ESSAYS ON MACROECONOMICS
AND LABOR ECONOMICS

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ABSTRACT

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This dissertation consists of three independent chapters at the intersection of macroeconomics and labor economics. The first chapter studies the job-search tradeoffs between full-time employment, part-time employment, and multiple job holdings. The second chapter explores the macroeconomic relationship between property crime and output in a dynamic stochastic general equilibrium framework. The third chapter studies the causal effect of property crime on output.

The first chapter develops a search-matching model of the labor market with part-time employment and multiple job holdings. The model is calibrated to data from the CPS between 2001 and 2004. Workers are able to choose their search intensity and are allowed to hold two jobs while firms can choose what type of worker to recruit. When compared to the canonical Diamond-Mortensen-Pissarides model, this model performs quite well while capturing some empirical regularities. First, the model generates recruiting and vacancy posting rates that move in opposite directions. Second, part-time employment is up to 10 times more responsive than full-time employment. Third, the model suggests that multiple job holding rates are more flexible than observed in the data with the rate changing by as much as 4 percentage points compared to 0.1 percentage points in the data. Finally, the full model is able to capture compositional changes during recessions with the full-time rate declining and the part-time rate increasing. It also produces an empirically consistent increase in

the unemployment rate as well as a decrease in output. The DMP model is more muted than in the data for both.

The second chapter explores 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.

The third chapter estimates the causal effect of property crime on real personal income per capita. Running system GMM on an unbalanced panel of MSA-year pairs suggests that property crime reduces real personal income per capita by a highly statistically significant 13.3%. This implies that the average person loses $4,869 (2009 dollars) per year with real annual personal income per capita totaling $36,615. The effect is driven primarily by larceny-theft and burglary with highly statistically significant coefficients of -0.179 and -0.110 respectively. Estimates for the effect of robbery are unstable, and the effect of motor vehicle theft is statistically significant, but smaller with a coefficient of -0.060.

1. A SEARCH THEORETIC MODEL OF PART-TIME EMPLOYMENT AND MULTIPLE JOB HOLDINGS

1.1 Introduction

Between 1996 and 2014, roughly 20% of the labor force were part-time workers or worked multiple jobs.[1] Faberman et al. (2017) suggest that a worker's job prospects, search behavior, and firm recruiting differ based on the workers employment status. Further, they suggest that roughly 55% of workers would be willing to take an additional job under the right circumstances.[2] Together, these facts suggest that modelling all jobs as full-time (FT) jobs overlooks some fundamental features of the labor market. Overlooking part-time (PT) employment and multiple job holdings (MJH) takes on greater importance given the persistently high rate of part-time employment following the 2007-2009 recession, which has become an area of growing interest. Valletta and van der List suggest the part-time employment rate is higher now than in the past, even with business cycles and industry accounted for (Economic Letters - FRBSF, 2015-19) In particular, they show that part-time employment for economic reasons is around one percentage point higher than in the past under similar circumstances, suggesting there may have been a structural change in the labor market. Further, the persistently high rate of part-time employment has prompted the Federal Open Market Committee to consider the part-time employment rate in addi-

[1] See Appendix A.

[2] This rate is comparable to the rate for employed workers looking for a new job and to findings from Paxson and Sicherman (1996) who suggest that 50% of all workers will have multiple jobs at some point in their life.

tion to the unemployment rate when gauging the status of the labor market (FOMC minutes from July 2016).

The goal of this paper is to explore the relationship between search frictions, part-time employment, and multiple job holdings. Part-time employment is closely related to multiple job holdings as search frictions can make taking a part-time job and looking for a secondary full-time job more attractive to workers. On the other hand, firms are also considering who they will recruit and hire and may look more or less favorably on multiple job holders and part-time workers depending on how difficult it is to match with a given type of worker. For instance, if firms observe that it is difficult to match with an unemployed worker, they may be more willing to accept a multiple job holder. In both cases, workers and firms can use part-time employment and multiple job holdings to smooth their expected outcomes.

To this end, I develop a model building on the Diamond-Mortensen-Pissarides (DMP) framework, extended to allow for PT employment and MJH. In the canonical DMP model, all jobs are assumed to be full-time and require the same skill set. In addition, workers can only hold one job. Extensions of the DMP model have allowed for variable productivity and skills, but there has been limited research allowing for both variable hours and multiple job holdings. In my model, workers search for full-time and part-time jobs simultaneously. In addition, they can hold multiple jobs. Firms can recruit part-time and full-time workers simultaneously as well as multiple job holders.

Separately calibrating my model to U.S. labor market data from December 2001 to December 2004 and January 2015 to December 2016, the model compares favorably to the DMP model and a model with only multiple job holdings along shared dimensions. Using data on job loss probabilities and the consumer Price Index for the 2007-2009 recession, the full model performs well at matching the unemployment rate response of 1.70 pp in the data with a difference of 2.64 pp compared to a difference of 0.2 pp in the DMP model. The results also suggest that multiple job holdings could be more responsive than what is observed with an decrease of 4 pp in the model compared to a decrease of 0.03 pp in the data. As suggested by Abraham et al. (2013), multiple job holdings can be difficult to observe in the data as workers and firms each have different incentives to report. This could be why it is difficult to establish the relationship between economic conditions and multiple job holding rates as the CPS may under-report or over-report depending on conditions.

Additionally, the standard DMP model is qualitatively consistent with the relationship between the unemployment rate and the full-time employment rate (a negative correlation of -0.66); however, the base model cannot say anything about the relationship between the unemployment rate and the part-time rate (A positive correlation of 0.51). By considering all jobs to be full-time jobs, the implications of policy and structural changes in the standard DMP model may not be consistent with a model that explicitly separates full-time and part-time employment. Full-time and part-time employment can respond differently, but because the full-time employment rate is over four times as large as the part-time employment rate, the response in FT employment dominates. In the full model, the part-time rate is typically 10 times more responsive than the full time rate in percentage terms, and up to twice as responsive in percentage point terms. The part-time employment rate does not always move in the same direction as the full-time employment rate as in the case of a change in recruiting cost. Multiple job holdings can also affect the observed part-time rate as in the case of recessionary conditions that lead to a higher than expected part-time rate as a result of a much lower multiple job holding rate. Altogether, this suggests that part-time employment and multiple job holdings can have implications for policy depending on who the policymaker cares about.

The next subsection discusses related literature followed by relevant stylized facts from the data. In Section 1.2, a simple environment and equilibrium with multiple job holdings, but only one type of job, is described. Section 1.3 presents the environment with both PT employment and multiple job holdings as well as the corresponding steady-state equilibrium. In Section 1.4, the model is calibrated to match U.S. data from December 2001 to December 2005. Finally, results are presented in Section 3.5 and discussed in section 1.6.

1.1.1 Related Literature

This paper builds on three branches the literature. First, I consider the literature on joint-search and multiple job holdings. Guler, Guvenen, and Violante (2012) construct a one-sided joint-search model of a household in which two individuals with pooled utility and consumption search for and hold jobs simultaneously. I extend their model to allow for firm choice regarding whether to hire a secondary worker and household and firm choice regarding FT versus PT employment.

Zhao (2016) extends the GGV model to multiple job holders and suggests that the opportunity to hold multiple jobs makes holding part-time work more valuable as it provides workers with more opportunities to find full-time work and smooth their income over states. I extend this model by introducing firms to the problem, and discuss the role of search and recruiting behavior in this context. Since previous work is only one sided, nothing can be said about the impact of firm-side labor market policy on employment status, worker flows, and search behavior. I am able to evaluate not only how policies affect workers, but also how firm choices affect workers. Firms prove to be especially important for determining outcomes.

The second branch of the literature is on search intensity. Pissarides (2000) provides a simple model for thinking about search intensity, but the model implies that workers should search less when the labor market is slack. To reconcile this with the fact that workers search harder under slack labor market conditions, Shimer (2004) uses an urn-ball matching function to induce higher search. I extend this framework by allowing workers to take two jobs simultaneously in a simplified framework. I also introduce multiple matching functions depending on a worker's current employment status and the job they are searching for.

Finally, I consider the literature on on-the-job search. Building off of Burdett and Mortensen's (1998) seminal work on on-the-job search, Christensen et al. (2005), Hornstein, Krusell, and Violante (2011), and Faberman et al. (2017) have introduced variable search intensity into models of on-the-job search. As in these papers, I allow for on-the-job search as well as variable search effort and success depending on a worker's employment status. Faberman et al. is especially pertinent as they find that employed workers differ from unemployed workers in their search behavior and firms recruiting to them differently as well. This is in line with Davis, Faberman, and Haltiwanger (2013) who find that firms often use informal recruiting methods when hiring workers. I include these elements by allowing for variable search intensity and recruiting intensity depending on a worker's current state. I extend these models by introducing firms which allows for endogenous wages. This generates differential wages across employment status which supports the fact that employed workers face a different offer distribution than unemployed workers. Finally, Gavazza, Mongey, and Violante (2018) find that firm recruiting intensity and vacancy rate move in opposition such that during recessions, vacancies decline while recruiting intensity increases. Similar behavior occurs in the presence of multiple job holding and part-time employment. While aggregate vacancies may decline, changes in recruiting intensity can increase the effective vacancy rate for certain types of jobs.

1.1.2 Stylized Facts

My model targets four facts from the Survey of Consumer Expenditure (SCE) used by Faberman et al. (2017). First, 55.5% of workers would be willing to take an additional job and 68.4% who would be willing to take a new job. Second, full-time workers on average have 1.18 jobs compared to 1.41 jobs for part-time workers (t = 5.1647). These two facts suggest that multiple job holdings is an option that workers consider when making employment decisions, and that it is particularly relevant for part-time workers. Third, workers who would be willing to take an additional job send out 1.13 applications per month which yield 0.5 contacts per month in addition to 1.55 unsolicited contacts per month. This is compared to unemployed workers who send out 6.97 applications per month and yield 0.72 contacts per month in addition to 0.57 unsolicited contacts per month. Those seeking an additional job not only display different job search behavior, but their success appears to be different from unemployed workers. Firms also seek out multiple job holders more actively than they do unemployed workers. While some of these differences are likely due to signaling and skill, some are likely due to matching frictions. These facts reinforce the notion that search by employed individuals is different than for unemployed individuals.

