maize is more dependent on fertilizer and pesticide, which subsistence farmers are not using to any significant degree.[20] In addition, the new hybrid maize varieties may be less resistant to severe weather, in particular drought, because GM maize is intended for irrigated fields. All this suggests an increase in the risk of catastrophic crop loss for subsistence farmers.

When seen in conjunction with the empirical analysis of the last section, the predictions of the theoretical model suggest at least two conclusions that are of relevance for the preservation of biodiversity in Mexico. First, further sharp increases in imports of maize from the U.S. will likely cause many subsistence farmers to leave their land and migrate to the cities of Mexico or the U.S. This is independent of whether there is any contamination of the indigenous varieties of maize with GM maize. The fact that, so far, maize output has reacted positively to the surge in imports from the U.S. and the subsequent large decrease in the price of maize should not be taken as a sign that

Mexican maize farmers are not under stress. On the contrary, it is a sure sign that farmers do react to the price decrease and that they react rationally. Their response entails more work effort, fewer purchases of off-farm products for household use, and, as a consequence, lower levels of utility. This will make off-farm migration ever more likely over time. However, if subsistence farmers leave the countryside in large numbers, the current levels of biodiversity can not be maintained: with no subsistence farmers, there is no biodiversity. Again, this is completely independent of the issue of contamination of the gene pool by GM maize.

Second, the analysis has suggested that a contamination of the indigenous varieties of maize with GM maize may have similar consequences as a further reduction in the relative price of maize. However, this conclusion is based on the as yet unproven assumption that any maize variety that is an unplanned hybrid of the indigenous varieties and GM maize will be more susceptible to environmental stress, such as droughts and pest infestation, than the current indigenous varieties and, as a consequence, average yields of maize farmers decline.

V SUMMARY AND CONCLUSIONS

The purpose of this paper is to model the economic behavior of Mexican maize farmers in order to predict what would be needed from an economic perspective to ensure continued biodiversity.

To that end, the paper attempts to establish empirically the connection between the large imports of maize from the U.S., the price of maize, acreage planted, and off-farm migration. The results suggest that U.S. imports have depressed the price of maize. Acreage, however, has reacted little. Finally, both declining acreage and maize yields are key driving forces of off-farm migration.

The paper develops a simple theoretical model to examine whether the empirical results are consistent with rational behavior on the part of farmers and to suggest policy actions to maintain biodiversity. The comparative static properties of the theoretical model are consistent with the key empirical facts. In particular, it is shown that an increase in production is fully consistent with a declining relative price of maize. But as maize farmers work more and can afford ever fewer off-farm products, their utility levels decline, which will eventually induce them to leave the farm in search of employment in the urban areas of Mexico or the U.S. It is suggested that the contamination of the indigenous maize varieties with GM maize may be interpreted as an alternative unfavorable movement in the terms of trade that subsistence farmers face. As a consequence, they may in the long run react to such a contamination in a manner that is similar to that of a reduction in the relative price of maize: they choose to migrate off-farm as utility levels fall below certain threshold levels.

Off-farm migration, however, has significant consequences. First, as many indigenous farmers stop production, the maize gene pool will contract, possibly by a very sizable amount. Although it is difficult to foresee all the consequences of such a result, it does not appear to bode well for the future security of the world's food supply since Mexico is home to the world's only self-sustaining genetic repository for maize. Second, as farmers leave their land, possibly in large numbers, Mexico's cities are likely to experience significant stress when the now landless farmers arrive and are looking for employment. Based on past experience, it appears unlikely that a large number of former subsistence farmers will find employment. An increase in illegal immigration to the United States is a likely consequence.

In the light of these results, the key policy issue appears to be how to stop a sufficient number of subsistence farmers from leaving their land. That is the prerequisite of keeping biodiversity, even in the absence of GM maize contamination. Given political reality, maize will continue to be imported from the U.S. Some effort may be worthwhile to contain the growth rate of imports. If that is not politically feasible and the relative price of maize continues to decline, cash subsidies may be an option to keep farmers on the land. These subsidies would be the price to be paid for maintaining biodiversity. They would constitute a transfer scheme that internalizes the positive external effects that are derived from biodiversity. The subsidies would also be the price to pay to keep Mexican farm workers from illegally immigrating to the U.S. Since Mexico, the U.S., and the world at large reap the benefits of continued Mexican biodiversity, it appears sensible to pay for the subsidies from an international fund rather than from the budget of a single country.

