Decomposing the Societal Opportunity Costs of Property Crime

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Abstract

In this paper, I explore how property crime can affect static and dynamic general equilibrium behavior of households and firms. I calibrate a model with a representative firm and heterogeneous households where households have the choice to commit property crime. In contrast to previous literature, I treat crime as a transfer rather than home production. This creates a feedback loop wherein negative productivity shocks increase property crime which further depresses legitimate work and capital accumulation. These responses by households are particularly important when thinking about the effect of property crime on the economy. Household and firm losses account for 24% of compensating variation (CV) and 37% of lost production. This suggests that behavioral responses are quite important when calculating the cost of property crime. Finally, on the margin, decreasing property crime by 1% increases social welfare by 0.19%, but the effect is diminishing suggesting that reducing crime entirely may not be optimal from a policymakers perspective.

Keywords: Crime, Welfare, Police, Public Goods, Business Cycles

JEL Codes: E26, E32, H41, K10

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1 Introduction

In 2009, the Global Retail Theft Barometer estimates U.S. firms lost $42.2 billion to retail theft while the FBI's Uniform Crime Reports put losses to property crime at $13.6 billion.[1] With non-trivial losses to property crime and significant resources devoted to the criminal justice system,[2] we would expect large changes in economic behavior as a result. The dead weight loss from these changes in behavior has the potential to be large with respect to the size of direct losses to property crime.

In this paper, I examine how the presence of property crime changes worker and firm behavior in a static and dynamic general equilibrium environment. The model consists of two heterogeneous workers who choose labor, crime, and capital, and a representative firm that chooses inputs to maximize profit. Unlike the previous literature where stolen goods come from nowhere, property crime results in income being transferred from the victim households to the perpetrator households. This is an important property of the model; without the market for stolen goods clearing, the only changes in behavior would come strictly from the changes in expected benefit of property crime, not from expected losses. In my model, there are additional changes in labor supply, capital accumulation, and theft induced by households losses to property crime.

My model suggests there are large societal losses to property crime that result from a negative feedback loop. Because productivity shocks are transitory,[3] the substitution effect towards leisure and spending time committing property crime dominates the income effect which result in higher property crime. As property crime increases, household income and firm productivity decrease. This starts the initial cycle over again which results in a larger dead weight loss.

[1] These numbers do not account for under-reporting of property crimes or the small sample of firms reporting, so they are likely underestimates of the actual losses. In addition, these numbers include retail theft, so the difference between the GRTB estimate and the UCR are quite stark.

[2] See Anderson (1999) where the estimated costs of all crime and prevention total $1 trillion.

[3] The shock hits, but dissipates over time until a new shock hits, so the substitution effect dominates the income effect.

I calibrate the the model to U.S. city data from a variety of sources including, but not limited to, the American Community Survey (ACS), FBI's Uniform Crime Reports (UCR), National Crime Victimization Survey (NCVS), and several data sets and reports from the Bureau of Justice Statistics (BJS) on the incarcerated population.[4] Examining both static and cyclical responses to productivity shocks, the model predicts that the losses from property crime are up to 11 times as large as the monetary value of the property reported stolen. Welfare losses from property crime range from 1.1 - 3.3% of GDP while output lost is about 2.8% of GDP. These values are in line with accounting studies that estimate the cost of crime. In addition, property crime accounts for 2% of cyclical volatility in output suggesting that the feedback loop that results from property crime exists. The inclusion of households losses to property crime accounts for 24% of the welfare cost and 37% of lost real output which suggests that policy experiments that ignore expected losses to property crime may result in incorrect conclusions. Back of the envelope estimates put the welfare loss at \$187 - \$568 billion for property crime alone. These losses are the result of firms and workers changing the labor, capital accumulation, and crime behavior in response to the opportunity to commit crime as well as being stolen from.

This paper proceeds as follows. In Section 2, I discuss the relevant literature and how this paper contributes to the literature. Section 3 lays out the environment, dynamic model, and dynamic equilibrium. Section 4 discusses the data and calibration strategy for the model and presents the calibration results. Section 5 presents the primary results and some robustness checks. Section 6 discusses the main results and shows the results of two counter-factual experiments. Finally, section 7 contains concluding remarks.

[4] Additional data sources include the BJS's National Corrections Reporting Program (NCRP), BJS's Survey of Inmates in State Correctional Facilities (SISCF), BJS's Survey of Inmates in Federal Correctional Facilities (SIFCF), BJS's "Prisoners in (YEAR)" Report , Bureau of Economic Analysis (BEA) data on personal income, Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics (LAUS), BLS' Occupational Employment Statistics (OES), U.S. Census Bureau's State and Local Government Finances (SLGF), and the Center for Retail Research's Global Retail Theft Barometer (GRTB). For a full list of sources, see Data Sources

2 Literature

The most relevant strand of the literature explores the causal effect of crime on economic outcomes and welfare. Usher (1987) provided an early model of theft that could be generalized to other forms of inefficiency including rent-seeking, tax evasion, etc. The author shows that the welfare losses from theft come from the loss of output from the thief, the alternative cost of defensive labor, and destruction of property, however, the author does not say much about the relative importance of each. Grossman & Kim (1995) suggest that poorer individuals are better off in an equilibrium where theft exists as opposed to one without theft.

Looking at some accounting studies and some empirical studies, Anderson (1999) estimates the total annual cost of all forms of crime in the U.S. is about $1 trillion dollars. The author includes the costs associated with the legal system, victim losses both monetary and emotional, deterrence, and the opportunity cost of a criminals time. Prior to Anderson, Zedlewski (1985), Cohen (1990), Cohen, Miller, and Rossman (1994), Colin (1994), Klaus (1994), and Cohen, Miller, and Wiersama (1996) each considered a subset of the costs and found estimates ranging from $19 - $728 billion dollars. Because these works are largely accounting for the direct costs of crime, they must simplify the behavioral costs of crime by assuming that non-criminals will behave the same without crime, and criminals will behave like non-criminals. By modeling behavior explicitly, I estimate how much this change in behavior matters with respect to property crime.

A number of authors have used Autoregressive Distributed Lag models (ARDL) to estimate the effect of crime on economic outcomes. Narayan & Smyth (2004) find support for fraud and motor vehicle theft granger causing male youth unemployment and male wages in Australia. Habibullah & Baharom (2008) conclude that armed robbery, daytime burglary, and motorcycle theft have a granger causal effect on economic conditions in Europe, but not vice versa. Detotto & Pulina (2009) conclude that all crime types except murder and fraud granger cause unemployment in Italy. Chen (2009) finds no support for any relationship between crime, unemployment, and income in Taiwan. Hazra & Cui also find no support in India. Unfortunately, these authors cannot establish causality, only granger causality, so their results could be biased. Finally, diverging from ARDL, Carboni $ Detotto (2016) use a spatial model to estimate the effect of crime on gross domestic product. They only find support for robbery having a negative effect on the economy.

Another strand of the literature explores the causal effect of economic outcomes on the choice to commit crime. Becker (1968) proposes that crime be thought of as a rational choice on the part of individuals. Chiricos (1987) reviews 68 studies on the relationship between unemployment and crime and reports that fewer than half find a positive relationship; however, the author suggests that there is support for a strong positive relationship between property crime and unemployment. Further, the author suggests that aggregation can lead to mixed results. Following the drop in crime in the 1990s, there was renewed interest in the question. Instrumenting for the unemployment rate, Raphael & Winter-Ebmer (2001) suggest that there is a positive relationship between property crime and unemployment. Exploring both the effect of wages and unemployment, Gould, Weinberg, & Mustard (2002) suggest that there is a strong negative relationship between wages and property crime as well as a strong positive relationship between unemployment and property crime. The effect of wages appears to be stronger than the effect of unemployment. Exploring the effects of economic incentives and deterrence, Corman & Mocan (2005) support the hypotheses that property crime is negatively related to wages and positively related to unemployment. Focusing on low wage workers, Machin & Meghir (2004) suggest that decreases in low wage worker's wages leads to increased crime. More recently, Yang (2017) finds that increasing low-skilled wages reduces recidivism. Freedman & Owens (2016) find that property crime increases in neighborhoods where some residents receive income transfers. Finally, Dix-Carneiro, Soares, & Ulyssea (2018) show that decreasing tariffs causes an increase in crime through its effect on labor market conditions, public goods provision, and inequality. Given the well documented issues related to unemployment volatility in macro models a la Shimer

(2005), these empirical results suggest that wages and hours may prove more fruitful in a macroeconomic context.

There has been some exploration of the relationship between unemployment and crime in the labor search literature. Burdett, Lagos, & Wright (2003) explore the relationship between job search and crime. The authors find multiple equilibria and suggest that this implies that two otherwise identical locations can have very different crime rates and that good labor market conditions are relatively easier to maintain when crime is low. Extending the model to on-the-job search, Burdett, Lagos, & Wright (2004) suggest that increasing the unemployment insurance replacement rate can increase both crime and unemployment. Contradicting this claim, Engelhardt, Rocheteau, & Rupert (2008) suggest that the effect depends on job duration and deterrence such that crime decreases when UI benefits increase. In line with the empirical literature, they suggest that wage subsidies can reduce crime. Finally, Engelhardt (2010) suggests that decreasing unemployment duration by half would reduce crime and recidivism by 5%.

In contrast to the search literature where crime has no victim, I include victimization and show that it could have a large effect on counter-factual policy analysis. Without victimization, the only reason other households respond to crime is because their wage changes. This puts a damper on the negative feedback loop that results from crime. In this paper, there exists both a criminal and a victim with any income gains to the criminal coming directly from the victim whether they are a household or a firm. Because households are directly exposed to theft, they change their behavior as a result. This creates additional inefficiency on top of the effect that property crime has on the wage.

3 Model

Household's Problem

There is a unit measure of heterogeneous households consisting of some fraction ϕ_h that are high-skilled households and some fraction $\phi_l = 1 - \phi_h$ that are low skilled. Skill refers to each household types labor income share. All households of type $i \in \{h, l\}$ are seeking to maximize their infinitely-lived net present value of utility (1). Each period, households choose their labor supply $N^s_{t,i}$, time for committing theft $s_{t,i}$, next periods capital stock $K_{t+1,i}$ and next periods non-incarcerated population $P_{t+1,i}$. Theft time can be allocated to theft from firms $s^y_{t,i}$ or theft from households $s^h_{t,i}$. Households also choose market consumption $C^m_{t,i}$, theft consumption $C^s_{t,i}$, and investment $I_{t,i}$, but these are determined by the prior choices.

$$\max_{\substack{P_{t+1,i},\ K_{t+1,i},\ I_{t,i} \\ N_{t,i},\ C^m_{t,i},\ C^s_{t,i} \\ s^h_{t,i},\ s^y_{t,i}}} E_0 \sum_{t=1}^{\infty} \beta^t \Big\{ P_{t,i} \Big(\log(\sigma_i + C^m_{t,i} + b_2 C^s_{t,i}) + \chi_i \log(1 - N_{t,i} - b(s^h_{t,i} + s^y_{t,i})) \Big) + (1 - P_{t,i}) log(\sigma_i \sigma + G_t) \Big\} \tag{1}$$

King-Plosser-Rebelo preferences are used for their balanced growth property. Utility from consumption and labor are separable with $\chi > 0$. The baseline level of subsistence is represented by σ_i. While incarcerated, individuals receive utility $log(\sigma_i \sigma)$ where σ is a multiplier for how much value the prison provides to the individual. Since incarcerated individuals receive no consumption, they must receive some baseline value or else we have $log(0)$ which is undefined. Each household seeks to maximize their utility subject to 4 constraints.