Finally, part-time workers send out twice as many job applications per month as do full-time workers, however, the success rate for full-time workers is higher with both receiving roughly 0.57 contacts per month. In addition, full-time workers receive 1.76 unsolicited contacts per month compared to 1.16 per month for part-time workers. This suggests that part-time worker search behavior is different from full-time worker search behavior and that the search frictions they face differ to a degree. In the canonical DMP model, all of these workers are treated the same despite having different search behavior and outcomes. If firms and workers are interacting differently depending on the worker's status, then the implications of the DMP model may miss compositional changes among the employed. To address this, my model treats unemployed workers, full-time workers, part-time workers, and multiple job holders differently to account for these differences.

Next, consider two stylized facts from the Current Population Survey (IPUMS-CPS). First, I calculate monthly worker flows[3] for potential workers aged 25-54 using the CPS. The structure of the CPS shows the employment status of workers for two four month periods, allowing for two sets of three monthly transitions. Focusing primarily on the time period from 2006 to 2012[4], the number of workers moving from unemployment to part-time employment increases despite a drop in the flow rate. Since the stock of unemployed workers is getting larger and firms and workers are shifting their search and recruiting to part-time work, the increased stock outweighs the lower job finding rate for workers.[5] While the 2001 recession seems to generate similar trends, the limited time frame makes it more difficult to parse from the overall trend.

Second, there is persistence in flows to part-time for economic reasons during the entire sample period. Flows between unemployment and part-time employment for economic reasons increased throughout the 2000s, and peaked following the 2007-2009 recession. While the monthly flow counts have tapered off, they are still at an elevated level compared to the beginning of the recession. Many workers would like full-time employment, but are unable to find anything other than part-time employ-

[3] The method used to derive worker flows is provided in Appendix A

[4] While the NBER limits the most recent recession to 2007-2009, a wider time period captures the entrance and exit from the trough.

[5] The flows between full-time and part-time employment as seen in Figure 1.1, are substantial month-to-month with an average of 3.7 million workers becoming part-time and 3.8 million becoming full-time. These transitions dwarf the other values combined. Warren (2016) provides a nice explanation for what is happening in this case by showing that firms facing search frictions and recruiting costs can find it optimal to switch workers between part-time and full-time rather than firing them in response to productivity shocks. My model will not be able to account for this effect as I perform my analysis using steady-states which do not allow for such a transition to exist endogenously in equilibrium. While I have considered the case of variable worker-firm productivity, the problem space becomes very intractable making it difficult to interpret.

ment suggesting there may have been a structural shift during the 2000s as suggested by Valletta and van der List (2015). Part-time work can be used by workers to smooth income while they search for a full-time job. This could lead to multiple job holdings as workers are not necessarily working the hours they desire.

Altonji and Paxson (1988) theorize workers switch jobs when faced with hourly constraints and are more willing to accept a pay cut. An alternative theory by Perlman (1966) and Shishko and Rostker (1976) suggests workers respond by holding second jobs. Paxson and Sicherman (1996) find workers faced with hourly constraints will respond by holding multiple jobs; However, the multiple job holding rate is acyclical. This suggests that the while there may be more workers willing to work multiple jobs, the contraction in the number of vacancies can cancel out any effect. It also suggests that it is caused by some structural elements of the economy that should not necessarily be overlooked, especially when looking at part-time employment.

Overall, it appears that unemployed, part-time, and full-time workers behave differently and have different labor market outcomes. They not only search in different ways, but they receive job offers in different ways as well suggesting firms view each type of worker differently. To get at some of these facts, I model the search frictions and trade-offs that workers and firms face when choosing search and recruiting intensity. I allow for these choices to be made based on current status and the desired job type. Once the equilibrium is described and the model is calibrated, I perturb some of the structural components of the model to see how they affect part-time employment and other labor market outcomes.

1.2 Multiple Job Holdings

In order to get a better understanding of the choices that workers are making, I consider a simplified framework with workers who can hold two jobs simultaneously, but there is no distinction between part-time and full-time employment. Multiple job holdings is particularly relevant when considering part-time employment as part-time workers are more likely to have multiple jobs and the option of additional employment increases the flow value of being a part-time worker. An unemployed worker's goal is to get at least one job offer and then search for an additional job once employed.

Environment

Consider a discrete time job search model where time goes on forever. There is a continuum of infinitely lived, risk-neutral workers with lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t y_t$$

where y_t is the worker's instantaneous income at time t and $\beta \in (0, 1)$ is the discount factor.

Workers can be in one of three states: unemployed, employed with one job (primary), or employed with two jobs (primary and secondary). While unemployed or employed in one job, workers are assumed to always be searching for a job, but can choose the intensity with which they search. Unemployed workers can choose search intensity s_1, but they must pay weakly convex search cost $\sigma_1(s_1)$, while workers with one job choose their search intensity s_2, but pay weakly convex search cost $\sigma_2(s_2)$. While unemployed, workers receive some value of leisure z_1. If a worker is employed in one job, they receive some residual value of leisure z_2 as well as primary wage w_1. If a worker has two jobs, then they receive both the primary wage w_1 and the secondary wage w_2, but they have no residual value of leisure. There is one type of firm that can be in one of three states: vacant, employing one primary worker, or employing one secondary worker. Firms can post vacancies v and choose whether to recruit to unemployed workers (a_1) or employed workers ($a_2 = 1 - a_1$) while paying weakly convex recruiting cost $C(a_1, a_2)$. Firms that hire a worker of type $i \in \{1, 2\}$ receive output p_i and pay wage w_i.

Workers and firms are matched pairwise according to two constant returns to scale (CRTS) matching functions, one for the primary jobs and one for secondary jobs. As before the matching function depends on the effective mass of firms $(a_i v)$ and the effective mass of workers $(s_i l)$ where $l \in \{u, l_1\}$. The rate at which matches of type $i \in \{1, 2\}$ are formed between a firm and worker is given by

$$m_i(\bar{s}_i l, a_i v)$$

where the effective mass of workers depends on average search intensity over all workers $\bar{s}_i$ and $l_i \in \{u, l_1\}$. As a simplification, denote average market tightness such that $m_i(\bar{\theta}_i) = m_i(\bar{s}_i l, a_i v)$ and denote individual market tightness as $m_i(\theta_i) = m_i(s_i l, \bar{s}_i l, a_i v)$. An unemployed worker who chooses to search with intensity s_1 matches with at least one firm with probability

$$q_1(\theta_1, u) = \frac{m_1(\theta_1)}{u}$$

upon which they can only accept one job offer. Notice that the probability of a match depends on individual search intensity in addition to average search intensity. Similar to unemployed workers, an employed worker who chooses to search with intensity s_2 matches with at least one firm with probability

$$q_2(\theta_2, l_1) = \frac{m_2(\theta_2)}{l_1}$$

which also depends on individual and average search intensity.[6] The probability that a firm fills their vacancy with a primary worker is

$$p_1(\bar{\theta}_1, v) = \frac{m_1(\bar{\theta}_1)}{v}$$

[6]In equilibrium, $\bar{s}_i = s_i$ and $\bar{\theta}_i = \theta_i$ since all workers are ex-ante homogeneous.

which does not depend on the individual level of search intensity. Finally, the probability that a firm fills their vacancy with a secondary worker is given by

$$p_2(\bar{\theta}_2, v) = \frac{m_2(\bar{\theta}_2)}{v}$$

which does not depend on individual search intensity as before.

After a worker and firm match for a primary job, they face some risk that the job is destroyed with probability λ_1, in which case the worker transitions to unemployment, and the firm decides whether to post a vacancy. Should they match for a secondary job, then workers and firms face risk that the job is destroyed with probability λ_2, in which case the worker transitions to holding one job and searching for a second, and the firm decides whether to post a vacancy. In addition, secondary firms also have some risk of becoming a primary employer if their employees primary job is destroyed with probability λ_1. While the job destruction probability is denoted differently for each job type, λ_2 could theoretically equal λ_1.

Equilibrium

At the beginning of each period, workers and firms find out if they matched. If a an unemployed worker matches with one firm, they agree with the firm on the primary wage. If an employed worker matches with a firm, they agree with the firm on the secondary wage. A worker with one job receives the primary wage as well as the residual value of leisure, and they choose their search intensity while paying some search cost. If a worker is employed in two jobs, they receive both the primary and secondary wage. If a worker remains unemployed, they receive the instantaneous value of leisure and choose their search intensity while paying some search cost. If a firm matches with a worker of type i, they receive the corresponding value of output and pay the corresponding wage. If a firm remains vacant, they choose their recruiting intensity and pay some recruiting cost.

Firm's Problem

Firms start by posting a vacancy and choosing recruiting intensity a_1 for unemployed workers and recruiting intensity $a_2 = 1 - a_1$ for employed workers. Firms choose their recruiting intensity to maximize flow value

$$V = \max_{a_1} \Big\{ - C(a_1, a_2) + \beta V + \beta p_1(\bar{\theta}_1, v)[J_1 - V] + \beta p_2(\bar{\theta}_2, v)[J_2 - V] \Big\} \tag{1.1}$$

where they pay recruiting cost $C(a_1, a_2)$ and match with a primary worker with probability $p_1(\bar{\theta}_1, v)$ and with a secondary worker with probability $p_2(\bar{\theta}_2, v)$. If they match with a primary worker, they receive flow value

$$J_1 = x_1 - w_1 + \beta J_1 + \beta\lambda_1[V - J_1] \tag{1.2}$$

where instantaneous income is the value of output x_1 and instantaneous cost is wage w_1. They also face some risk that the job is destroyed with probability λ_1 in which case they choose whether to open a vacancy. If they match with a secondary worker, they receive flow value

$$J_2 = x_2 - w_2 + \beta J_2 + \beta\lambda_2[V - J_2] + \beta\lambda_1[J_1 - J_2] \tag{1.3}$$

where instantaneous income is the value of output x_2 and instantaneous cost is wage w_2. They also face some risk that the job is destroyed with probability λ_2 in which case they choose whether to open a vacancy. They also face some risk that their employees primary job is destroyed with probability λ_1 in which case they become the primary employer. Because the goods market is perfectly competitive, firms will post vacancies until the flow value of posting an additional vacancy $V = 0$ in equilibrium.