Mathematical Appendix

$$H^b = \begin{bmatrix} \dfrac{-\beta^2\theta^\alpha l^\delta}{(m-\overline{m})^{\beta+2}} & \dfrac{\delta\beta\theta^\alpha}{(m-\overline{m})^\beta l^\delta} & -1 \\ \dfrac{\theta^\alpha\delta\beta}{(m-\overline{m})^\beta l^\delta} & \dfrac{-\theta^\alpha(m-\overline{m})^\beta\delta^2}{l^{\delta+2}} & -\dfrac{p\phi z}{(1-l)^\phi} \\ -1 & -\dfrac{p\phi z}{(1-l)^\phi} & 0 \end{bmatrix} > 0$$

$$H^b = \begin{bmatrix} \dfrac{-\beta^2\theta^\alpha l^\delta}{(m-\overline{m})^{\beta+2}} & \dfrac{\delta\beta\theta^\alpha}{(m-\overline{m})^\beta l^\delta} & -1 \\ \dfrac{\theta^\alpha\delta\beta}{(m-\overline{m})^\beta l^\delta} & \dfrac{-\theta^\alpha(m-\overline{m})^\beta\delta^2}{l^{\delta+2}} & -\dfrac{p\phi z}{(1-l)^\phi} \\ -1 & -\dfrac{p\phi z}{(1-l)^\phi} & 0 \end{bmatrix} \begin{bmatrix} dm \\ dl \\ d\lambda \end{bmatrix} = -\begin{bmatrix} 0 \\ \dfrac{\lambda\phi z}{(1-l)^\phi} \\ z(1-l)-\theta \end{bmatrix}$$

$$\frac{\partial l}{\partial p} = \frac{-\beta^2\theta^\alpha l^\delta}{(m-\overline{m})^{\beta+2}}\left\{0-\left[-\frac{p\phi z}{(1-l)^\phi}*(-(z(1-l)-\theta))\right]\right\}$$
$$+(-1)\left\{\left[\frac{\theta^\alpha\delta\beta}{(m-\overline{m})^\beta l^\delta}*(-(z(1-l)-\theta)\right]-\left[(-1)*-\frac{\lambda\phi z}{(1-l)^\phi}\right]\right\}$$

Both the first and second terms are positive, which gives the result $\dfrac{\partial l}{\partial p} > 0$.

NOTES

[1] *Transgenic* denotes contamination of native plant varieties with genetically modified varieties.

[2] Qist and Chapela (2001) allege that GM maize has polluted the native varieties in the Oaxaca region of southern Mexico. This article set off a firestorm of debate (Hodgson, 2002) and has come under intense scrutiny from the scientific community. The primary concern is that GM varieties could displace native varieties and possibly cause introgressive hybridization with the wild relatives of maize, such as *teosinte,* which would forever alter the gene pool.

[3] The Mexican moratorium was enacted largely due to strong political opposition from activist groups representing the country's indigenous farmers, not due to scientific evidence. The ban does not include other genetically modified crops and it does not include imports of GM maize for the purpose of consumption. See in this context Gilbreth and Otero (2001) for an overview of the armed uprising against the Mexican government in the wake of NAFTA.

[4] A non-economic approach is taken by the recent report on maize and biodiversity in Mexico published by the Commission for Environmental Cooperation (2004), and the background studies that were commissioned for that report.

[5] *Bacillus thuringiensis* is a soil bacteria that is toxic to certain pests, especially the European corn borer. *Bt-toxin,* genetically derived from the above mentioned bacteria and currently patented by Monsanto Co., creates crystalline formations on the stalks of maize which act as insecticide.

[6] See Nadal (2002) for an account of the agriculture reform measures taken by the Mexican Government after signing the North American Free Trade Agreement (NAFTA) in 1994.

[7] Boyce (1996) notes that the subsistence farmers of Mexico have also incorporated hybrid modified seeds for years, and artificially selected for desirable traits from these seed stocks. Most researchers agree that this assimilation of "improved" seeds into the gene pool is at a very low level. However, GM seeds pose different risks that are not yet well understood by either the farmers or commercial plant breeders (McAfee 2003).

[8] Mexico's *ethnolinguistic* diversity. with more than 200 language groups among the indigenous peoples, is believed to facilitate local attachments to specific maize varieties (Perales et al. 2005).