The law of motion for capital evolves according to (2).

$$E_t\{P_{t+1,i} K_{t+1,i}\} = P_{t,i}[(1 - d)K_{t,i} + I_{t,i}] \tag{2}$$

Each period, households capital stock depends on last periods capital stock less depreciation d plus what was invested in the previous period. Each household is subject to the market budget constraint (3) where market consumption equals labor income and capital income minus the fraction T_t which is stolen and the fraction $\tau^g + \tau^p$ which is used to fund policing and public goods provision $G_{t,i}$.

$$C^m_{t,i} + I_{t,i} = (w_{t,i}N_{t,i} + R_t K_{t,i})(1 - f_{t,p})(1 - T_t)(1 - \tau^g - \tau^p) + G_{t,i}(1 - T_t) \tag{3}$$

The budget constraint does not include any goods that are stolen by the household as theft is its own form of consumption. In addition, labor and capital used for policing $f_{t,p}$ are paid the same wage and rental rate as resources used for production of real goods, but since they do not produce real goods, I either need to introduce a price or treat their income as not real. Either case results in the same outcome. The value of consumption from theft is determined by (4).

$$C^s_{t,i} = (1 - \rho^y_t)\left[a^y_{t,i}(s^y_{t,i})^\eta Y_t\right] + (1 - \rho^h_t)\left[a^h_{t,i}(s^h_{t,i})^\eta V_t\right] \tag{4}$$

Each worker has theft technology $a^y_{t,i}$ which determines productivity when engaging in theft from a firm and $a^h_{t,i}$ which determines productivity when engaging in theft from other households. A worker who engages in theft devotes time $s^y_{t,i}$ which allows them to steal some fraction of aggregate output Y_t. They also devote time $s^h_{t,i}$ to stealing from other households which allows them to steal some fraction of aggregate household income V_t. Finally, the non-incarcerated population evolves according to equation 5

$$E_t\{P_{t+1,i}\} = P_{t,i} + \zeta(1 - P_{t,i}) - (\rho^y_t + \rho^h_t)\theta_t(\sum_{i\in\{h,l\}} \phi_i C^s_{t,i})(s^y_{t,i} + s^h_{t,i})^\delta P_{t,i} \tag{5}$$

Households committing theft face some probability of getting caught ρ^h_t for household theft and ρ^y_t for firm theft. If they are caught, they receive no consumption from theft. They also face some probability θ_t that they are sent to jail which is itself a function of theft which can be seen in (5). Households in jail are released with probability ζ_t. This means that some fraction of each household type is incarcerated $1 - P_{t,i}$ and some fraction is non-incarcerated $P_{t,i}$. If an individual is incarcerated, their capital is distributed to the non-incarcerated population of their same type. Likewise, upon release, capital is distributed evenly among the non-incarcerated population.[5]

Households do not internalize how their own choice of theft impacts their outcomes. Consequently, T_t and V_t are determined outside the households problem.

$$\begin{aligned} V_t = {} & \phi_h P_{t,h}[(w_{t,h}N_{t,h} + R_t K_{t,h})(1 - f_{t,p})(1 - \tau^g - \tau^p) + G_{t,h}] \\ & + \phi_l P_{t,l}[(w_{t,l}N_{t,l} + R_t K_{t,l})(1 - f_{t,p})(1 - \tau^g - \tau^p) + G_{t,h}] \end{aligned} \tag{6}$$

$$T_t = (1 - \rho_t^h) \sum_{i \in \{h,l\}} \phi_i P_{t,i} a_{t,i}^h (s_{t,i}^h)^\eta \tag{7}$$

V_t is the value of aggregate income and T_t is fraction of total income that each households tries to steal. Each households shares a proportional burden of theft such that households with higher labor income lose the same fraction to theft as a household with lower labor income. While there is evidence to suggest that lower income households are 1.2 times more likely to be a property crime victim, there is no indication of how much is stolen during each incident.[6] I relax this assumption in Appendix C by increasing the burden of property crime on lower income individuals. The results from this exercise suggest that assuming an equal burden is a lower bound on the welfare cost of property crime as well as the output cost of property crime.

The utilitarian government is benign, so it spends today's revenue Revenue_t on policing and transfers to maximize household utility as in (9). It has no way of smoothing revenue over time by borrowing or lending.[7]

$$\text{Revenue}_t = [\phi_h P_{t,h}(w_{t,h}N_{t,h} + R_t K_{t,h}) + \phi_l P_{t,l}(w_{t,l}N_{t,l} + R_t K_{t,l})](\tau^g + \tau^p)(1 - f_{t,p}) \tag{8}$$

[5]This transfer is negligible and simplifies the process of keeping track of capital. I considered an alternative version of the model with capital being held by inmates, but the issue of redistribution upon re-entering the non-incarcerated population is still present.

[6]The Bureau of Justice Statistics publishes "Criminal Victimization" annually. Using the National Crime Victimization Survey, they provide estimates of how often individuals of a certain income group are victims of a property crime; however, they do not do the same for education and they do not say how much individual groups lose on average. In the public use files for the NCVS, much of this information is top-coded.

[7]I relax this assumption in Appendix D by allowing the government to borrow. This reduces government spending to an AR(1) process where $log(G_t) = (1 - \rho_g)log(\omega Y) + \rho_g log(G_{t-1}) + \varepsilon_{g,t}$. Overall, the effect on the primary results are negligible and the effect on the counterfactual policy analysis is similar to the case of unequal transfers and the case of an unequal burden of crime.

$$\text{Revenue}_t^p = f_{t,p} \sum_i \phi_i P_{t,i}(N_{t,i} w_{t,i} + K_{t,i} R_t) \tag{9}$$

$$= \frac{\tau_p}{\tau_p + \tau_g} \text{Revenue}_t \tag{10}$$

Revenue_t^p is utilized for policing while Revenue_t minus Revenue_t^p is used for public goods provision in the form of household transfers.[8] Some fraction $f_{t,p}$ of labor supply and capital is used to prevent theft. These resources are not used for firm production. Finally, police revenue transforms the probabilities of getting caught (11).

$$\rho_t^i = z_p \rho^i \Big(\sum_{i \in \{h,l\}} \sum_{j \in \{h,y\}} s_{t,i}^j \Big)^{-1} (\text{Revenue}_t^p)^{\eta_p} \tag{11}$$

Law enforcement total factor productivity z_p ensures that the average probability over all time periods is the same as the underlying probability of getting caught suggested by the data and η_p determines the curvature of policing in response to revenue.

Firm's Problem

Firms are identical and maximize their profit every period by choosing total capital input $\mathbb{K}_t$,[9] total high-skilled labor input $\mathbb{H}_t$, and total low-skilled labor input $\mathbb{L}_t$. Firms are static optimizers who solve (12).

$$\max_{\mathbb{H}_t, \mathbb{L}_t, \mathbb{K}_t} \quad Q_t(z_t) \mathbb{K}_t^{\alpha}\, \mathbb{H}_t^{\gamma}\, \mathbb{L}_t^{1-\alpha-\gamma} - R_t \mathbb{K}_t - w_{t,H} \mathbb{H}_t - w_{t,L} \mathbb{L}_t \tag{12}$$

Since the market is perfectly competitive, firms have zero profit in equilibrium such that wage $w_{i,t}$ equals the marginal product of labor and R_t equals the marginal product of capital. Firms have a constant returns to scale Cobb-Douglas production function with high skilled labor share parameter γ and capital share parameter α. Losses to theft depend on the population of households committing theft, their time input, and the probability that they

[8] Counterfactual experiments are performed on police expenditure wherein revenue intended for policing or public goods provision can be shifted around to the other.

[9] Neither household's capital is assumed to be more productive than the other households.

are not caught. Q_t captures these factors as well as total factor productivity.

$$Q_t = z_t - (1-\rho_t^y) \sum_{i \in \{H,L\}} \phi_i P_{t,i} a_{t,i}^y (s_{t,i}^y)^\eta$$

Total factor productivity z_t follows an AR(1) process. This introduces short term fluctuations which generate business cycles.

$$\log(z_t) = \rho_z \log(z_{t-1}) + \varepsilon_{z,t}$$

General Equilibrium

Equilibrium allocations are solved for by maximizing each household's utility (1) subject to constraints (5), (3), (4), and (2) such that $P_{t+1,i}$ $N_{t,i}$, $C_{t,i}^m$, $C_{t,i}^s$, $s_{t,i}^y$, $s_{t,i}^h$, $K_{t,i}$, and $I_{t,i}$ ≥ 0. The firm's problem (12) is solved for $\mathbb{K}_t$, $\mathbb{H}_t$, and $\mathbb{L}_t$ subject to (3). Finally, markets must clear in equilibrium, so the resource constraints for each household type must hold, the government budget constraint must hold, and firm inputs must equal household labor and capital supplies.

$$\mathbb{K}_t = (1-f_{t,p})\phi_h P_{t,h} K_{t,h} + (1-f_{t,p})\phi_l P_{t,l} K_{t,l} \tag{13}$$

$$\mathbb{H}_t = (1-f_{t,p})\phi_h P_{t,h} N_{t,h} \tag{14}$$

$$\mathbb{L}_t = (1-f_{t,p})\phi_l P_{t,l} N_{t,l} \tag{15}$$

Labor demand for each skill type is equal to the weighted sum of each non-incarcerated household's labor supply. Similarly, capital demand equals the weighted sum of non-incarcerated households's capital stock. In both cases, some fraction of labor and capital supplied is utilized for policing rather than production.

Solving the household's problem gives eight equilibrium conditions for each household type. First, households face a trade-off between leisure and consumption each period (16).

$$\frac{\partial U_{t,i}(\cdot)}{\partial N_{t,i}} = w_{t,i}(1-f_{t,p})(1-T_t)(1-\tau^g-\tau^p)\frac{\partial U_{t,i}(\cdot)}{\partial C_{t,i}^m} \tag{16}$$

Any increase in labor supply decreases utility from leisure while increasing utility from consumption of market goods. Increased consumption of stolen goods can decrease the marginal utility from market consumption, and the amount of time invested in crime can increase the marginal disutility from labor supply.

Households face a similar trade-off between leisure and theft consumption, but this relationship depends on the probability that a household will have to forego next period consumption if they are caught committing a crime.

$$(1-\rho_t^y)a_{t,i}^y(s_{t,i}^y)^{\eta-1}Y_t = (1-\rho_t^h)a_{t,i}^h(s_{t,i}^h)^{\eta-1}V_t \tag{17}$$

Households must be indifferent between a little more time devoted to household theft and a little more time devoted to theft from firms in (17), since both choices have the same effect on the marginal utility of leisure. Second, households face a trade-off between consumption today and consumption tomorrow when choosing how much crime to commit in (25) in Appendix A. If a household increases theft today, they get direct utility from increased consumption of stolen goods, but they increase the probability of going to jail if they get caught. This increases the disutility of committing theft since they would have to forego consumption tomorrow.

The Euler equation for each household is fairly standard with households facing a trade-off between consumption today and consumption tomorrow. Importantly, theft acts as a tax on the return to capital which induces households to hold less capital and invest less.

$$\frac{\partial U_{t,i}}{\partial C_{t,i}^m} = \beta E_t\Big\{\frac{\partial U_{t+1,i}}{\partial C_{t+1,i}^m}\big(R_{t+1}(1-f_{t+1,p})(1-T_{t+1})(1-\tau^g-\tau^p)+(1-d)\big)\Big\} \tag{18}$$

In the steady-state, who holds what amount of capital becomes indeterminate, so some fraction of capital is held by each household type in the steady state. Out of steady-state, households will choose next period's capital according to their individual euler equations until converging back to the steady-state and abiding by the splitting rule. Households are constrained by their aggregate resource constraints (3) and (4). Next period's non-incarcerated population is defined by flow equation (5) and the law of motion for capital (2) determines how the capital stock evolves.