The choice of recruiting intensity for full-time workers a_f is given by equation (1.2)

$$\frac{\partial C}{\partial a_1} = \beta \frac{\partial p_1(\bar{\theta}_1, v)}{\partial a_1} J_1 + \beta \frac{\partial p_2(\bar{\theta}_2, v)}{\partial a_1} J_2$$

where firms do not account for the effect that recruiting has on wages. As the firm increases their recruiting intensity for unemployed workers they pay some direct cost of recruiting denoted on the LHS. On the RHS, there are both costs and benefits. First, there are gains to the probability that the firm matches with an unemployed worker, but costs due to a fall in the probability of matching with an employed worker.

Worker's Problem

Unemployed workers receive some value of leisure z_1 and choose their search intensity in order to maximize the flow value

$$U = \max_{s_1} \quad \Big\{ z_1 \big(1 - h_1(s_1)^{\nu}\big) + \beta \big(U + q_1(\theta_1, u)[E_1 - U]\big) \Big\} \tag{1.4}$$

where they pay search cost $z_1 h_1(s_1)^{\nu}$. Their choice of search intensity affects the probability that they match with one firm for a primary job with probability $q_1(\theta_1, u)$. If a worker has only one job, they choose their search intensity to maximize their flow value

$$E_1 = \max_{s_1} \quad \Big\{ w_1 + z_2 \big(1 - h_2(s_2)^{\nu}\big) + \beta E_1 + \beta \lambda_1 [U - E_1] + \beta q_2(\theta_2, l_1)[E_2 - E_1] \Big\} \tag{1.5}$$

where wage w_1 and residual value of leisure z_2 is their instantaneous income. They face some risk that the job is destroyed with probability λ_1 in which case they become unemployed, and some probability $q_2(\theta_2, s_2)$ that they match with a secondary firm and become a multiple job holder. If a worker has two jobs, they receive flow value

$$E_2 = w_1 + w_2 + \beta E_2 + \beta(\lambda_1 + \lambda_2)[E_1 - E_2] \tag{1.6}$$

where the wages w_1 and w_2 are their instantaneous income and they face some risk of losing one job with probability $(\lambda_1 + \lambda_2)$ in which case they transition to single job holding.

The choice of search intensity s_1 for an unemployed worker is given by equation (1.7)

$$z_1 h_1(s_1)^{\nu-1} = \beta\Big(\frac{\partial q_1(\theta_1, u)}{\partial s_1}[E_1 - U] + q_1(\theta_1, u)\frac{\partial[E_1 - U]}{\partial s_1}\Big) \tag{1.7}$$

where $\alpha_1 = 1 - \beta(1 - \lambda_1)$, $\alpha_2 = 1 - \beta(1 - \lambda_1 - \lambda_2)$, $\alpha_{1u} = \alpha_1 + \beta(q_1(1) + q_1(2))$, and $\alpha_{21} = \alpha_2 + \beta q_2(1)$. On the LHS, workers pay some direct cost from increasing search intensity s_1 while the RHS denotes the indirect costs and benefits of increasing search intensity. If an unemployed worker increases their search intensity, they increase the probability of matching with any number of firms. The choice of search intensity s_2 for an employed worker is given by equation (1.8).

$$z_2 h_2(s_2)^{\nu-1} = \beta\Big(\frac{\partial q_2(\theta_2, l_1)}{\partial s_2}[E_2 - E_1] + q_2(\theta_2, l_1)\frac{\partial[E_2 - E_1]}{\partial s_2} - \beta\lambda_1\frac{\partial[E_1 - U]}{\partial s_2}\Big) \tag{1.8}$$

The LHS contains the direct cost of increasing search intensity s_2 while the RHS contains both costs and benefits. Focusing on the RHS, the worker gains through an increase in the probability that they match with a secondary firm.

Wage Determination

When a worker-firm match is formed, they bargain over the wage which reduces to the axiomatic Nash Bargaining solution.[7] Workers and firms have full information about each other and the worker has bargaining power γ while the firm has bargaining power $1-\gamma$. Thus the wage for a job of type $i \in \{1,2\}$ is determined by

$$w_1 = \text{argmax}(E_1 - U)^{\gamma}(J_1 - V)^{1-\gamma} \tag{1.9}$$

$$w_2 = \text{argmax}(E_2 - E_1)^{\gamma}(J_2 - V)^{1-\gamma} \tag{1.10}$$

which yields a system of two equations for wages w_1 and w_2 as in equations (1.11) and (1.12).

$$w_1 = \frac{\gamma\alpha_{21}x_1 - (1-\gamma)[\alpha_{21}(z_2 - z_1 + \sigma_1 - \sigma_2) + \beta q_2(\theta_2, l_1)(w_2 - z_2 + \sigma_2)]}{\alpha_{21}} \tag{1.11}$$

$$w_2 = \frac{\gamma\alpha_{1u}\big[\alpha_1 x_2 + \beta\lambda_1(x_1 - w_1)\big] - (1-\gamma)\alpha_1\big[\alpha_{1u}(\sigma_2 - z_2) + \beta\lambda_1(w_1 + z_2 - z_1 + \sigma_1 - \sigma_1)\big]}{\alpha_{1u}\alpha_1} \tag{1.12}$$

The wage for a job of type i depends not only on the surplus generated from creating a job of type i, but also on the surplus generated from creating a job of type $-i$. If x_2 were to increase without a corresponding increase in x_1, then w_2 would increase while w_1 decreases. Similarly, if x_1 were to increase, w_1 would decrease while w_2 decreases.

Steady-State

Definition 1.2.1 *The steady-state equilibrium consists of a list (u, l_1, v, a_1, w_1, w_2, s_1, s_2) that solves the unemployment flow equation*

$$q_1(\theta_1, u)u = \lambda_1(l_1), \tag{1.13}$$

[7]The Nash bargaining solution used here is introduced in Diamond (1982) and Pissarides (1984a). Justification for this solution is provided in Binmore, Rubinstein, & Wolinsky.

the single job holder employment flow equation

$$\big[q_2(\theta_2, l_1) + \lambda_1\big] l_1 = q_1(\theta_1, u)u + (\lambda_1 + \lambda_2) l_2, \tag{1.14}$$

the job creation condition for vacancies

$$C(a_1, a_2) = \beta p_1(\theta_1, v)\Big(\frac{x_1 - w_1}{\alpha_1}\Big) + \beta p_2(\theta_2, v)\Big(\frac{\alpha_1(x_2 - w_2) + \beta\lambda_1(x_1 - w_1)}{\alpha_1\alpha_2}\Big), \tag{1.15}$$

the firm's recruiting intensity maximization equation (1.2), two wage setting conditions (1.11) and (1.12), and the worker's two search intensity maximization equations (1.7) and (1.8).

When workers and firms have the option to hold multiple jobs, their choices depend on not only on their current employment status, but also their future employment status which could include a second job. Search intensity and recruiting intensity depend not only on the direct and indirect costs and benefits of searching/recruiting for a given type of job, but also the indirect costs and benefits for the other type of job. Even if the two types of jobs are identical in every way, the problem does not reduce to the standard DMP model unless multiple job holdings is turned off entirely. All together, this suggests that multiple job holdings should be considered alongside part-time and full-time employment.

1.3 Part-Time Employment and Multiple Job Holdings

Now that I have described the multiple job holding choice, I consider the full model with both multiple job holdings and a full-time/part-time choice. Because it is extremely rare to go from unemployed to multiple job holdings and vice versa, I do not allow a worker to accept more than one offer per period. This simplifies the model and the analysis without causing major problems since the probability is so small that excluding it will not have much effect on behavior.

Environment

As before, consider a discrete time job search model where time goes on forever. There is a continuum of infinitely lived, risk-neutral workers with lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t y_t$$

where y_t is the worker's instantaneous income at time t and $\beta \in (0,1)$ is the discount factor.

Workers can be in one of 6 states: unemployed, employed in a part-time job, employed in a full-time job, employed in a primary part-time job and secondary full-time job, employed in two part-time jobs, and employed in a primary full-time job and secondary part-time job. Each worker is endowed with 240 hours of time per month with a full-time job taking 160 hours and a part-time job taking 80 hours.[8] Workers can search for a job until they have at most two jobs. There is one type of firm that can be in one of 6 states: vacant, employing a primary, secondary, or dual part-time worker, and employing a primary or secondary full-time worker. Firms can only employ one worker regardless of how much time the job takes. With endogenous wages and endogenous recruiting intensity, firms are indifferent between hiring a worker for a full-time job or a part-time job.

Workers and firms are matched pairwise according to five CRTS matching functions depending on the worker's state. Vacant firms choose their recruiting intensity for full-time and part-time jobs as well as for primary and secondary job holders which effects the rate at which they match with a given type of worker. In addition, workers can choose search intensity which effects the rate at which they match with a firm for a given job type. Thus, the matching function depends on the

[8] A histogram of primary working hours shows a mass of workers at 20 hours and another at 40 hours of work per week which is equivalent 80 and 160 hours per month assuming 4 weeks in a month. In addition, a histogram of secondary work hours shows a big mass of workers at 10 hours and another at 20 hours. For simplicity, I ignore the 10 hour mass and focus on 20.

effective mass of firms and the effective mass of workers. The rate at which matches are formed between a firm and an unemployed worker in state is given by

$$m_i u(s_{iu}, \bar{s}_{iu}, u, a_s, a_i, v) = \frac{s_{iu} u(1-a_s)a_i v}{\bar{s}_{iu} u + (1-a_s)a_i v}$$

where u is the mass of unemployed workers searching for a job of type $i \in$\{full-time (f), part-time(p)\}, and v is the mass of vacancies. Unemployed workers search for full-time jobs and part-time jobs with respective search intensities s_{fu} and s_{pu} while firms recruit to full-time and part-time workers with respective recruiting intensities a_f where $a_p = 1 - a_f$. In addition, firms choose to recruit to unemployed workers with intensity $(1-a_s)$ with a_s being the recruiting intensity for secondary job holders. One way to think of recruiting intensity is as the effective fraction of vacancies that are directed toward each type of worker. The rate of matching also depends on the average search intensity for a job of type i denoted by $\bar{s}_{iu}$.[9] The rate at which vacancies are filled with an unemployed worker and a job of type i is given by

$$p_{iu} = \frac{s_{iu} u(1-a_s)a_i}{\bar{s}_{iu} u + (1-a_s)a_i v}$$

while the job finding rate for unemployed workers for a job of type i is given by

$$q_{iu} = \frac{s_{iu}(1-a_s)a_i v}{\bar{s}_{iu} u + (1-a_s)a_i v}.$$

The rate at which secondary matches for a job of type i are formed between a firm and worker who is in state $j \in$\{full-time (f), part-time (p)\} is given by

$$m_i j(s_{ij}, \bar{s}_{ij}, l_j, a_s, a_i, v) = \frac{s_{ij} l_j a_s a_i v}{\bar{s}_{ij} l_j + a_s a_i v}$$