[9] According to Boyce (1996), *Bipolaris maydis*, the fungus responsible for Southern Leaf Blight, was infective to plants with the genetic makeup shared by approximately 85percent of the maize grown in the U.S. in 1970.

[10] *Ex situ: off site.* Organizations such as the International Maize and Wheat Improvement Center (CIMMYT) are engaged in facilitating the genetic diversity of wheat and maize to aid developing countries in establishing food security and overall agricultural productivity. See Bellon (2001).

[11] Although this paper only concerns the effects of GM maize, it should be noted that subsistence farmers in Mexico have shown some preferences for creolized varieties derived from cross-pollination between native varieties and modern hybridized varieties. However, Bellon et al. (2005) have shown that in areas with high genetic diversity such as Chiapas, farmers are relatively indifferent to the benefits of creolization.

[12] American farmers often use several different varieties of maize with different plant and harvest dates, albeit on separate plots of land. This was pointed out to one of the authors in a conversation with Matthew Garner, a Tennessee farmer.

[13] This is also one of the central themes of Diamond (1997).

[14] In SAS, unobserved component modeling can be found in the ETS package under the name UCM.

[15] After estimation of the model parameters, a Kalman filter is applied to determine the state vectors μ_t and β_t for each time period.

[16] For completeness, it should be mentioned that more unobserved components can be added to a structural time series model than just a stochastic trend. Other components may be a stochastic cycle or a stochastic seasonal or a stochastic autoregressive component.

[17] The consumer price index is included because it has been suggested (Campbell and Hendricks 2006) that its increase has caused subsistence farmers to raise acreage.

[18] *p* represents the terms of trade for the subsistence farmer.

[19] See equations 8 through 16 in Barnum and Squire (1980) for further reference.

[20] In fact, distributors of genetically modified maize varieties mandate that new seed is purchased for every new planting season. This raises intellectual property rights issues. Compare on that the controversial 2001 Monsanto Inc. vs. Percy Schmeiser verdict in Canadian Supreme Court. Schmeiser was convicted of patent right violation for saving and knowingly replanting the seeds from his canola field, after being infected with Roundup-Ready®Monsanto Co. canola.

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CONCLUSION

The first essay of the dissertation is entitled, "Are Gangs a Substitute for Legitimate Employment? Investigating the Impact of Labor Market Effects on Gang Affiliation." Empirical research on street gangs is sparse. The sociology literature maintains that gang participation is not the product of a rational choice. This essay adds to the literature estimates of local labor market effects on individual gang participation. The local unemployment rate is a proxy for the availability of legitimate employment. I use data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97) to model the probability of gang involvement. The effect of the local unemployment rate is statistically significant and positive, across a variety of model specifications. Robustness checks reveal gang participation of individuals less than sixteen years-of-age (the legal minimum age for most jobs) is not responsive to the local unemployment rate. However, sixteen and seventeen year olds appear to respond to labor market conditions. Gang participation among individuals with lower ASVAB scores is more sensitive to the local unemployment rate.

The second essay, "The Effects of Inflation and Demographic Change on Property Crime: A Structural Time-Series Approach," examines the effects of inflation and demographic change on aggregate property crime rates. The economics of crime literature is extended by using a structural time-series modeling approach, which captures the systematic influence of unobserved variables in a stochastic trend. As a result, the estimates are consistent without incorporating endogenous deterrence in the model. Inflation is statistically significant, positive, and persistent for all property crime rates examined. The conclusion is that price stability contributes considerably to the reduction of property crimes.

The third essay entitled, "The Decline in Maize Prices, Biodiversity, and Subsistence Farming in Mexico," examines the production decisions of indigenous maize farmers in Mexico. Concern over the loss of genetic diversity in the world's field crops has increased due to the commercial introduction of genetically modified crops. Mexico is particularly sensitive to this issue, as it is the center of genetic diversity for maize and home to a large number of indigenous farmers who propagate this diversity. This paper analyzes to what extent the biodiversity of maize may be endangered as subsistence farmers face decreasing market prices of maize. Off-farm migration is suggested as a potential rational response of farmers to the large and rapidly growing imports of maize from the U.S., a large share of which consists of genetically modified maize. The maize imports from the U.S. are seen not only as worsening the terms of trade of subsistence farmers but also as raising the risk of lower yields as indigenous varieties of maize may lose their resilience to environmental stress through contamination with genetically modified maize.