Finally, solving for the firm's problem (12) yields three equations that pin down wages and the return on capital.

$$w_{t,H} = \gamma Q_t \mathbb{K}_t^{\alpha} \mathbb{H}_t^{\gamma-1} \mathbb{L}_t^{1-\alpha-\gamma} \tag{19}$$

$$w_{t,L} = (1-\alpha-\gamma) Q_t \mathbb{K}_t^{\alpha} \mathbb{H}_t^{\gamma-1} \mathbb{L}_t^{-\alpha-\gamma} \tag{20}$$

$$R_t = \alpha Q_t \mathbb{K}_t^{\alpha-1} \mathbb{H}_t^{\gamma} \mathbb{L}_t^{1-\alpha-\gamma} \tag{21}$$

Each wage (19) and (20) is determined by the marginal product of labor for each worker type. This depends on their marginal product of labor as well as how much theft occurs. In this case, more theft always lowers the total factor productivity for each worker type. Likewise, the rate of return for capital (21) is determined by the marginal product of capital.

4 Calibration

I start by collecting data from the FBI's Uniform Crime Reports which provides crime rates for 181 Metropolitan Statistical Areas (MSA) as well as the U.S. This data set is merged with

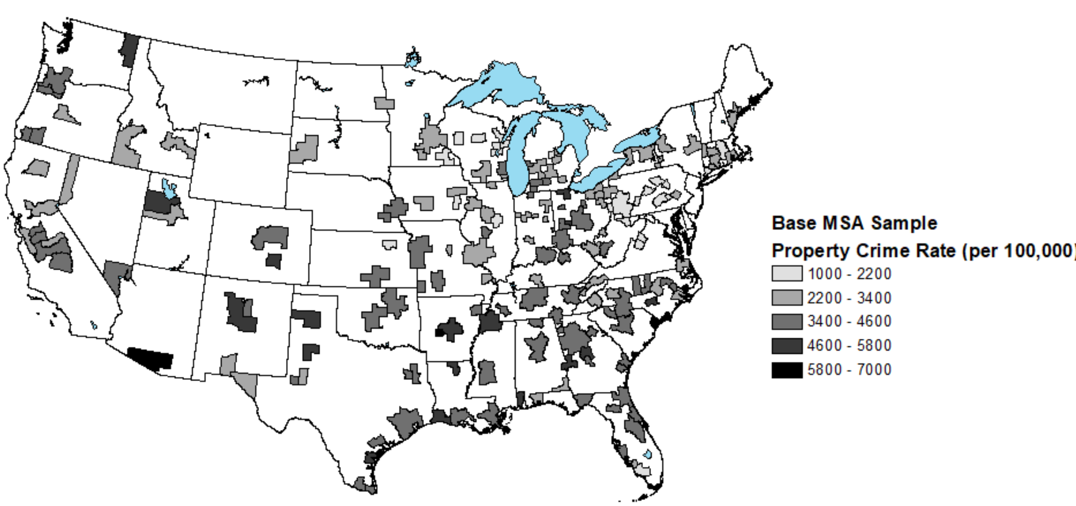


Figure 1: Map of MSAs Used

Table 1: Calibrated Parameters

	Description	Value	Target
β	discount factor	0.97	3% return on 10-year T-bills
α	capital output share	0.33	capital expenditure share
ρ^h	probability of being caught stealing from HH	0.044	clearance data
ρ^y	probability of being caught stealing from firm	0.064	clearance data
ζ	probability of release from prison	0.8	average prison sentence
z	TFP	1	numeraire
d	capital depreciation rate	0.1	average depreciation rate for all capital
ϕ_h	percent of population that is high-skilled	0.387	ACS
ϕ_l	percent of population that is low-skilled	0.613	ACS
τ_p	tax for policing	0.006	SLGF
τ_g	tax for policing	0.12	SLGF
η_p	curvature of policing to revenue	0.5	decreasing returns to revenue

per capita personal income data from the Bureau of Economic Analysis (BEA), and the Local Area Unemployment Statistics (LAUS) data set from the Bureau of Labor Statistics (BLS). The unbalanced panel consists of 181 MSAs over 14 years. MSA-year pairs are dropped due to overlap with other MSAs or missing observations. MSAs provide a reasonable connection between the markets for labor and crime.

Adding in household losses from crime, I end up with data over an 11 year period. Table 1 shows the fixed calibrated parameters. The discount factor $\beta = 0.97$, capital output share $\alpha = 0.33$, and capital depreciation rate $d = 0.1$ are calibrated in a standard manner. The percent of the population that is high\low-skilled ϕ_i is set to match the percent of the population with and without some secondary education in the American Community Survey (ACS).

The tax rates τ_i are set to match data from State and Local Government Finances (SLGF). The curvature of the policing η_p is set to ensure that their are decreasing returns to police revenue. Total factor productivity z is chosen as the numeraire. Additionally, I calibrate the baseline probability of getting caught committing a crime and the baseline probability of release from prison. The baseline probability of getting caught committing a crime is determined based on data from the UCR. The probability of release from prison ζ is set as 1 divided by the average sentence length of prisoners observed in the BJS' annual

Table 2: Jointly Calibrated Parameters

	Description	Value	Target
χ_h	elasticity of labor supply for H	0.698	hours
χ_l	elasticity of labor supply for L	0.735	
σ_h	baseline utility for H	0.303	hours IRF
σ_l	baseline utility for L	0.166	
σ	incarcerated baseline utility	0.902	PCR IRF, value of theft, and skill prison population ratio
a_h^y	TFP for theft from firms for H	0.045	
a_l^y	TFP for theft from firms for L	0.028	
a_h^h	TFP for theft from HH for H	0.032	
a_l^h	TFP for theft from HH for L	0.030	
b	theft time discount	0.014	
b_2	theft consumption discount	0.484	
δ	curvature of jail probability function	2.590	
η	curvature of crime value function	0.929	
ρ_z	AR(1) process	0.608	output IRF
ε_z	shock to TFP	0.020	
θ	scaling factor: probability of prison	1839	prison population
γ	high-skill labor output share	0.372	wage ratio
z_p	TFP for law enforcement	3.771	transform on ρ^h and ρ^y equals 1

"Prisoners in (YEAR)" report which lists the average sentence length for prisoners convicted of a property crime.

I use the simulated method of moments to jointly calibrate the remaining 18 parameters of the baseline model. Three of these parameters are calibrated to specific moments. The scaling factor for the probability of going to jail $\theta = 1839$ is calibrated so that the fraction of the population in prison is the same as observed in data from the Bureau of Justice Statistics' National Corrections Reporting Program (NCRP). The high-skill labor output share $\gamma = 0.372$ is calibrated to match the wage ratio of high-skilled workers to low-skilled workers observed in the ACS. Finally, the total factor productivity for the law enforcement function $z_p = 3.771$ is set to ensure that $\rho^i * law_{enf} = \rho^i$.

Panel VAR[10] is used to generate impulse response functions which can be used to match the model IRFs to what agents are doing in the data. Total hours worked is aggregated over all individuals since the results are sensitive to whether low-skilled or high-skilled hours respond first. I use the remaining uncalibrated parameters to minimize the sum of squared

[10]Results of the panel VAR are available in Appendix A

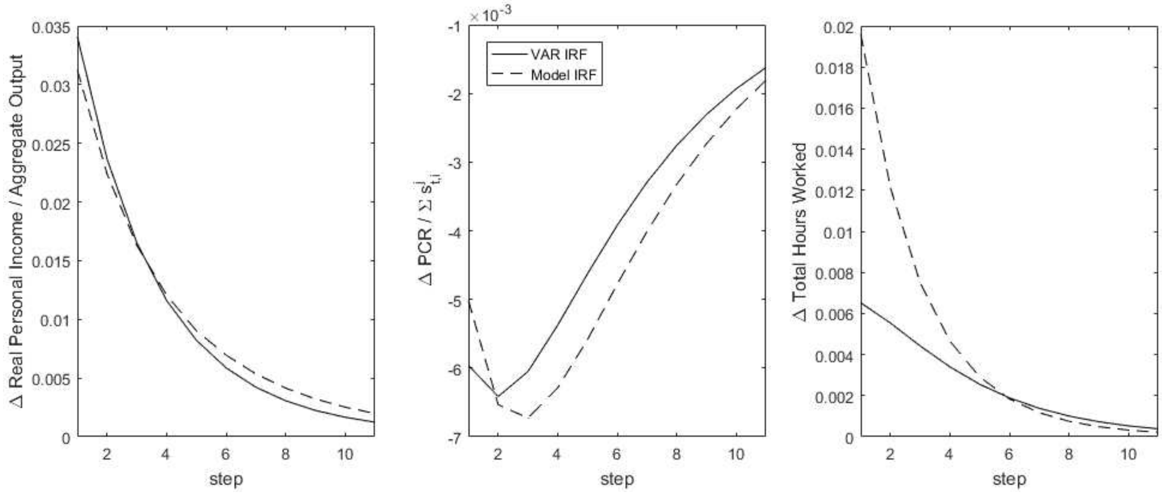
Table 3: Moments and Errors

	Moment	Value	% Error
High-skill hours	0.336	0.326	2.99
Low-skill hours	0.3	0.301	0.39
Property Crime Rate	0.096	0.217	126
Value of HH theft	0.0025	0.0025	1.35
Value of Firm theft	0.0025	0.0026	4.05
Prison population	0.0017	0.0018	4.51
Prison skill ratio	0.14	0.14	2.36
Skill premium	2.13	1.84	13.4

errors of the difference between the model generated impulse response functions (IRFs) and the IRFs from panel VAR. Table 2 shows the results from matching 15 parameters to 18 moments. I calibrate ρ_z and ε_z to match the level initial peak of the income IRF and the subsequent path of the income IRF. The elasticity of labor supply χ_i and the baseline utility σ_i are calibrated to match the level of hours and the IRF. Finally, the total factor productivities for theft a_i^j, the theft time discount b, the theft consumption discount b_2, the curvature of jail probability δ, and the curvature of crime value η are calibrated to match the property crime rate IRF, the value of firm and household theft, and the high\low-skill prison population ratio.

Looking at Figure 2a and Table 3, The model matches the theoretical moments match the data well. Given that there is no wage rigidity in the model, it is not surprising that total hours worked is more responsive in the model IRF than in the data IRF. One potential concern is the large difference between the theoretical moment for the property crime rate. My assumption in the model is that effort and crime rates are correlated, so being off on the level is not as much of a problem as being off on the IRF. Since the IRFs are not that different, the results should be largely unaffected.