[9]I depart from the urn-ball matching function in Section B as it tends to break down for extreme differences in recruiting and search intensities. Stevens (2007) shows that while the urn-ball matching function desirable properties in a discrete time framework, it does not satisfy the property that $m(0, v) = m(u, 0)$. As an alternative Stevens proposes the “telephone-line” matching technology that I implement here. This technology has the added benefit of working in continuous-time.

where l_j is the mass of workers currently working a job of type j. Full-time workers search for part-time jobs with intensity s_{pf} while part-time workers searchers for full-time and part-time jobs with respective search intensities s_{fp} and s_{pp}. As before, firms recruit for full-time and part-time workers and choose secondary recruiting intensity a_s. The rate at which vacancies are filled with a worker of type j and a job of type i is given by

$$p_{ij}(s_{ij}, \bar{s}_{ij}, l_j, a_s, a_i, v) = \frac{s_{ij} l_j a_s a_i}{\bar{s}_{ij} l_j + a_s a_i v}$$

while the job finding rate for a worker of type j for a job of type i is given by

$$q_{ij}(s_{ij}, \bar{s}_{ij}, l_j, a_s, a_i, v) = \frac{s_{ij} a_s a_i v}{\bar{s}_{ij} l_j + a_s a_i v}.$$

Workers who choose to search with intensity $s_{ij} > 0$ must pay some cost defined by the weakly convex cost function $\sigma_j(s_{ij})$. Firms recruiting with intensity $a_f \in [0, 1]$ and $a_s \in [0, 1]$ must pay weakly convex recruiting cost $C(a_f, a_s)$.

The matching functions exhibit two important traits for workers as they capture frictions due to congestion as well as exhibiting increasing returns to personal search intensity. As workers increase their search intensity on average ($\bar{s}_{ij}$), the effective mass of workers searching for a job increases which results in a lower job finding rate. On the other hand, as an individual worker increases their search intensity (s_{ij}), they increase their personal job finding rate. In a steady-state equilibrium, individual search intensity and average search intensity for all workers are the same.

For both workers and firms, jobs are destroyed when job specific shocks arrive to occupied jobs at an exogenous Poisson rate depending on the type of job. Thus, shocks arrive to primary part-time jobs at rate $\lambda_{p\to u}$, secondary part-time jobs at rate $\lambda_{pf\to f}$, secondary dual part-time jobs at rate $\lambda_{pp\to p}$, primary full-time jobs at rate $\lambda_{f\to u}$, and finally secondary full-time jobs at rate $\lambda_{pf\to p}$. In this model, these shocks move worker productivity from being high enough to make production profitable to being low enough to lead to worker-firm separation. Because the surplus generated for each job depends on the previous state, the necessary shock required to make a given job unproductive differs depending on the prior and current job status. In addition to job loss, full-time workers transition to part-time work at rate $\lambda_{f\to p}$ while part-time workers transition to full-time work at rate $\lambda_{p\to f}$.

While unemployed, workers receive some flow value from leisure $\chi_u b$ where b is the base value of leisure and χ_u transforms b based on the current state, which in this case is unemployment. Part-time workers receive value of leisure $\chi_p b$ and full-time workers receive some value of leisure $\chi_f b$, both being transformed based on the respective state. This reflects the fact that workers have 240 hours of time per month, but a full-time job only uses 160 and a part-time job only uses 80.

Upon being matched, each full-time firm-worker pair produces final output x_f expressed in units of utility, and each part-time firm-worker pair produces final output $x_p = x_f(0.5^{2/3})$.[10] Firm-worker pairs bargain over the wage that workers receive and firms pay depending on the state that the worker is in and moving into. Firms must also pay a full-time employment tax T when they employ a full-time worker.

Equilibrium

At the beginning of each period, workers receive their remaining value of leisure and wages if they are employed. Firms receive the final value of output and pay

[10]The evidence regarding worker productivity suggest that while part-time workers tend to be paid less than their full-time counterparts, most of this difference is due to difference in job requirements and worker heterogeneity. There does not appear to be any sizable difference between productivity for a part-time worker and a full-time worker who are otherwise identical. Since my model is assuming homogeneous worker types for now, I will assume that the final value of output for a part-time worker only differs based on the number of hours worked compared to a full-time worker. I assume that the production function is Cobb-Douglas in time spent working, so a worker who work half as much as a full-time worker produces $(0.5^{2/3})$ what a full-time worker produces. The two thirds comes from the labor share in the standard C-D function. For reference, see Aaronson and French (2004), Hirsch (2005), Manning and Petrongolo (2008), and Künn-Nelen, de Grip, and Fouarge (2013)

wages. Workers then choose how intensely to search for various jobs depending on their current state while vacant firms choose how many vacancies to post and how intensely to recruit for part-time and full-time jobs as well as how intensely to recruit for unemployed and employed workers. At the end of the period, some workers and firms match at a Poisson rate and then bargain over the wage.

Firms Problem

All firms start out posting one vacancy and choosing recruiting intensity for FT (a_f) and PT ($a_p = 1 - a_f$) jobs as well as primary ($1 - a_s$) and secondary jobs (a_s) while paying recruiting cost $C(a_f, a_s)$. They receive flow value

$$\begin{aligned}(1-\beta)V = \max_{a_f, a_s} \Big\{ & - C(a_f, a_s) + \beta[p_{fu}(J_f - V) + p_{fp}(J_{f\leftarrow p} - V)] \\ & + \beta[p_{pu}(J_p - V) + p_{pp}(J_{p\leftarrow p} - V) + p_{pf}(J_{p\leftarrow f} - V)]\Big\} \end{aligned} \tag{1.16}$$

and face some possibility that their FT vacancy is filled by unemployed or PT workers at rates p_{fu} and p_{fp} respectively. They also face some possibility that their PT vacancy is filled by unemployed, PT, or FT workers at rates p_{pu}, p_{pp}, and p_{pf}.

If a firm matches with an unemployed FT job seeker, they receive flow value

$$(1-\beta)J_f = x_f - w_{f\leftarrow u} - T + \beta\lambda_{f\to u}[V - J_f] + \beta\lambda_{f\to p}[J_p - J_f] \tag{1.17}$$

in which case the firm receives the final value of output p, but they must pay wage $w_{f\leftarrow u}$. If a firm matches with a PT worker, they receive flow value

$$(1-\beta)J_{f\leftarrow p} = x_f - w_{f\leftarrow p} - T + \beta\lambda_{fp\to p}[V - J_{f\leftarrow p}] + \beta\lambda_{p\to u}[J_f - J_{f\leftarrow p}] \tag{1.18}$$

in which case they receive the final value of output x_f, but they must pay wage $w_{f\leftarrow p}$. At this point, neither firm has any open vacancies, but they face some risk of their FT job being destroyed at rates $\lambda_{f\to u}$ or $\lambda_{fp\to p}$ respectively. In addition, a FT employer that matches with an unemployed worker faces some risk of the FT job becoming a PT job at rate $\lambda_{f\to p}$.

If a firm matches with an unemployed PT job seeker, they receive flow value

$$(1-\beta)J_p = x_p - w_{p\leftarrow u} + \beta\lambda_{p\to u}[V - J_p] + \beta\lambda_{p\to f}[J_f - J_p] \tag{1.19}$$

in which case the firm receives the final value of output $0.5p$, but they must pay wage $w_{p\leftarrow u}$. If a firm matches with a FT worker, they receive flow value

$$(1-\beta)J_{p\leftarrow p} = x_p - w_{p\leftarrow p} + \beta\lambda_{pp\to p}[V - J_{p\leftarrow p}] + \beta\lambda_{p\to u}[J_p - J_{p\leftarrow p}] \tag{1.20}$$

in which case they receive the final value of output $0.5p$, and they pay wage $w_{p\leftarrow f}$. If a firm matches with a PT worker, they receive flow value

$$(1-\beta)J_{p\leftarrow f} = x_p - w_{p\leftarrow f} + \beta\lambda_{fp\to f}[V - J_{p\leftarrow f}] + \beta\lambda_{f\to u}[J_p - J_{p\leftarrow f}] \tag{1.21}$$

in which case they receive the final value of output x_p, and they pay wage $w_{p\leftarrow p}$. Depending on if the firm matches with an unemployed, FT, or PT worker, the firm faces some risk that their PT job will be destroyed at rate $\lambda_{p\to u}$, $\lambda_{fp\to f}$, or $\lambda_{pp\to p}$ respectively. In addition, a PT employer that matches with an unemployed worker faces some risk of the PT job becoming a FT job at rate $\lambda_{p\to f}$. While it is possible for the firm to have more than one PT worker, the model is restricted to one PT worker as allowing for additional PT workers causes the number of states to grow exponentially leading to the model becoming intractable. In addition, the trade-off between FT and PT workers is my primary concern, so having additional states is outside the realm of my analysis.

Worker's Problem

All unemployed workers receive some value of leisure $\chi_u b$ where χ_i is the fraction of the unemployed value of leisure that a worker receives when they are in state i.[11] They choose their search intensities for FT and PT jobs simultaneously while paying cost $\sigma_u(s_{fu}, s_{pu})$. While unemployed, workers receive flow value

$$(1-\beta)U = \max_{s_{fu},s_{pu}} \Big\{\chi_u b - \sigma_u(s_{fu}, s_{pu}) + \beta q_{fu}[E_f - U] + \beta q_{pu}[E_p - U]\Big\} \quad (1.22)$$

and continue search until they receive a PT or FT job offer.

If an unemployed worker accepts a FT job, they receive flow value

$$(1-\beta)E_f = \max_{s_{pf}} \Big\{w_{f\leftarrow u} + \chi_f b - \sigma_f(s_{pf}) + \beta\theta_p q_p[E_{fp} - E_f] + \beta\lambda_{f\to p}[E_p - E_f] + \beta\lambda_{f\to u}[U - E_f]\Big\} \quad (1.23)$$

and start searching for a PT job while receiving primary wage $w_{f\leftarrow u}$ and some leftover value of leisure $\chi_f b$. In addition, they pay search cost $\sigma_f(s_{pf})$. While in this state, the worker faces some risk of losing their FT job at Poisson rate $\lambda_{f\to u}$ or having their FT job become a PT job at rate $\lambda_{f\to p}$. Upon accepting a secondary PT job in addition to their FT job, the worker receives flow value

$$(1-\beta)E_{fp} = w_{f\leftarrow u} + w_{p\leftarrow f} + \beta\lambda_{fp\to f}[E_f - E_{fp}] + \beta\lambda_{f\to u}[E_p - E_{fp}] \quad (1.24)$$

wherein they receive primary FT wage $w_{f\leftarrow u}$ and secondary PT wage $w_{p\leftarrow f}$. Since they no longer have any unused time, they receive no value of leisure and do not search for any jobs. They also face risk of losing their FT job at rate $\lambda_{f\to u}$ and their PT job at rate $\lambda_{fp\to f}$.

Should an unemployed worker accept a PT job, they receive flow value

$$(1-\beta)E_p = \max_{s_{fp},s_{pp}} \Big\{w_{p\leftarrow u} + \chi_p b - \sigma_p(s_{fp}, s_{pp}) + \beta q_{fp}[E_{pf} - E_p] + \beta q_{pp}[E_{pp} - E_p]$$

[11] I assume that $\chi_{pp} = \chi_f$ since a workers with two part-time jobs and full-time workers both work 40 hours per week.

$$+ \beta\lambda_{p\to f}[E_f - E_p] + \beta\lambda_{p\to u}[U - E_p]\Big\} \tag{1.25}$$

while searching for both a PT and a FT job simultaneously. They receive primary wage $w_{p\leftarrow u}$ and some leftover value of leisure $\chi_p(b)$ while paying search cost $\sigma_p(s_{fp}, s_{pp})$. While in this state, they face some risk that they lose their primary PT job at rate $\lambda_{p\to u}$ and some risk that their PT job becomes a FT job at rate $\lambda_{p\to f}$. Upon accepting a secondary FT job in addition to their PT job, the worker receives flow value

$$(1-\beta)E_{pf} = w_{f\leftarrow p} + w_{p\leftarrow u} + \beta\lambda_{p\to u}[E_f - E_{pf}] + \beta\lambda_{fp\to p}[E_p - E_{pf}] \tag{1.26}$$

wherein they receive primary PT wage $w_{p\leftarrow u}$ and secondary FT wage $w_{f\leftarrow p}$. Since they no longer have any unused time, they receive no value of leisure and do not search for any jobs. They also face risk of losing their FT job at rate $\lambda_{fp\to p}$ and their PT job at rate $\lambda_{p\to u}$. Upon accepting a dual PT job in addition to their primary PT job, the worker receives flow value

$$(1-\beta)E_{pp} = w_{p\leftarrow u} + w_{p\leftarrow p} + \chi_{pp}b + \beta(\lambda_{p\to u} + \lambda_{pp\to p})[E_p - E_{pp}] \tag{1.27}$$

wherein they receive primary PT wage $w_{p\leftarrow u}$ and dual PT wage $w_{f\leftarrow p}$. They also receive leftover value of leisure $\chi_{pp}b$. Finally, they face some risk of losing their primary PT job at rate $\lambda_{p\to u}$ and their dual PT job at rate $\lambda_{pp\to p}$. At this point, they do not search for any additional jobs. While it is possible for workers in the real world to hold more than two jobs, this restriction matches well with the data.[12]

[12] Averett (2001) finds that moonlighting men tend to hold one full-time job and one part-time job while women tend to hold two part-time jobs. Similarly, Hipple (2010) finds that 92% of multiple job holders only hold two jobs.

Job Creation Condition

The number of vacancies in equilibrium is determined endogenously by the job creation condition. First, set the flow value of posting a vacancy $V = 0$. The number of vacancies in the market is endogenous and depends on each firms profit maximization. As such, profit maximization implies that the value of one more vacancy is zero as positive value would result in an additional vacancy. This zero profit condition arises from the goods market being perfectly competitive. Thus, the flow value of posting a vacancy is $V = 0$. This allows for solving equations (1.17)-(1.21) for the flow values themselves. Plugging these equations into equation (1.16) gives the job creation condition

$$C(a_f, a_s) = \beta\Big(p_{fu}J_f + p_{fp}J_{f\leftarrow p} + p_{pu}J_p + p_{pp}J_{p\leftarrow p} + p_{pf}J_{p\leftarrow f}\Big) \tag{1.28}$$

which defines the firms choice to post a vacancy.

Wage Determination

When a worker-firm match is formed, they engage in an alternative offers bargaining game, which reduces to the axiomatic Nash Bargaining solution, to determine each wage. The worker of type $j \in \{u, f, p\}$ and the firm have full information about each other such that they bargain over the total surplus generated by the match for a job of type $i \in \{f, p\}$. Thus, each wage $w_{i\leftarrow j}$ is determined by equations (1.29) if the worker is unemployed and (1.30) if the worker is employed.

$$w_{i\leftarrow u} = \text{argmax} \;\; (E_i - U)^{\gamma_i}(J_i - V)^{1-\gamma_i} \tag{1.29}$$

$$w_{i\leftarrow j} = \text{argmax} \;\; (E_{ji} - E_j)^{\gamma_i}(J_{i\leftarrow j} - V)^{1-\gamma_i} \tag{1.30}$$

Optimal Search and Recruiting Intensity

Workers choose their search intensity optimally to maximize the flow value of their current state. Workers do not internalize the impact their search intensity will have on wages. Each worker chooses their search intensity until the marginal cost of search is equivalent to the marginal benefit which comes from changes in matching rates and the value of future states.

$$0 = \frac{\partial \sigma_u}{\partial s_{ui}} + \beta \frac{\partial q_{iu}}{\partial s_{iu}}[E_i - U] + \beta q_{iu} \frac{\partial [E_i - U]}{\partial s_{iu}} + \beta q_{-iu} \frac{\partial [E_{-i} - U]}{\partial s_{iu}} \quad \forall\ i \in \{f, p\} \tag{1.31}$$

$$\begin{aligned} 0 = & \frac{\partial \sigma_j}{\partial s_{ij}} + \beta \frac{\partial q_{ij}}{\partial s_{ij}}[E_{ji} - E_j] + \beta \sum_i q_{ij} \frac{\partial [E_{ji} - E_j]}{\partial s_{ij}} - \beta \lambda_{ju} \frac{\partial [E_j - U]}{\partial s_{ij}} \\ & - \beta \lambda_{j,-j} \frac{\partial [E_{-j} - E_j]}{\partial s_{ij}} \quad \forall\ (i, j) \in \{(f, p), (p, f), (p, p)\} \end{aligned} \tag{1.32}$$

Equations (1.31) and (1.32) respectively define the optimal search intensity s_{fu} for an unemployed worker searching for a FT job, the optimal search intensity s_{pu} for an unemployed worker searching for a PT job, the optimal search intensity s_{pf} for a single FT job holder searching for a PT job, the optimal search intensity s_{fp} for a single PT job holder searching for a FT job, and the optimal search intensity s_{pp} for a single PT job holder searching for a secondary PT job.

$$\frac{\partial C_v(a_f, a_s)}{\partial a_f} = \beta \sum_i \sum_j \frac{\partial p_{ij}}{a_f} J_{ij} \quad \forall (i, j) \in \{(f, u), (p, u), (p, f), (f, p), (p, p)\} \tag{1.33}$$

$$\frac{\partial C_v(a_f, a_s)}{\partial a_s} = \beta \sum_i \sum_j \frac{\partial p_{ij}}{a_s} J_{ij} \quad \forall (i, j) \in \{(f, u), (p, u), (p, f), (f, p), (p, p)\} \tag{1.34}$$

Similar to workers, firms choose their recruiting intensities a_f and a_s optimally to maximize the flow value of their current state. As with workers, firms do not internalize the impact that their decisions will have on market conditions such that they take wages as a given. Equation (1.33) defines the optimal recruiting intensity (a_f) for a firm recruiting for a full-time worker. This implicitly defines the recruiting intensity ($a_p = 1 - a_f$) for a firm searching for a full-time worker. Similarly, equation (1.34) defines the optimal recruiting intensity (a_s) for firms that want to hire a worker who already has a primary job. Again, this implicitly defines the recruiting intensity ($1 - a_s$) for a firm looking to hire an unemployed worker. In both cases, firms adjust their recruiting intensity until the marginal cost of recruiting intensity is equivalent to the marginal benefit which come from changes in the vacancy filling rates and the cost of recruiting.