I use compensating variation (CV) as my measure of welfare cost. Welfare is measured as the infinitely discounted future utility of households summed up over all time periods and



(a) IRFs

	Real Personal Income *Aggregate Output*			*PCR* $\sum_i \sum_j \phi^i P_i s_i^j$			*Total Hours Worked* $\sum_i \phi^i P_i N_i$		
Step	1	5	10	1	5	10	1	5	10
Moment	0.034	0.008	0.002	-0.006	-0.005	-0.002	0.007	0.003	0.001
Model IRF	0.031	0.009	0.003	-0.005	-0.006	-0.002	0.020	0.003	0.000
% Error	8.3	9.9	52.1	8.3	20.7	15.3	200	13.8	38.8

(b) % Error for IRFs

Figure 2: Orthogonalized Shock to Real Personal Income per Capita

Figure 2a compares the IRFs from VAR (solid line) to the IRFs from the model (dashed line). Real personal income per capita from the data is compared to the model generated aggregate output. Second, the property crime rate from the data is compared to the aggregate effort put into crime by households. Finally, total hours worked in the data is compared to total hours worked by households in the model. Figure 2b shows the percent error for steps 1, 5, and 10 in Figure 2a.

household types.

$$\text{Welfare} = \sum_{i \in \{h,l\}} \sum_{t=1}^{T} \beta^t \phi_i U_{t,i}(P_{t,i}, C_{t,i}^m, C_{t,i}^s, N_{t,i}, s_{t,i}^h, s_{t,i}^y, \mathbf{comp}_i) \tag{22}$$

Compensating variation is how much consumption I have to give households such that they are indifferent between 2 different scenarios. Given different household types, the social planner could be solving a different welfare problem depending on who they care about. In the most general sense, the social planner is trying to solve for the level of compensation

comp_i^* needed such that both household types are indifferent between the model with crime and one with less crime. If there is no crime, I use $s^j_{i,t}$, but if there is $1-x\%$ less crime, then I calculate CV using $s^j_{i,ss}$ for both before and after since I am taking control of $s^j_{i,t}$.

$$\sum_{t=1}^{T} \beta^t \phi_i \Big\{ U_{t,i}(P_{t,i}, C^m_{t,i}, C^s_{t,i}, N_{t,i}, s^h_{t,i}, s^y_{t,i}, \text{comp}_i^*) \\ - U_{t,i}(P^2_{t,i}, C^{m,2}_{t,i}, C^{s,2}_{t,i}, N^2_{t,i}, xs^h_{t,i}, xs^y_{t,i}) \Big\} = 0 \quad \forall i \in \{h, l\} \tag{23}$$

5 Results

To get an idea of how well the model performs, I compare the results to prior work. First, what happens if more police are hired as a result of more revenue for policing? Increasing the tax for policing, the steady-state results suggest that a 1% increase in police employment results in a 0.33% reduction in property crime and a 0.37% reduction in the value of all theft. Compare these numbers to Levitt (2002) where he finds that a 1% increase in police employment reduces the property crime rate by 0.21 - 0.5%. This provides some external validation for my model given that my non-targeted results are within the bounds found by Levitt. Second, how does the calibrated theft consumption discount compare to the literature. In particular, I consider the fencing value of stolen goods. This value represents what fraction of the original value a thief can receive from resale. Roumasset & Hadreas (1977) suggest that the fencing value may be about 50% of the original value, Stevenson, Forsythe, & Weatherburn (2001) suggest that the rate may be in the range of 25-33%, and Walsh (1977) and Steffensmeier (1986) both conclude that the rate is in the range of 30-50%. The discount rate for theft consumption in my model is about 48% which is towards the upper end of the literature, but still reasonable. This result also provides some external validation for the model as this moment was not targeted.

The IRFs for the dynamic model can be seen in Figure 7 in Appendix F. Given a positive shock to TFP, hours worked responds positively while overall theft and the value of theft decline. However, the value of theft from households increases as the value of households increases more than the value of firms. This creates a trade-off which causes households to switch from stealing from firms to households and since the value of households increased more than overall output, individuals steal more from households; however, the increase in the value household theft is negligible. This result seems strange, but it stems from how theft from firms is structured. Theft is subtracted from TFP, so an increase in TFP results in a small increase in labor and capital supplied which makes household theft more favorable.

Capital and market consumption respond with a lag as individuals smooth their consumption over the course of the shock. Interestingly, the prison population increases for high-skilled households, but declines for low-skilled households. This is because the welfare gains of the shock for high-skilled households is lower, so there is now an incentive to commit more household theft. This leads to an increase in high-skilled theft, but a decline in low-skilled theft which results in the observed prison population responses. Overall, the dynamic results are fairly robust to unforeseen shocks to every parameter as seen in Appendix F. The only IRFs affected by shocks to the underlying parameters are ones related to crime due to the relatively small size of crime compared to outcomes like labor and capital. The fraction of labor and capital that goes towards policing is the most responsive outcome due to how dependent it is on labor, capital, wages, rate of return on capital, and population.

Table 4: Compensating Variation: Crime, 1% Less Crime, and No Crime

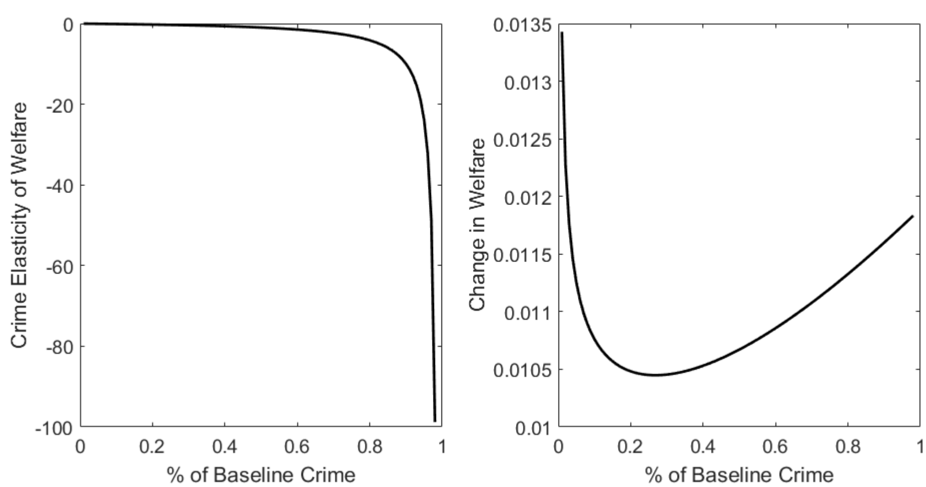
SPP type	High-Skilled CV	Low-Skilled CV	Aggregate CV
$\Delta s_{i,ss} = -1\%$	0.10	0.09	0.19
$\Delta s_{i,ss} = -100\%$	1.04	0.57	1.61
$\Delta s_{i,t} = -100\%$	1.06	0.75	1.81

CV is measured as the percentage of the net present value of output. The first row shows CV in the case of a 1% decline in crime where CV compares two models with $s^j_{i,ss}$ and $0.99 s^j_{i,ss}$. The second row does the same for a 100% decline in crime with CV comparing two models with $s^j_{i,ss}$ and $s^j_{i,ss} = 0$. The third row shows a comparison between two models with $s^j_{i,t}$ and $s^j_{i,t} = 0$. For robustness checks and additional CV measures, see Appendices E and F

5.1 Welfare Analysis

Looking at Table 4, a 1% decrease in crime in row 1 results in a welfare gain of 0.19%, so the elasticity is -0.19. On the other hand, a 100% decrease in crime in row 2 results in an elasticity of -0.016. This suggests that there are large welfare gains at the margin, but the effect diminishes before becoming larger close to zero as seen in Figure 3. The non-monotonic shape results from policing being less effective when there is less crime. As crime approaches zero, the effectiveness of policing goes to infinity at an exponential rate. Intuitively, if only one person is committing crime, then all police resources can be devoted to catching that individual. Getting rid of that last bit of crime frees up resources being devoted to policing. From the perspective of policymakers, there are diminishing returns to decreasing crime, so as more resources are spent on preventing crime, the marginal benefit in terms of social welfare is declining, so there may be a point at which it is no longer optimal to prevent crime. While there is a large potential benefit when property crime is near zero, getting rid of property crime entirely is unlikely and policing resources are likely going to be spent on violent crime anyways, so the last gain is probably never going to be realized even if property crime was wiped out.

Figure 3: Effect of Crime on Social Welfare



In the third row, households must be compensated with 1.81% of baseline output if the social planner cares about making both household types just as well off as they would be if crime was zero. High-skilled households must be compensated a third more than low-skilled households since they have higher marginal productivity by definition. The fact that they make up a smaller proportion of the population mitigates the difference between the two household types. Comparing CV when crime is fixed in the second row and when crime is allowed to vary over the business cycle in the third row, CV increases when individuals are allowed to choose how much crime to commit over the business cycle. This suggests that crime generates a negative feedback loop.

5.2 Decomposition

Table 5: Comparison: CV and Output

	Baseline	Fixed C^s	Fixed T	Fixed C^s, T	Fixed N	Fixed P	Fixed ϕ_p	Fixed I
CV	1.81	2.66	1.02	1.87	1.53	2.81	2.42	2.29
% difference	-	46.9	-43.6	3.31	-15.5	55.2	33.7	26.5
%Δ Output	2.79	2.25	1.77	1.24	1.70	2.27	1.80	1.70
% difference	-	-19.3	-36.5	-55.7	-38.9	-18.5	-35.4	-39.1
%$\Delta\frac{\text{std}}{\text{mean}}$ Output	-1.98	-1.80	-1.47	-1.28	-39.9	-1.89	-1.88	7.97
% difference	-	9.1	25.8	35.4	-1900	4.5	5.1	-303

CV is measured as the percentage of the net present value of output. In all cases, CV assumes that crime decreases 100% and the social planner is attempting to make both households just as well off. To refresh everyone's memory, C^s is crime consumption, T refers to all losses by firms and households, N is labor supply, P is the non-incarcerated population, ϕ_p is the fraction of resources used for policing, and I is investment. Additional Discussion in Appendix E.

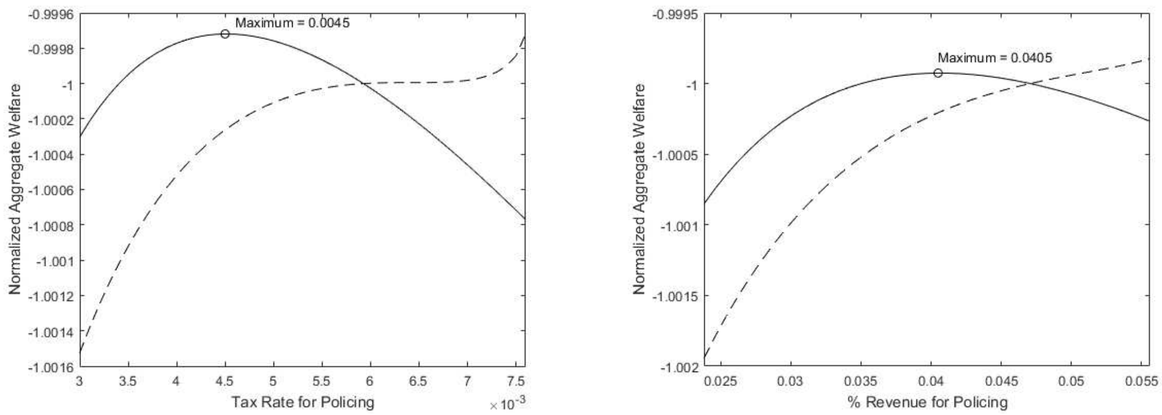
To get a sense of what drives my results, I individually fix several endogenous variables and compare the two environments as in Table 5. To calculate the relative importance of each channel, I divide the absolute value of the change in CV for each channel by the sum of the absolute value of the change in CV for all channels. Overall, the direct channels for property crime account for 81% of CV with the remaining effects coming from changes to labor supply and investment. This suggests that my estimates for the effect of property crime on welfare are not being biased too much by the overly large response in labor supply shown in the IRFs.