Worker Flows

In the steady-state, the mean rate of unemployment, single FT, single PT, primary FT and secondary PT, primary PT and secondary FT, and dual PT job holdings should be constant. In a given time interval without growth or turnover in the labor force, the mean number of workers who enter into unemployment is $[\lambda_{p\to u} l_p + \lambda_{f\to u} l_f] Ldt$ where l_f is the rate of single FT job holdings, and l_p is the rate of single PT job holdings. During the same time interval, the mean number of workers moving out of unemployment is $[q_{fu} + q_{pu}]uLdt$ where u is the unemployment rate. In the steady state, the evolution of the mean rate of unemployment as

$$\dot{u} = \lambda_{p\to u} l_p + \lambda_{f\to u} l_p - [q_{fu} + q_{pu}]u$$

which can be rewritten to define the unemployment rate as in equation (1.35).

$$\lambda_{p\to u} l_p + \lambda_{f\to u} l_f = [q_{fu} + q_{pu}]u \tag{1.35}$$

Over the same time interaval, flows into single PT job holdings (l_p) is

$$[q_{pu}u + (\lambda_{p\to u} + \lambda_{pp\to p}) l_{pp}] Ldt + \lambda_{f\to u} l_{fp} Ldt + \lambda_{fp\to p} l_{pf} Ldt + \lambda_{f\to p} l_f Ldt$$

where l_{pp} is the rate of dual PT job holdings, l_{fp} is the rate of primary FT and secondary PT job holdings, and l_{pf} is the rate of primary PT and secondary FT job holdings. By assuming that all employment rates must sum to one, $l_{pf} = 1 - u - l_f - l_p - l_{pp} - l_{fp}$. Outflows are $[q_{fp} + q_{pp} + \lambda_{p\to u} + \lambda_{p\to f}]l_p L dt$. In the steady state, we can write the evolution of the mean rate of single PT job holdings as

$$\begin{aligned}\dot{l}_p = q_{pu}u + (\lambda_{p\to u} + \lambda_{pp\to p})l_{pp} + \lambda_{f\to u}l_{fp} + \lambda_{fp\to p}l_{pf} + \lambda_{f\to p}l_f \\ - [q_{fp} + q_{pp} + \lambda_{p\to u} + \lambda_{p\to f}]l_p\end{aligned}$$

which can be rewritten to define the rate of single PT job holdings as in equation (1.36).

$$q_{pu}u + (\lambda_{p\to u} + \lambda_{pp\to p})l_{pp} + \lambda_{f\to u}l_{fp} + \lambda_{fp\to p}l_{pf} + \lambda_{f\to p}l_f = [q_{fp} + q_{pp} + \lambda_{p\to u} + \lambda_{p\to f}]l_p \tag{1.36}$$

Similarly, the for single FT job holdings, dual PT job holdings, and primary FT and secondary PT job holdings are

$$q_{fu}u - q_{pf}l_f + \lambda_{fp\to f}l_{fp} + \lambda_{p\to u}l_{pf} + \lambda_{p\to f}l_p = \lambda_{f\to u}l_f + \lambda_{f\to p}l_f, \tag{1.37}$$

$$q_{pp}l_p = (\lambda_{p\to u} + \lambda_{pp\to p})l_{pp}, \tag{1.38}$$

and

$$q_{pf}l_f = (\lambda_{f\to u} + \lambda_{fp\to f})l_{fp}, \tag{1.39}$$

respectively.

Steady-State

Definition 1.3.1 *The steady-state equilibrium consists of a vector (u, l_p, l_f, l_{fp}, l_{pp}, v, a_f, a_s, $w_{f\leftarrow u}$, $w_{f\leftarrow p}$, $w_{p\leftarrow u}$, $w_{p\leftarrow f}$, $w_{p\leftarrow p}$, s_{fu}, s_{pu}, s_{pf}, s_{fp}, and s_{pp}) that solves the unemployment flow equation (1.35), part-time single job holdings flow equation (1.36), full-time single job holdings flow equation (1.37), the part-time dual job holdings flow equation (1.38), the primary full and secondary part-time job holdings flow equation*

(1.39), the job creation condition for vacancies (1.28), the firm's recruiting intensity maximization equations (1.33) and (1.34), five wage setting conditions (1.29) and (1.30), and the worker's five search intensity maximization equations (1.31) and (1.32).

1.4 Calibration

The model is calibrated to match monthly data from the U.S. from December 2001 to December 2004. This time frame serves as a baseline which can be perturbed to analyze the effects of recessions. All fixed parameters are summarized in Table 1.1. First, the job destruction rates $\lambda_{f\to u} - \lambda_{fp\to f}$ are set according to HP filtered monthly data on workers employment status from the Current Population Survey (CPS). The design of the CPS allows one to distinguish how many jobs an individual has and whether they are full-time or part-time jobs. Since workers can be observed for two sets of four consecutive months, there are 6 observations per worker for flows between different states. Aggregating up, the average primary full-time rate $\lambda_{f\to u} = 0.023$, secondary full-time rate $\lambda_{fp\to p} = 0.037$, primary part-time rate $\lambda_{p\to u} = 0.046$, secondary dual part-time rate $\lambda_{pp\to p} = 0.156$, and the secondary part-time rate $\lambda_{fp\to f} = 0.191$.[13]

The value of leisure $\chi_i b$ is $\chi_u b = b$ which serves as the based value of leisure. Using annual data from the 2003-2015 American Time Use Survey (ATUS), I calculate the average amount of time an individual has for leisure based on whether they are unemployed, part-time, full-time, or working multiple jobs. The data suggests that part-time workers have 29.36% as much time for leisure as unemployed workers while full-time workers have 5.4% as much leisure as unemployed workers. Thus, the value of leisure for part-time workers $\chi_p b$ and $\chi_f b$ are set equal to 29.36% and 5.4% of the value of leisure b for unemployed workers respectively. The final value of output for

[13]The derivation method is outlined in Appendix A.

full-time workers $x_f = 1$ is chosen as the numeraire. The final value of output for part-time workers is calculated based on a Cobb-Douglas production function that depends on hours worked and a labor share of 2/3. The discount rate $\beta = (1 - r) = 0.9959$ is set according to a real annual interest rate of 5 percent. The full-time employment tax $T = 0$ is set as a baseline which can be perturbed. The worker's share of the surplus generated from a match $\gamma_f = \gamma_p = 0.5$ are set in order to satisfy the Hosios condition.

All jointly calibrated parameters are summarized in Table 1.2 following a monthly frequency. Workers receive some value of leisure $b = 0.9668$ which is calibrated so the ratio of effective vacancies to the aggregate unemployment level is 0.44 to match the CPS and JOLTS data. The total cost of recruiting intensities a_f and a_s is

$$C(a_f, a_s) = c(1 - a_s)(a_f + a_p) + Ca_s(a_f + a_p)$$

where c is the marginal cost of posting an additional vacancy to unemployed workers and C is the marginal cost of posting to employed workers. Since there is no concrete evidence to suggest that recruiting for part-time workers is more costly that recruiting for full-time workers, the recruiting cost is the same for both types, but I assume that recruiting costs for employed and unemployed workers differ as the methods of contact can differ. The cost parameter $c = 0.3418$ is calibrated based on data summarized in Silva & Toledo (2009) which suggests that the average cost of recruiting for and hiring a new employee is roughly 30.23% of the worker's output. The cost parameter $C = 0.2929$ is calibrated with the search cost parameters in order to match matching probabilities for workers.

The total cost of search intensity while unemployed, employed full-time, and employed part-time are

$$\sigma_u(s_{fu}, s_{pu}) = \chi_u b(1 - h_f s_{fu} - h_p s_{pu})$$

$$\sigma_f(s_{pf}) = \chi_f b(1 - H_f h_p s_{pf})$$

$$\sigma_p(s_{fp}, s_{pp}) = \chi_p b(1 - H_p h_f s_{fp} - H_p h_p s_{pp})$$

where h_f is the cost of search for a full-time job and h_p is the cost of searching for a part-time job. While employed in a full-time or part-time job, these cost parameters are transformed by H_f and H_p to reflect additional constraints on an individuals ability to find a job while working as well as reflecting an aversion to holding a second job. Combined, with the cost parameter C, these values are calibrated to match the average job finding probabilities for a worker of type $i \in \{u, f, p\}$ finding a job of type $j \in \{f, p\}$ which are estimated using monthly CPS data from December 2001 to December 2004.[14]

1.5 Results

Calibrating the baseline model to the data as outlined in the previous section generates the results displayed in Table 1.3. The rate of unemployment and each employment rate are all within a reasonable distance of the actual observed values. The first thing that stands out in Table 1.3 is that workers search more intensely for part-time jobs than full-time jobs with search intensity $s_{pu} > s_{fu}$ and $s_{pp} > s_{fp}$. This is primarily because firms recruit more intensely for full-time workers with $a_f = 0.6761$ being twice as large as recruiting intensity for part-time workers. Because a_f is so high, there is a lower incentive for workers to search for a full-time job compared to a part-time job.

The wage for primary part-time jobs is greater than part-time worker productivity. This result likely stems from the probability that the job could become a full-time job at some point. In addition, for firms, they are willing to take on the

[14]Using the same method used for estimating job loss probabilities. The derivation method is outlined in Appendix A.

loss because they can avoid paying the cost of posting and maintaining a vacancy in addition to perhaps ending up with a full-time worker. In an attempt to mitigate this result, the leisure values of being employed χ_f and χ_p were calibrated in lieu of the cost parameters H_f and H_p, but this did not affect the results as they function in similar ways in equilibrium. Since H_f and H_p function as disutility parameters for search, I opted to stick with this calibration strategy.

Comparing Models

One of the purposes of this paper is to examine how well a model of part-time employment and multiple job holdings compares to the standard Diamond-Mortensen-Pissarides model. Given shocks to the final value of output, the cost of search, and the cost of recruiting, the full model compares favorably to the DMP model while also showing changes in employment composition. In addition, turning off part-time employment and focusing on MJH compares favorably as well. In the tables below, each exogenous parameter is perturbed for the DMP model, the model with MJH, and the model with both PT employment and MJH. Finally, I compare how the models perform when parameters are set according to their levels during the 2007-2009 recession.

First, the final value of output is perturbed as in Table 1.4. For the models with MJH and the full model, all final values of output are perturbed by the same percentage. In all cases, the unemployment rate decreases as the final value of output increases by 1%. Focusing on the models with the baseline value of leisure, the DMP model and full model compare very favorably with the decreases in the unemployment rate being almost identical at 59.81% and 58.73% respectively. Of interest is the changing composition of part-time employment and full-time employment. In the DMP model, employment increases by 5.27%, but FT employment rate increases by

2.64% in the full model. Making up the rest of the gap between the two models, the PT employment rate increases by 18.65%. Given how well the two models compare in employment, they do not compare well for the vacancy rate. As the final value of output increases, the vacancy rate drops in the full model compared to an increase in the DMP model. This is because firms are shifting their recruiting behavior from secondary workers to primary workers in the full model.

The same set of comparative statics are performed with the baseline value of leisure reduced by 1% as in the second set of columns in Table 1.4. Given a lower value of leisure, the full model becomes more responsive to a shock to the final value of output while the DMP and MJH models are less responsive. For instance, the unemployment rate response drops from 59.81% to 36.43% for the DMP model while it increases from 58.73% to 99.01% in the full model. In addition, the PT rate increases by 22.3% compared to a 18.65% increase in the baseline full model. On the other hand, the FT rate and vacancy rate responses becomes smaller for all the models. This suggest that part-time employment plays an important role as a means of smoothing income and employment for workers and firms when they have the ability to change their search and recruiting behaviors.

Next, I examine an increase in the cost of search in Table 1.5. For the DMP model, there is only one search cost while the MJH and full models have more than one search cost which are increased by the same percentage. The results are quite different for the three models. In the full model, an increase in the cost of search leads to a large increase in search for part-time employment which results in an increase in employment and a decrease in the unemployment rate. These stark differences harken back to the comparative statics for the cost of full-time and part-time search in the previous section. For an increase in the cost of full-time search, the comparative statics look similar to the results for the DMP and MJH models, but a proportional increase in the cost of part-time search dominates this effect and results in lower unemployment and higher employment rates, especially for part-time employment. Looking again at the case of a lower value of leisure, the unemployment rate and part-time rate are more responsive in the full model compared to the DMP and MJH models while the full-time rate and vacancy rate are less responsive. This result is qualitatively consistent with the results from the case of a shock to the final value of output.

Now, consider an increase in the cost of recruiting for all types of workers in Table 1.6. As in the case of an increase in the cost of search, the DMP model differs from the full model, but, unlike previously, the MJH model compares favorably. Increasing recruiting cost leads to lower vacancy rates across the board as it becomes more costly for the firm to post a vacancy. This leads to an increase in the unemployment rate in the DMP and MJH model. On the other hand, an increase in the cost of recruiting leads to firms shifting towards posting secondary vacancies and part-time vacancies which results in a higher part-time rate. In turn, this leads to an decrease in the unemployment rate. In the absence of part-time employment, the DMP and MJH models behave similarly.

Finally, I compare how the models perform when there is a recessionary shock. To accomplish this, I set parameters according to their levels during the 2007-2009 recession as in Table 1.7. According to the Bureau of Labor Statistics (BLS), the largest drop in the Consumer Price Index (CPI) was from September 2008 to December 2008 when prices fell by 3.34%. Thus, I decrease the final values of output x_f and x_p by 3.34%. In addition, each job destruction and transition rate is set according to the average value from the CPS. Comparing the steady-state values for each set of parameters should be sufficient as there are few dynamic elements in these models.

Nash Bargaining will result in the model moving to the new steady-state very quickly if dynamics were introduced.

The results in Table 1.8 suggest that the full model has some advantages over the DMP model. The full model does well at matching the responses in the unemployment rate, full-time rate, and part-time rate, especially their values at the trough of the recession. Unfortunately, the response in the MJH rate was too strong with the MJH dropping to 0.12% as opposed to the lowest rate observed in the data at 5.29%. The DMP model produces relatively muted respones with the unemployment rate jumping from 8.1% to 8.3% which is below both the average and the trough values in the data. In addition, the decline in real GDP is only 0.22% which is far below the average and trough values from the Bureau of Economic Analysis at -1.69 and -3.98 respectively. The full model does provide a stronger response in real GDP with a decline of 6.8%. This is largely a result of the strong decline in the multiple job holding rate. Overall, the full model captures compositional changes among employed workers which are not captured by the DMP model.

1.6 Discussion

The primary objective of this paper was to understand how workers and firms interact in a market with multiple job holdings. The second objective was to see how they might behave differently than in the standard Diamond-Mortensen-Pissarides model with only one job. First, consider how firms respond to changes in productivity. As the final value of output increases, firms create fewer vacancies, but due to shifting recruiting behavior, the effective vacancy rate for unemployed workers is actually higher while the effective vacancy rate is lower for workers who already have a job. Compare this with the conclusion by Gavazza, Mongey and Violante (2018) who suggest that vacancies and recruiting behavior are often working in different directions, especially during recessions. One major difference is that in the model presented here, recruiting behavior also takes into account multiple job holders whereas GMV does not. In addition, the ability of firms to hire part time workers becomes important as well when considering shocks to the cost of recruiting. When recruiting becomes more expensive, firms shift towards less costly recruitment of already employed workers as well as workers searching for part-time jobs. This can actually lead to a 16% lower unemployment rate, but also a 17% higher part-time rate such that workers may be worse off on average. These results suggest that the ability to shift recruitment from primary to secondary and full-time to part-time play an important role in firm responses. In their absence, firms become less responsive and act in opposite ways.

Common in the empirical literature is the notion that some workers take part-time jobs as a means of smoothing their income, especially during recessions when the rate of workers who are part-time for economic reasons increases. This general idea seems to hold. For instance, decreasing the value of leisure results in a lower unemployment rate and higher full-time and part-time rates, however, the part-time rate increases by 20% compared to a 2.5% increase in the full-time rate. This corresponds to the part-time rate increasing by roughly 3 percentage points compared to full-time's 2 pp increase. This corroborates the notion that part-time employment is an important margin for adjustment as unemployment becomes less valuable. In addition, as the value of leisure falls, unemployment and part-time employment become much more responsive to shocks as seen with increasing search cost, recruiting cost, and final value of output. In particular, the part-time employment response increases while the full-time rate decreases further supporting the use of part-time employment as a means of smoothing ones utility.

Overall, the model presented here performs relatively well compared to the DMP model when introducing recessionary shocks. In this case, plugging in data from the 2007-2009 recession generates a large increase in the unemployment rate from 7.6% to 10.24% compared with the DMP models increase from 8.1 - 8.3%. The average and trough value for the unemployment rate are 8.84% and 9.3% respectively. The full model also produces a sharp decline in the full-time employment rate from 75.8% to 70.5% compared to the data suggesting a rate of 69.0% on average. In addition, the part-time employment rate jumps from 16.6% to 19.2% which is in line with the observed increase to 17.0% in the data. Most of the overshooting in the part-time rate is due to the larger than expected decline in the multiple job holding rate.

One possible reason why multiple job holdings may not be responsive in the data is due to reporting problems. Discussing the stark difference between household and establishment level employment data, Abraham et al. (2013) conclude that multiple job holdings is likely under-reported during recessions, but it is possible that the effect could be in the opposite direction as there are competing incentives for firms to not report workers and workers to not report income. These incentives change depending on market conditions and are mostly related to shielding wages from taxes. In this light, my model produces an unlikely decline in the multiple job holdings rate, but it suggests that the rate may decline contrary to the conclusions of Hirsh, Husain, & Winters (2016). Given the shortcomings of the data on multiple job holdings, it may be hard to distinguish which is the correct conclusion.

1.7 Conclusion

In this paper, I start by documenting several facts regarding part-time employment and multiple job holdings. Data from the Survey of Consumer Expenditure suggests that a worker's search behavior and job offers depend on their current employment status. In addition, multiple job holdings appears to be more important for part-time workers as they are more willing to work multiple jobs than are full-time workers. To this end, I construct a search theoretic model that includes both part-time employment and multiple job holdings in addition to full-time employment. I allow for firms to recruit to different types of workers in different ways and I allow workers to choose their search intensity depending on their current employment status.

Allowing for part-time work and multiple job holdings in the Diamond-Mortensen-Pissarides model generates some novel results. First, variable recruiting results in the vacancy rate responding to shocks in the opposite direction of the DMP model. Despite this, the effective vacancy rate for a given job can still move in the same direction. Second, when comparing the full model to the DMP model, a recessionary shock in the full model produces results that are more in line with the data. This includes a larger jump in the unemployment rate and output as well as capturing the compositional changes within the employment rate. Finally, multiple job holdings are important when part-time employment is included. The model suggest that multiple job holding rates can vary quite dramatically and this drives some of the response in the part-time employment rate. The model presented here provides a way of looking behind the veil to see how firms and workers are responding. Given the importance of multiple job holdings in this model, future work should consider how firm size effects part-time employment and multiple job holdings.

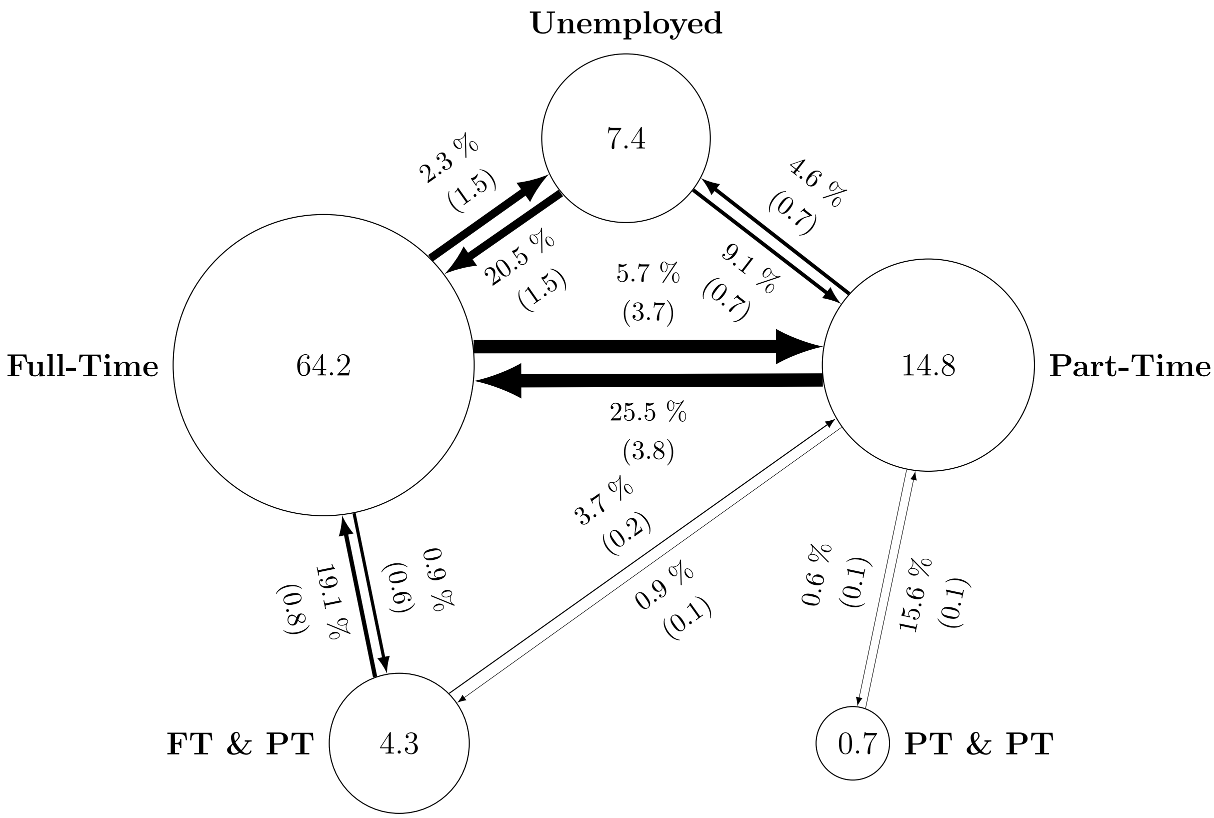


Figure 1.1.: Non-Recession Worker Flows (25-54 Age Group)

Average calculated using HP-filtered monthly CPS data from December 2001 to December 2004. HP filtered data is used to remain consistent with Figure D.1. Numbers inside circle represent average monthly count in millions. Percentages above/below arrows represent average monthly probability of moving from one employment status to another. Finally, number in parentheses above/below arrows represent average monthly count of workers transitioning from one employment status to another.