With respect to the direct effects of property crime, the second column shows the effect of the opportunity to steal which accounts for 26% of CV and 19% of lost real output. Fixing theft consumption C^{τ} results in CV increasing by 46.9% from 1.81% of output to 2.66% of output. In the other direction, the third column shows the effect of victimization which accounts for 24% of CV and 37% of lost real output. Fixing losses to theft T and $Q - z$ results in CV decreasing to 1.02 as households are not that much better off in a world without crime. These results suggest that the effect of losses to property crime are large enough that omitting household and firm losses from a model of property crime would bias the results of any policy analysis. In particular, the differences in output and CV suggest that households will be at a different point on their utility curve depending on what channels are present. Interestingly, the size of the effects diverge when comparing the changes in CV and lost real output. The effect of victimization on CV is smaller than the effect on output while the opposite is true for the opportunity to steal. This is because having the opportunity to steal functions as an insurance mechanism, so it brings positive welfare to households while victimization is always a negative outcome. The two remaining direct channels are incarceration and policing. Incarceration is the largest contributor to CV at 31% with the remaining 19% due to policing. The direct effects of property crime as a whole account for 81% of CV and 58% of lost output.

One concern from the calibration was the size of the labor response and the effect it might have on welfare. Overall, it only account for 7% of CV which is fairly large, but is dwarfed by the other effects including the investment channel which accounts for 12% of CV. That being said, it has an enormous effect on volatility and an average sized affect on output relative to other channels. This suggests that my estimates of CV should not be biased by a large amount.

Finally, I compare the dynamic panel data estimates in Appendix A to the model results as an out of sample check. The DPD estimates suggest that a 100% reduction in property crime would increase per capita personal income by 3.2 - 13.3%. The model results in Table 5 suggest that the same reduction in property crime would increase income by 2.8%. Assuming GDP is $17 trillion, this would translate to $476 billion; however, since the ability to commit crime offers utility to households, the social welfare cost will be lower.

5.3 Policing



(a) (b)

Figure 4: Optimal Taxation for Policing

(a) shows welfare for changes in the tax rate for policing while (b) shows welfare for changes in the share of tax revenue that goes towards policing. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to an alternative calibration where the low-skilled household receives twice what the high-skilled household receives.

Related to the fact that police do not directly contribute to output, how is policing valued by households? Using my model, I calculate the optimal level of taxation for policing property crime. This proves tricky as households get utility from being able to commit property crime in addition to having it prevented, and if there are more police, then there are fewer workers earning income. This last effect is so strong that households in the model would prefer if there was no policing, but they like police if . Given that governments might not care about utility from property crime, it needs to be factored out when performing the welfare analysis. Thus, the social planner is trying to solve for the level of compensation

$\text{comp}^*_{i,j}$

$$\sum_{t=1}^{T} \beta^t \phi_i \Big\{ U_{t,i}(\cdot, \bar{C}^s_i, \tau^{p,j}, \text{comp}^*_i) - U_{t,i}(\cdot, \bar{C}^s_i, \tau^{p*}, 0) \Big\} = 0 \;\; \forall i \in \{h, l\}, \; j \in [\underline{\tau^p} \; \overline{\tau^p}] \tag{24}$$

needed such that both household types i are indifferent between the current level of taxation τ^{p*} and every other level of taxation $\tau^{p,j}$. The level of consumption derived from theft is kept constant so that changes in the value of theft are not factored into utility. In a similar vein, a social planner might not want to change the tax rate for policing, but may want to change the overall share of revenue that goes towards policing in order to maximize welfare. This would imply that additional revenue that goes towards policing is not spent on public goods and vice versa.

Looking at Figures 4a and 4b, households would be better off with a lower tax rate for policing and a lower share of revenue going towards policing. In particular, households prefer that the tax rate be 0.0045 which is 25% lower than the baseline value of 0.006. As for the revenue share, households prefer that 0.0405 % of revenue go towards policing. This translates to a tax rate of 0.0051 for policing and a tax rate of 0.129 for public goods. The value for the revenue share is closer to the baseline value suggesting that households have a distaste for additional taxation. Looking at Figures 13a and 13b in Appendix F, high-skilled households would prefer a lower tax rate than low-skilled households, but they would prefer a higher share of revenue go towards policing. This stems from the opportunity cost of taxation. If they are taxed and they receive a consumption transfer as a result, they are worse off than they would be if they could put that income towards capital accumulation whereas the low-skilled households receive a lower marginal benefit since the marginal utility from consumption is higher for them since they have lower consumption. It is important to note that these numbers are assuming that all revenue goes towards policing property crime and not towards other services like preventing and investigating violent crimes. That being said, these results do suggest that households may prefer that fewer resources go towards property crime prevention and investigation. This is not a far-fetched results as property crime has one of the lowest reporting rates and many cases are never closed due to the difficulty of finding the perpetrator and the value of property relative to a human life.[11]

The dashed line is Figures 4a and 4b show the importance of how transfers are divided between the two households. The solid line corresponds to an even split between all households while the dashed line corresponds to a an alternative calibration where low-skilled households receive a transfer that is twice as large as that for high-skilled households. In the alternative calibration, households would prefer higher taxes for policing and they would prefer that a larger share of revenue go towards policing. This result is driven by differences in the jointly calibrated parameters which make the opportunity cost of additional taxation lower.

5.4 Transfers

Table 6: Responses to Transfers

	Elasticity of Total Losses		Elasticity of Crime Effort	
	$G_l = G_h$	$G_l = 2G_h$	$G_l = G_h$	$G_l = 2G_h$
Transfers to LS Workers (Revenue Clearing)	0.003	-0.01	-0.001	-0.05
Transfers to LS Workers (Fixed HS Transfers)	0.06	0.05	0.07	0.01
Transfer Multiplier	0.08	0.09	0.009	0.05
Consumption Transfer	-0.01	-0.03	0.001	-0.02

Finally, I consider the how government transfers to households affect household behavior. Transfers can be thought of as 'carrots' in the 'sticks' vs 'carrots' debate on how to reduce crime.[12] I consider four different transfer cases. First, what happens if more government transfers go towards low-skilled households at the expense of high-skilled household transfers? Second, what if low-skilled households receive higher transfers, but high-skilled households receive the same share of transfers as they do in the baseline model? Third, what

[11] Langton et al. (2012) use the National Crime Victimization Survey to investigate why people do not report crime. They find that property crime, especially theft, is rarely reported compared to more violent crimes. The primary reasons given were the belief that the police did not care and the belief that the police would not catch the perpetrator.

[12] Corman & Mocan (2005) is titled "Carrots, Sticks, and Broken Windows."

if both households receive higher transfers without raising taxes? Finally, what happens if households receive consumption transfers as opposed to income transfers?

The first row of Table 6 and Figure 8 show the effect of increased transfers to low-skilled households at the expense of high-skilled households. Overall, there seems to be little to no effect on the amount of effort put into property crime while the effect on aggregate losses to property crime as a percentage of output depends on how transfers are structured before perturbing the model. Looking at the first plot, the solid line suggests that in the baseline model where both households receive the same level of transfer, increasing transfers has little to no effect since any decrease in crime by low-skilled households is countered by an increase in crime by high-skilled households. On the other hand, if low-skilled households receive twice the transfer that high-skilled households receive (dashed line), then aggregate losses to property crime decline. This is because the decrease in property crime by low-skilled households outweighs the increase in property crime by high-skilled households. This suggests that the debate around the effect of increased transfers on property crime depends heavily on how much value households currently receive from government transfers.

The second row as well as Figure 9 show the effect of increased transfers to low-skilled households while high-skilled households receive the same level of transfers as they do in the baseline model. Interestingly, aggregate losses to property crime as a percentage of output increase as transfers increase regardless of the initial level of transfers. As transfers to households are increased, the expected value of household theft increases driving households to steal more from other households as a result. This increase in expected value outweighs any decrease in property crime directly resulting from higher consumption.

The third row as well as Figure 10 show the effect of increased transfers to both types of households. As in the previous case, aggregate losses to property crime as a percentage of output increase as transfers increase regardless of the initial level of transfers. The increase in expected value from household theft outweighs any decrease in property crime directly resulting from higher consumption and lower marginal utility of consumption. As with the previous case, the effect of transfers depends not only on how households respond to higher income, but also on how households respond to increased incentives to commit crime.

Finally, the fourth row and Figure 11 show the effect of increased consumption transfers. These transfers show up in utility, not the budget constraint as in the three prior cases. As with the first case, the effect of these transfers depends on the initial distribution of transfers to households. In the baseline case represented by a solid line, aggregate losses to property crime as a percentage of output increases slightly, but mostly stays the same. Neither household changes their behavior very much. On the other hand, if low-skilled households receive twice the transfer that high-skilled households receive, aggregate losses to property crime as a percentage of output clearly declines as both households put in less effort and commit less property crime.

Going back to the question of whether 'sticks' or 'carrots' are more effective at preventing property crime, the results are ambiguous. Transfers to households can be effective as in Figures 8 and 11, but the effect depends heavily on how transfers are currently structured. Overall, there appears to be little effect of transfers on property crime which is in line with some recent working papers from Marie & van de Werve (2018) and Posso (2018). Importantly, this is only true for cash transfers without additional requirements such as work requirements. Increased transfers to households without requiring the government budget constraint to clear as in Figures 9 and 10 have the opposite effect on property crime with effort and losses increasing as a result. The effect of increased punishment is more clearly defined with losses and effort declining unambiguously regardless of which parameter is changed.[13]

6 Conclusion

Estimates of the cost of property crime hinge on who the social planner cares about, how behavior is allowed to change in response to property crime, and how welfare is defined.

[13]Figures 5 and 6 both show that property crime declines with increasing punishment.

Comparing a world with and without property crime, the model suggests that property crime decreases welfare by 1.1-3.3% and decreases output by 2.8%. To put these numbers in perspective, with GDP at around $17 trillion, the cost ranges from $187 - $568 billion. These estimates are within the range of prior work. In addition, the marginal welfare benefit of decreasing crime is diminishing suggesting that while crime has a high cost, there may be a point at which the marginal benefit of decreasing crime does not outweigh the marginal cost.

Diverging from previous work, any value generated from property crime is at the expense of other agents whether they be households or other agents. The effect of losses to property crime is comparable to the effect of being able to commit theft, accounting for 24% of the welfare cost and 37% of the output loss. Omitting this channel has the potential to bias any welfare and policy analysis which assumes that households and firms do not face any direct cost.

Finally, the results for policing and transfers depend on the initial structure of transfers as well as whether or not the government budget constraint clears. In the baseline case where every household receives the same transfer, households would prefer less revenue go towards policing. In addition, increased transfers have no effect on property crime. If anything, losses and effort may increase with increasing transfers. On the other hand, if low-skilled households start out with higher transfers than high-skilled households, households would prefer more revenue go towards policing. Transfers would also be more likely to decrease losses and effort associated with property crime.

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Appendices

A Additional Equations

$$\beta E_t\{U_{t+1,i} - U^0_{t,1,i}\} = \xi_{t,i} - \beta E_t\Big\{(1 - \zeta - (\rho^y_{t+1} + \rho^h_{t+1})\theta_t(\sum_{i\in\{h,l\}} \phi_i C^s_{t+1,i})(s^y_{t+1,i} + s^h_{t+1,i})^\delta)\xi_{t+1,i} - \frac{\partial U_{t+1,i}}{\partial C^m_{t+1,i}}\big[(1-d)K_{t+1,i} + I_{t+1,i}\big]\Big\} + \frac{\partial U_{t,i}}{\partial C^m_{t,i}} K_{t+1,i} \tag{25}$$

$$\xi_{t,i} = \frac{\dfrac{\partial U_{t,i}}{\partial s^y_{t,i}} + \dfrac{\partial C^s_{t,i}}{\partial s^y_{t,i}}\dfrac{\partial U_{t,i}}{\partial C^m_{t,i}}}{(\rho^y_t + \rho^h_t)\theta_t\delta(\sum_{i\in\{h,l\}} \phi_i C^s_{t,i})(s^y_{t,i} + s^h_{t,i})^{\delta-1}}$$

$$U_{t,i} = \log(\sigma_i + C^m_{t,i} + b_2 C^s_{t,i}) + \chi_i \log(1 - N_{t,i} - (s^h_{t,i} + s^y_{t,i}))$$

$$U^0_{t,i} = \log(\sigma_i\sigma + G_t)$$

B Summary Statistics and Regressions

Table 7: Summary Statistics

Variable	Obs	MSAs	Years	Mean	Std. Dev.	Min	Max
Personal Income per capita	2180	181	14	36457.6	9276.3	15499	118695
Property Crime Rate	2133	181	14	3429.8	1091.2	1108	8694.9
Larceny/Theft Rate	2156	181	14	2378.3	723.8	854.7	5459.2
Robbery	2180	181	14	105.0	61.5	3.6	458.5
Burglary	2163	181	14	789.2	337.0	158.7	2859.2
Labor Force (100,000s)	2180	181	14	6.0	7.6	0.5	45.3

Table 8: Panel VAR

VARIABLES	(1) RPINC$_t$	(2) Hours$_t$	(3) PCR$_t$	(4)
RPINC$_{t-1}$	0.688***	0.051***	-0.099	
	(0.031)	(0.019)	(0.070)	
Hours$_{t-1}$	-0.020	0.587***	0.298***	
	(0.049)	(0.031)	(0.111)	
PCR$_{t-1}$	-0.057***	0.006	0.836***	
	(0.012)	(0.008)	(0.028)	
Observations	670	670	670	670

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

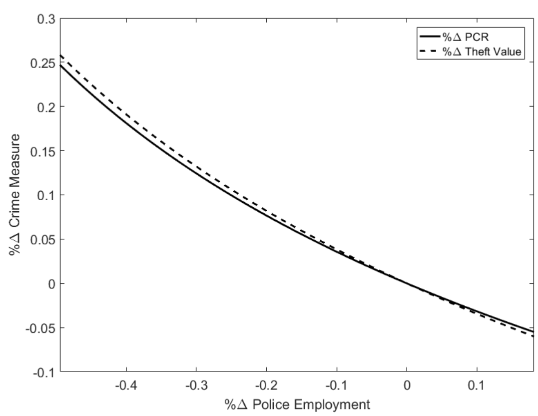


Figure 5: Effect of Policing on Property Crime

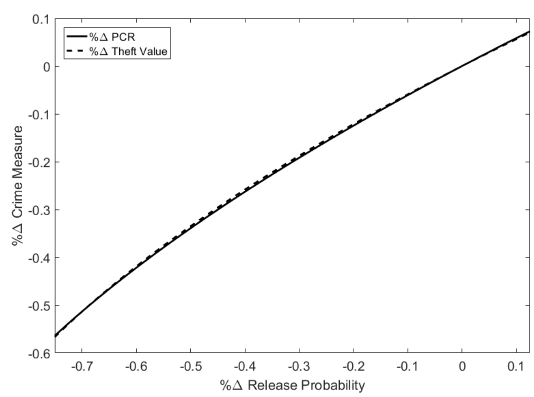


Figure 6: Effect of Release Probability on Property Crime

Table 9: Baseline Blundell-Bond Estimation Results

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) lag(2 2)	(5) collapse
$log(RPINC_{t-1})$	1.046***	1.028***	1.033***	1.070***	0.867***
	(0.0192)	(0.0177)	(0.0174)	(0.0264)	(0.259)
$log(PCR_t)$	-0.0318	-0.0593***	-0.0582***	-0.0681***	-0.133**
	(0.0225)	(0.0152)	(0.0135)	(0.0104)	(0.0567)
pct_child		0.143***	0.111	0.170***	-0.0311
		(0.0426)	(0.0830)	(0.0571)	(0.277)
Constant	-0.199	0.147	0.0908	-0.238	2.492
	(0.262)	(0.186)	(0.195)	(0.306)	(3.214)
Observations	1,864	1,224	1,224	1,224	1,224
Number of geoFIPS	180	141	141	141	141
Instruments	166	162	162	52	26
AB test for AR(2)	0.0825	0.118	0.119	0.121	0.161
AB test for AR(3)	0.800	0.557	0.555	0.562	0.534
Hansen test	0.273	0.897	0.887	0.166	0.199
ΔRPINC wrt 1 std ΔPCR	-0.468	-0.862	-0.845	-0.989	-1.935

se pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

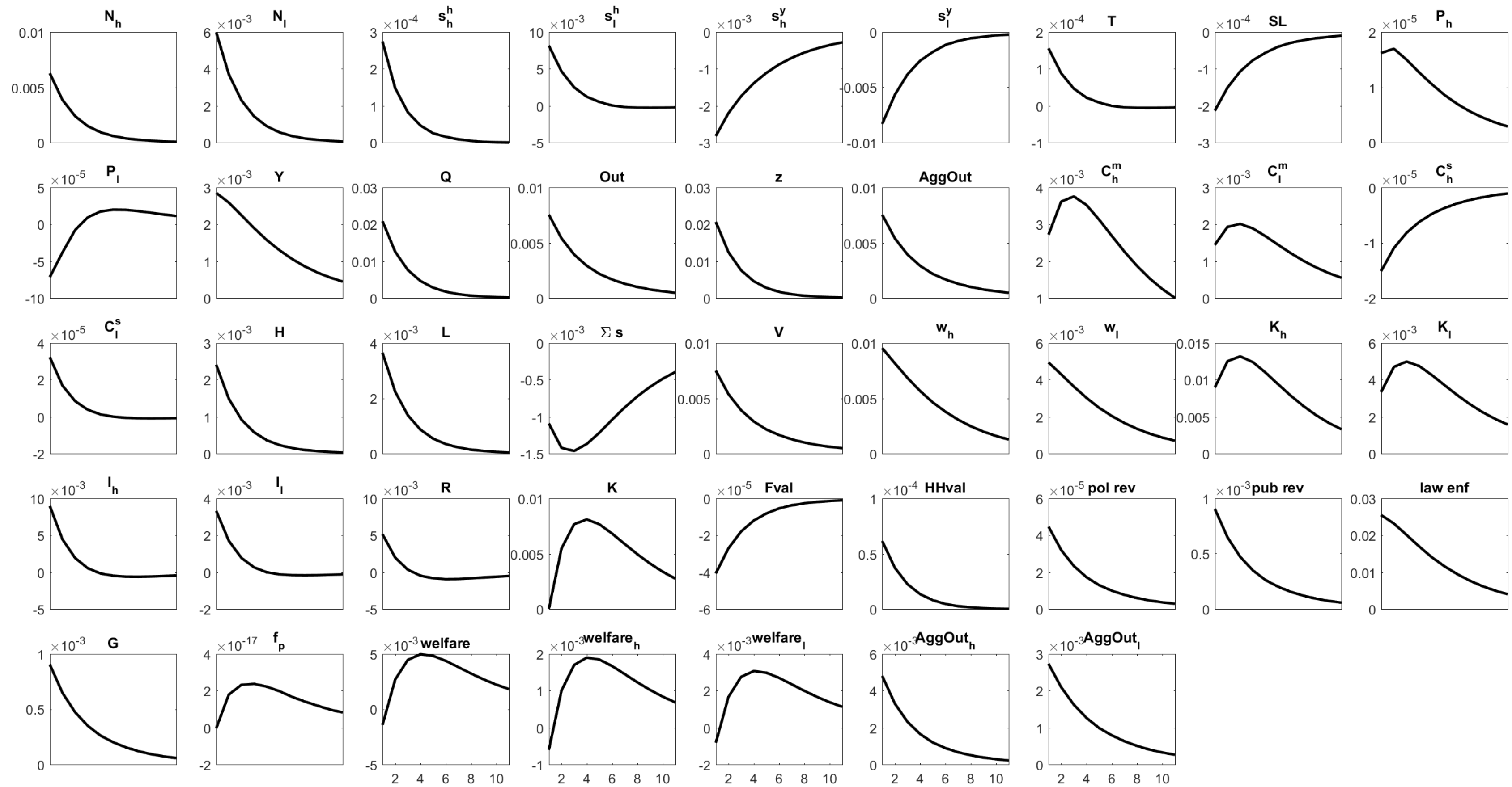


Figure 7: Orthogonalized shock to TFP

C Unequal Burden of Crime

One of the stronger assumptions in the baseline model assumes that both households types bear the same burden of crime. This means that both have the same fraction of their income stolen. I relax this assumption based on data from the BJS which suggests that those in the lowest 60% of income are 1 - 1.2 times more likely to be a victim of a crime. Extrapolating a little, I assume that the percentage stolen from low-skilled households is 1.2 times the percentage stolen from high-skilled households.

$$T_{t,l} = 1.2T_{t,h} \tag{26}$$

This introduces a few differences with the baseline model. Given that $T_{t,i}$ factors into the households euler equation, having different values for each households implies that the steady-state value of R is unique to each household.

$$\frac{\partial U_{t,i}}{\partial C^m_{t,i}} = \beta E_t \Big\{ \frac{\partial U_{t+1,i}}{\partial C^m_{t+1,i}} \big(R_{t+1,i}(1 - f_{t+1,p})(1 - T_{t+1,i})(1 - \tau^g - \tau^p) + (1 - d) \big) \Big\} \tag{27}$$

This means that the capital income share for each household type must be different. Thus, capitals share of income is defined by α as in the baseline model, but the high-skilled household's capital share is $\kappa\alpha$ while the low-skilled household's capital share is $(1 - \kappa)\alpha$

$$\max_{\mathbb{H}_t, \mathbb{L}_t, \mathbb{K}_{t,h}, \mathbb{K}_{t,l}} \quad Q_t(z_t)\mathbb{K}^{\kappa\alpha}_{t,h}\ \mathbb{K}^{(1-\kappa)\alpha}_{t,l}\ \mathbb{H}^{\gamma}_t\ \mathbb{L}^{1-\alpha-\gamma}_t - R_{t,h}\mathbb{K}_{t,h} - R_{t,l}\mathbb{K}_{t,l} - w_{t,H}\mathbb{H}_t - w_{t,L}\mathbb{L}_t \tag{28}$$

Calibration for the model with unequal burden mirrors that of the baseline with the addition of κ as seen in Table 10. I choose $\kappa = 0.75$ so that the ratio of high-skilled aggregate household capital to low-skilled aggregate household capital is equal to 3.

As seen in Table 11, CV for the unequal burden model is about 10% larger than for the equal burden model. CV increases from 1.77 percent of NPV of output to 1.96 percent. In addition, Lost output increases from 3.04 percent of NPV of output to 3.12 percent. This

Table 10: Jointly Calibrated Parameters

	Description	Value	Target
χ_h	elasticity of labor supply for H	0.537	hours
χ_l	elasticity of labor supply for L	0.765	
σ_h	baseline utility for H	0.348	hours IRF
σ_l	baseline utility for L	0.112	
σ	incarcerated baseline utility	0.841	PCR IRF, value of theft, and skill prison population ratio
a_h^y	TFP for theft from firms for H	0.061	
a_l^y	TFP for theft from firms for L	0.036	
a_h^h	TFP for theft from HH for H	0.046	
a_l^h	TFP for theft from HH for L	0.039	
b	theft time discount	0.021	
b_2	theft consumption discount	0.491	
δ	curvature of jail probability function	2.054	
η	curvature of crime value function	0.882	
ρ_z	AR(1) process	0.583	output IRF
ε_z	shock to TFP	0.022	
θ	probability of going to jail	$2.078x10^3$	prison population
γ	high-skill labor output share	0.381	wage ratio
z_p	TFP for law enforcement	0.278	transform on ρ^h and ρ^y equals 1
κ	high-skill share of capital output share	0.750	$\mathbb{K}_{t,h}/\mathbb{K}_{t,l} = 3$

is only a 2.6% difference in output. The differences are smaller for the baseline model where the capital ratio is 4. The model fit for the unequal burden model was poor when the capital ratio was calibrated to be 4. This is likely because the value for κ was approaching 1.

Table 11: CV Comparison

	High-Skilled CV	Low-Skilled CV	Aggregate CV
Equal burden ($\mathbb{K}_{t,h}/\mathbb{K}_{t,l} = 4$)	1.06	0.75	1.81
Equal burden ($\mathbb{K}_{t,h}/\mathbb{K}_{t,l} = 3$)	1.02	0.75	1.77
Unequal burden ($\mathbb{K}_{t,h}/\mathbb{K}_{t,l} = 3$)	1.09	0.87	1.96

CV measured as percentage of the net present value of output. Equal burden refers to the baseline model.

D Government Borrowing

With government borrowing and no lump sum taxes, the model becomes more complicated since debt will not drop out of the consumer's budget constraint even if the aggregate resource constraint holds. On the other hand, because state and local government's must balance their budgets in the long run, debt to GDP D_{ss}/Y_{ss} should be zero. Beginning with the government's budget constraint,

$$\mathsf{G}_t = \tau^g \sum_i \phi_i P_{t,i}\big[(w_{t,i}N_{t,i} + R_t K_{t,i})\big](1 - f_{t,p})(1 - T_t) - (1 + r_{t-1})\mathsf{D}_t + \mathsf{D}_{t+1} \tag{29}$$

we can divide both sides by GDP $\mathsf{Y_t}$ and look at the steady state.

$$\frac{\mathsf{G}}{\mathsf{Y}} = \tau^g \frac{\sum_i \phi_i P_i\big[(w_i N_i + RK_i)\big](1 - f_p)(1 - T)}{\mathsf{Y}} - r\frac{\mathsf{D}}{\mathsf{Y}} \tag{30}$$

Since steady state debt to GDP is zero, either G or τ^g will fluctuate to maintain the long-run equilibrium. A similar process plays out for f_p and tau^p for policing. In this case, I assume that G_t and $f_{t,p}$ follow an AR(1) process.

$$\log(G_t) = (1 - \rho_g)\log(\tau^g Q_{ss} Y_{ss}) + \rho_g \log(G_{t-1})$$
$$\log(f_{t,p}) = (1 - \rho_p)\log(\tau^p Q_{ss} Y_{ss}) + \rho_p \log(f_{t-1,p})$$

E Social Planner

If the social planner only cares about one household type, they will solve the above problem for just one household type, but give both types the same level of compensation. Finally, if they cannot distinguish between household types or are prevented from doing so, they will solve for the minimum level of compensation needed such that households are indifferent on

Table 12: Compensating Variation: Crime, 1% Less Crime, and No Crime

SPP type	High-Skilled CV	Low-Skilled CV	Aggregate CV
$\Delta s_i = -1\%$	0.10	0.09	0.19
$\Delta s_i = -100\%$	1.04	0.57	1.61
Both	1.06	0.75	1.81
HS	–	–	3.34
LS	–	–	1.08
Overall	–	–	1.54

CV is measured as the percentage of the net present value of output. The first row shows CV in the case of a 1% decline in crime where CV compares two models with $s^j_{i,ss}$ and $0.99s^j_{i,ss}$. The second row does the same for a 100% decline in crime with CV comparing two models with $s^j_{i,ss}$ and $s^j_{i,ss} = 0$. The third through sixth rows show a comparison between two models with $s^j_{i,t}$ and $s^j_{i,t} = 0$. The first through third rows assume that the social planner wants both households to be indifferent. The fourth and fifth rows assume the social planner only cares about the high and low-skilled households respectively. Finally, the sixth row assumes that the social planner cannot discriminate, so they only care about making households indifferent on average.

average.

$$\sum_{i\in\{h,l\}}\sum_{t=1}^{T}\beta^t\phi_i\Big\{U_{t,i}(P_{t,i},C^m_{t,i},C^s_{t,i},N_{t,i},s^h_{t,i},s^y_{t,i},\text{comp}^*) \\ - U_{t,i}(P^2_{t,i},C^{m,2}_{t,i},C^{s,2}_{t,i},N^2_{t,i},xs^h_{t,i},xs^y_{t,i})\Big\} = 0 \tag{31}$$

This implies that some households will be over-compensated and some households under-compensated.

If the social planner only cares about the high-skilled type, but compensates everyone the same, they must provide 3.34% of output in compensation. Similarly, if they only care about the low-skilled types, they must provide 1.08% of output in compensation. In both cases, the household type that the social planner ignores is not being compensated at their optimum. This results in behavioral changes on the part of the ignored households such that the household type the social planner cares about ends up with a different level of compensation than they would in the case of both types being independently compensated. If the social planner only cares about average utility, or they are prevented from discriminating

Table 13: Comparison: CV and Output

	Baseline	Fixed C^s	Fixed T	Fixed C^s, T	Fixed N	Fixed P	Fixed ϕ_p	Fixed I
CV	1.81	2.66	1.02	1.87	1.53	2.81	2.42	2.29
% difference	-	46.9	-43.6	3.31	-15.5	55.2	33.7	26.5
%Δ Output	2.79	2.25	1.77	1.24	1.70	2.27	1.80	1.70
% difference	-	-19.3	-36.5	-55.7	-38.9	-18.5	-35.4	-39.1
%$\Delta\frac{\text{std}}{\text{mean}}$ Output	-1.98	-1.80	-1.47	-1.28	-39.9	-1.89	-1.88	7.97
% difference	-	9.1	25.8	35.4	-1900	4.5	5.1	-303

CV is measured as the percentage of the net present value of output. In all cases, CV assumes that crime decreases 100% and the social planner is attempting to make both households just as well off. To refresh everyone's memory, C^s is crime consumption, T refers to all losses by firms and households, N is labor supply, P is the non-incarcerated population, ϕ_p is the fraction of resources used for policing, and I is investment.

based on type, they must compensate households 1.54% of output. This is lower than the 1.81% from the case of independent compensation since the high-skilled types are now worse off than under independent compensation while the low-skilled types are better off. In the end, it cancels out. Ultimately, the cost of property crime depends on who one cares about and depends on whether one cares about the value that comes from having the ability to commit property crime. This is a big reason why the welfare cost of property crime is significantly lower than the value of lost output that I calculated earlier (1.8% vs 3.5%).

Holding labor supply N fixed in column 5 reduces CV by 15.5% suggesting that households are responding to the presence of theft by changing their labor supply. Taking away the ability to change behavior is a detriment to households as a result. This is further re-enforced by a 35.5% decline in the output response. This can be attributed to labor supply not changing even though the marginal product of labor, the marginal utility of consumption, and the marginal utility of labor increased. In a similar vein, holding ϕ_{police} fixed to prevent the police from transitioning to productive labor decreases the output response by 32.2% as these workers are not productive. Fixing investment I decreases the output response by 35.5% as investment is not at the optimum resulting in capital accumulation being lower than desired. Finally, looking at the effect that fixing the incarcerated population has gives some insight into some of the more unusual outcomes in the table above. When the incarcerated population is released, all resources are redistributed among the households which actually reduces welfare as all resources are more spread out.

F Robustness

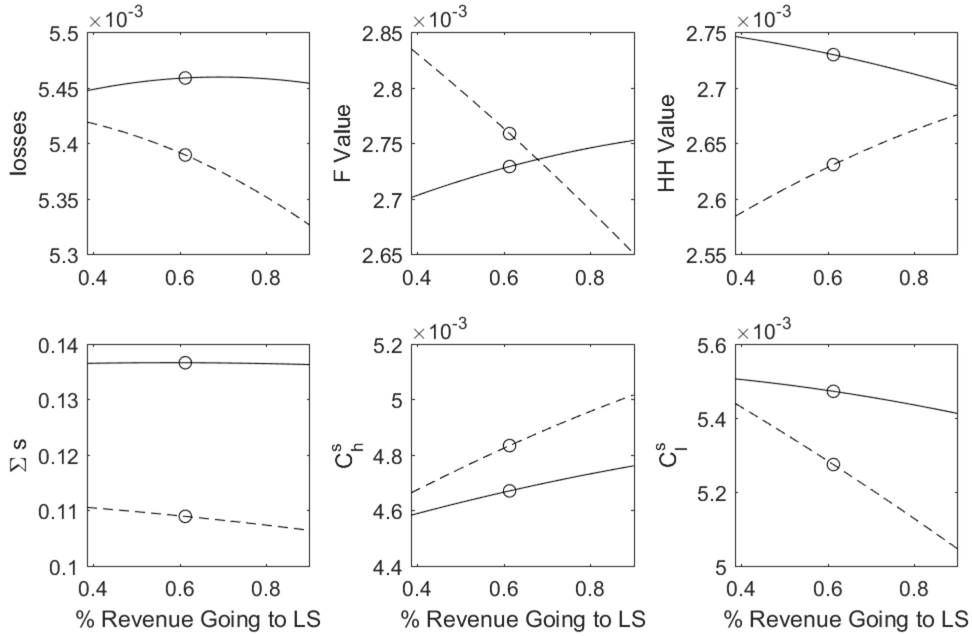


Figure 8: Transfers to LS Workers (Revenue Clearing)

Figure 8 shows the impact of changes in transfers to low-skilled workers. As transfers to low-skilled workers increase, transfers to high-skilled workers decrease. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to an alternative calibration where the low-skilled household receives twice what the high-skilled household receives.

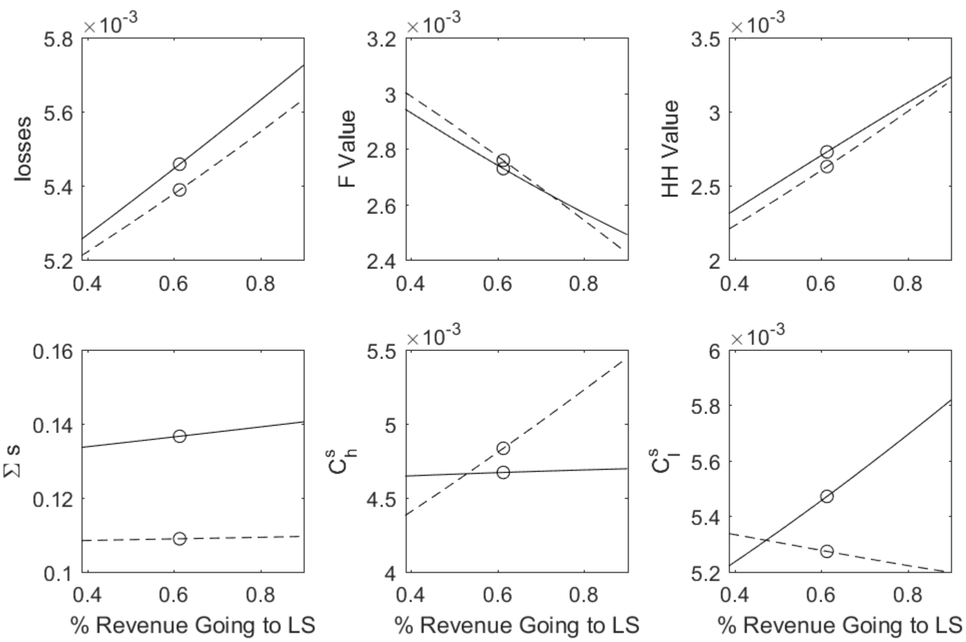


Figure 9: Transfers to LS Workers (Fixed HS Transfers)

Figure 9 shows the impact of changes in transfers to low-skilled workers with fixed transfers to high-skilled workers. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to an alternative calibration where the low-skilled household receives twice what the high-skilled household receives.

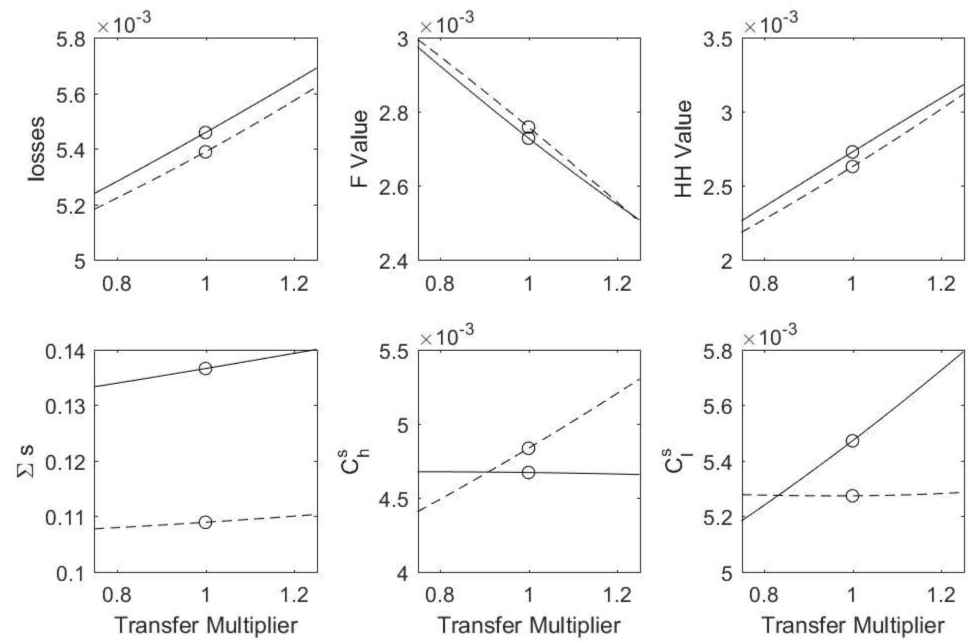


Figure 10: Transfer Multiplier

Figure 10 shows the impact of changes in transfers holding tax revenue constant. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to an alternative calibration where the low-skilled household receives twice what the high-skilled household receives.

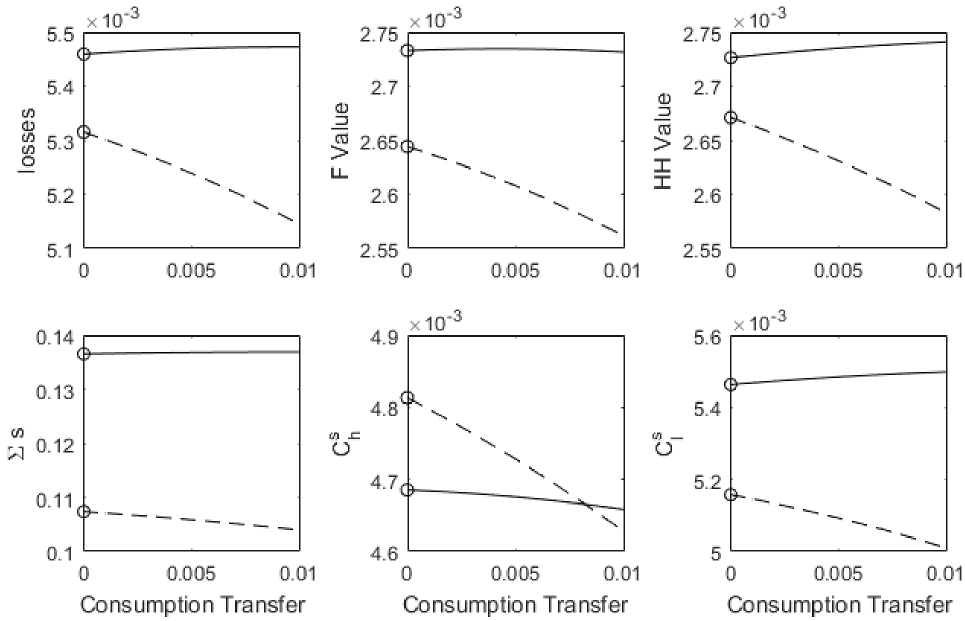


Figure 11: Consumption Transfer

Figure 10 shows the impact of consumption transfers that do not show up in the budget constraint. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to an alternative calibration where the low-skilled household receives twice what the high-skilled household receives.

Table 14: Calibrated Parameters

	Description	Baseline	Unequal Transfers	Unequal Burden	Government Borrowing
χ_h	elasticity of labor supply for H	0.698	0.719	0.537	0.699
χ_l	elasticity of labor supply for L	0.735	0.655	0.765	0.740
σ_h	baseline utility for H	0.303	0.300	0.348	0.303
σ_l	baseline utility for L	0.166	0.188	0.112	0.170
σ	incarcerated baseline utility	0.902	0.969	0.841	0.937
a_h^y	TFP for theft from firms for H	0.045	0.051	0.061	0.047
a_l^y	TFP for theft from firms for L	0.028	0.035	0.036	0.028
a_h^h	TFP for theft from HH for H	0.032	0.060	0.046	0.033
a_l^h	TFP for theft from HH for L	0.030	0.031	0.039	0.030
b	theft time discount	0.014	0.021	0.021	0.015
b_2	theft consumption discount	0.484	0.475	0.491	0.490
δ	curvature of jail probability function	2.590	2.373	2.054	2.608
η	curvature of crime value function	0.929	0.921	0.882	0.933
ρ_z	AR(1) process	0.608	0.607	0.583	0.609
ε_z	shock to TFP	0.020	0.020	0.022	0.020
θ	marginal probability of going to jail	1839	2119	2078	1871
γ	high-skill labor output share	0.372	0.390	0.381	0.371
z_p	TFP for law enforcement	3.771	2.992	2.784	3.734

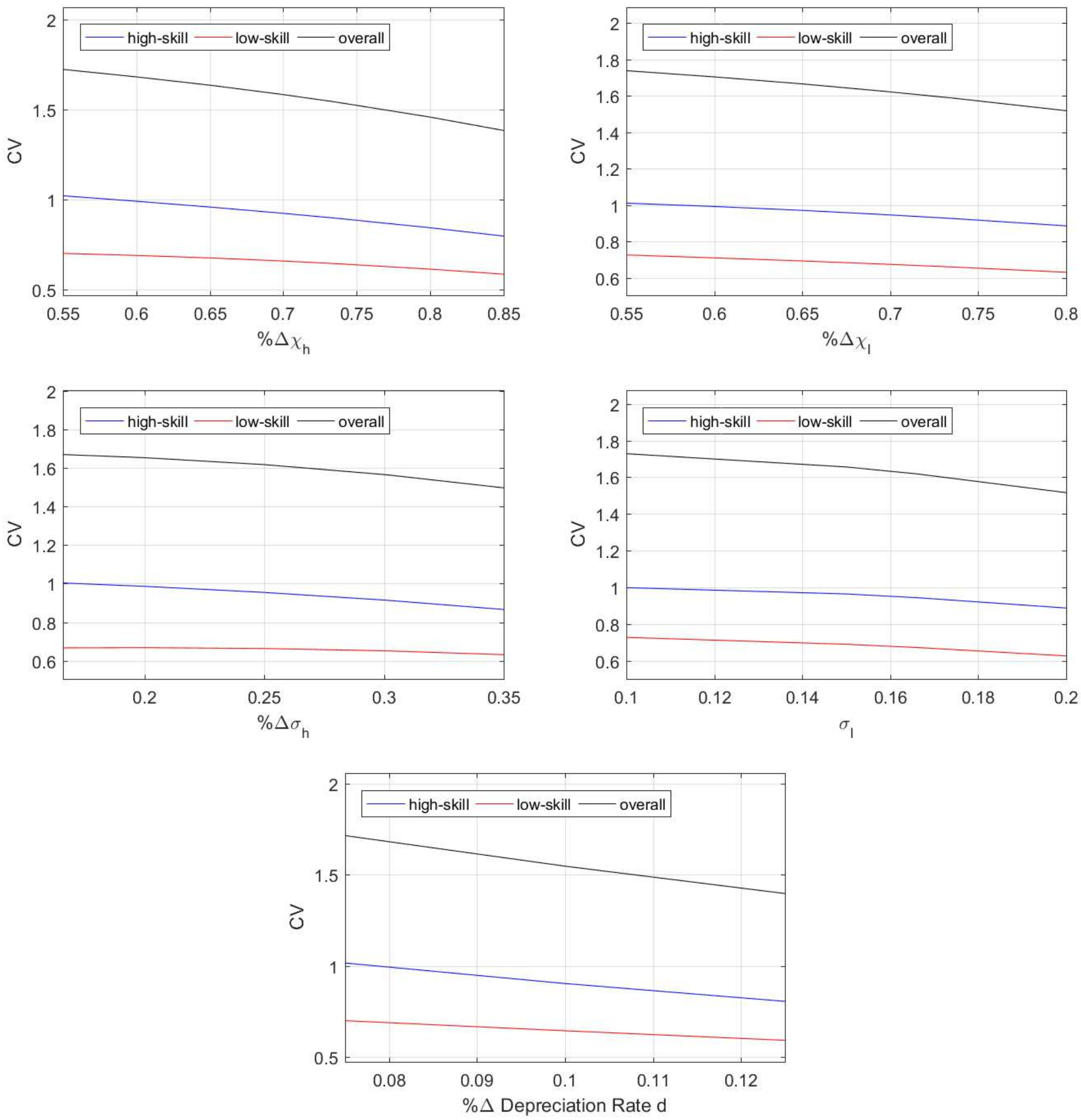
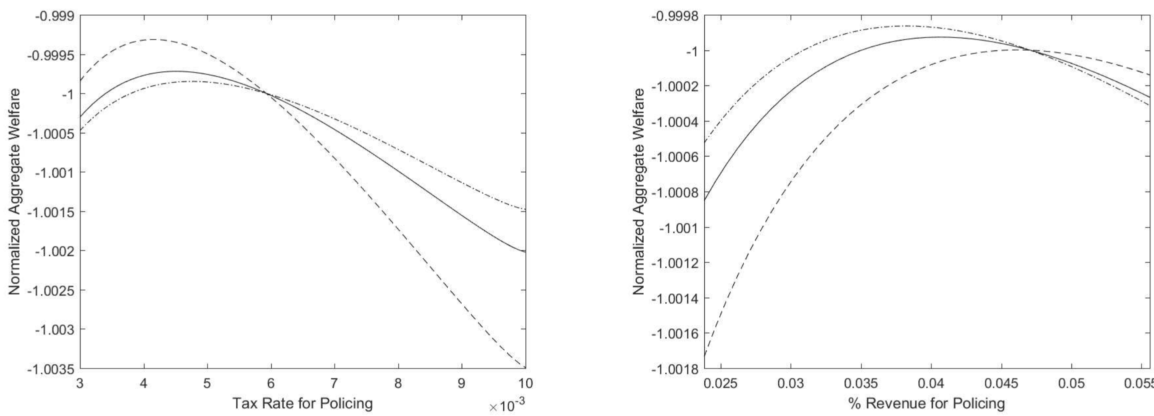


Figure 12: Robustness of CV to Changes in Baseline Parameterization



(a) (b)

Figure 13: Optimal Taxation for Policing

(a) shows welfare for changes in the tax rate for policing while (b) shows welfare for changes in the share of tax revenue that goes towards policing. The solid line corresponds to the baseline calibration with both household types receiving the same level of government transfers. The dashed line corresponds to high-skilled households while the dash-dotted line corresponds to low-skilled households. The solid line represents overall welfare.