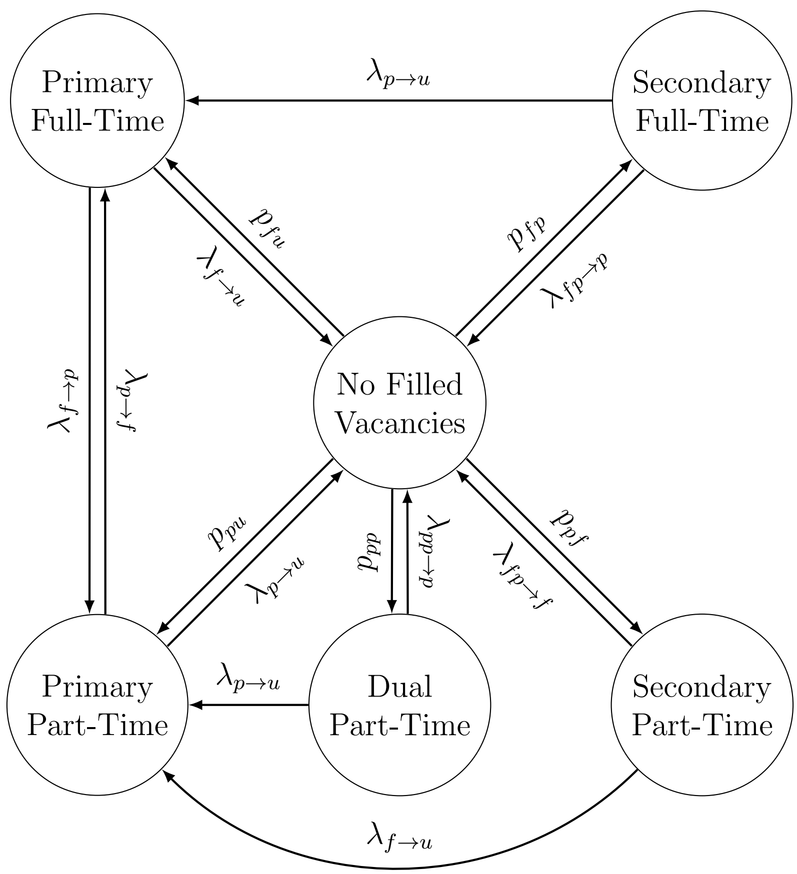


Figure 1.2.: Firm Flows

Figure 1.2 shows the different types of workers a firm could have as well as how their relationship with their worker could evolve. From the firms perspective, their pairing could be destroyed, or their worker's other pairing could be destroyed.

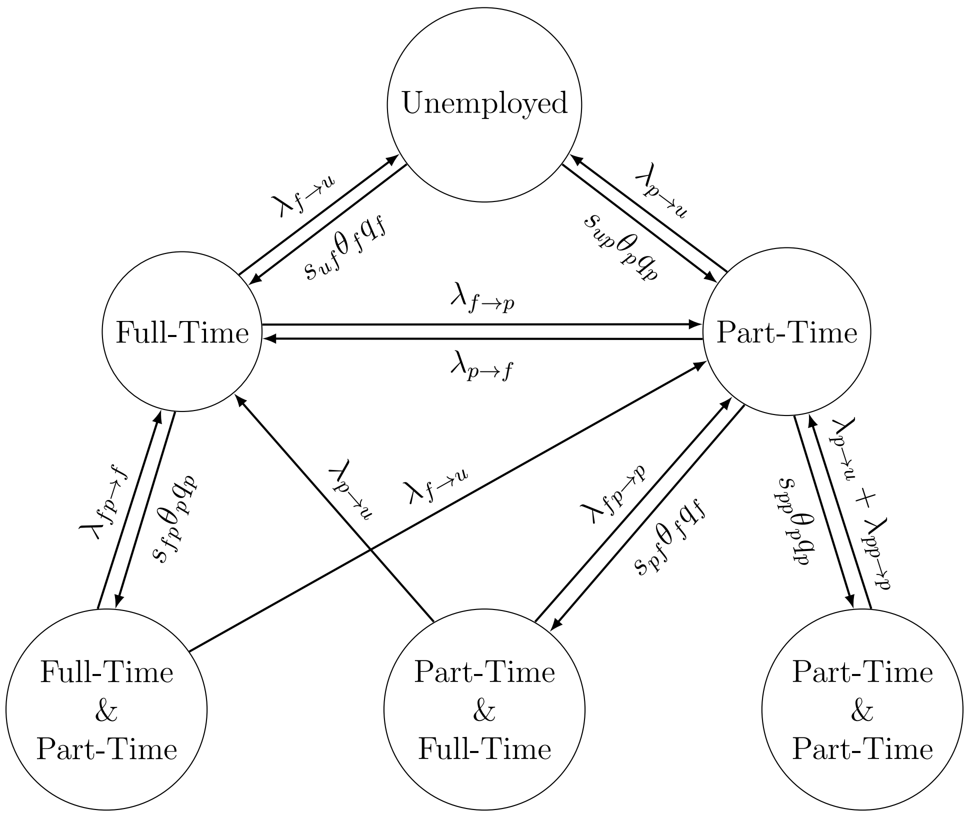


Figure 1.3.: Worker Flows

Figure 1.3 shows the different states a worker could be in as well as how their current state could evolve through getting a new job or having one of their jobs destroyed.

Table 1.1.: Independently Calibrated Parameters

Parameter	Value	Target/Source
$\lambda_{f\to u}$	0.023	CPS probability of losing primary FT job = 0.023
$\lambda_{fp\to p}$	0.037	CPS probability of losing secondary FT job = 0.037
$\lambda_{p\to u}$	0.046	CPS probability of losing primary PT job = 0.046
$\lambda_{pp\to p}$	0.156	CPS probability of losing secondary dual PT job = 0.156
$\lambda_{fp\to f}$	0.191	CPS probability of losing secondary PT job = 0.191
χ_u	1	Base value of leisure
χ_p	0.2936	% of unemployed leisure time for PT worker from ATUS
χ_f	0.0540	% of unemployed leisure time for FT worker from ATUS
x_f	1	$x_f = (1^{2/3})$
x_p	0.63	$x_p = (0.5^{2/3})$
$r = (1-\beta)$	0.00407	Annual interest rate 5%
T	0	Baseline
γ_f	0.5	Hosios Condition
γ_p	0.5	Hosios Condition

Table 1.2.: Jointly Calibrated Parameters

Parameter	Value	Targets
h_f	0.0432	Probability of finding primary FT job $q_{fu} = 0.205$
h_p	0.0040	Probability of finding primary PT job $q_{pu} = 0.091$
H_f	7784	Probability of finding secondary PT job $q_{fp} = 0.009$
H_p	1347	Probability of finding secondary dual PT job $q_{pp} = 0.006$
C	0.2929	Probability of finding secondary FT job $q_{pf} = 0.009$
c	0.3418	Total cost of recruiting = 0.3203 (Silva & Toledo (2009))
b	0.9668	Ratio of effective vacancies to unemployed $a_s v/u = 0.44$

All Targets matched with sum of squared errors $< 10^{-10}$

Table 1.3.: Baseline Results

Variable		Baseline	Data	Variable		Baseline	$w_{j\leftarrow i}/w_{f\leftarrow u}$
Unemployment Rate	u	0.0804	0.0764	Primary FT wage	$w_{f\leftarrow u}$	0.9434	1
FT Rate	l_f	0.7151	0.7074	Primary PT wage	$w_{p\leftarrow u}$	0.7796	0.8264
PT Rate	l_p	0.1594	0.1597	Secondary PT wage	$w_{p\leftarrow f}$	0.3243	0.3438
FT/PT Rate	l_{fp}	0.0289	0.0473	Secondary FT wage	$w_{f\leftarrow p}$	0.5984	0.6343
PT/PT Rate	l_{pp}	0.0126	0.0079	Dual PT wage	$w_{p\leftarrow p}$	0.3923	0.4158
Variable		Baseline	s_{ji}/s_{fu}	Variable		Baseline	
U search for FT	s_{fu}	0.4454	1	Vacancy Rate	v	0.0805	
U search for FT	s_{pu}	0.1817	0.4079	FT Recruiting	a_f	0.6761	
FT search for PT	s_{pf}	0.0099	0.0222	Primary Recruiting	a_s	0.4393	
PT search for FT	s_{fp}	0.0065	0.0146				
PT search for PT	s_{pp}	0.0205	0.0460				

Table 1.3 shows the steady-state results for the calibrated model. To put the wage in perspective, I divide each by the primary FT wage to get $w_{j\leftarrow i}/w_{f\leftarrow u}$. Similarly, I divide each search intensity by the search intensity for a primary FT job to get s_{ji}/s_{fu}.

Table 1.4.: 1% increase in final value of output

	Baseline Value of Leisure			99% Baseline Value of Leisure		
	DMP	MJH	Full	DMP	MJH	Full
%Δ Unemp. Rate	-59.81	-45.34	-58.73	-36.43	-35.61	-99.01
%Δ FT Rate	5.27	4.00	2.64	1.23	1.66	-0.39
%Δ PT Rate	-	-	18.65	-	-	22.30
%Δ MJH Rate	-	167.46	-99.83	-	61.37	-37.85e3
%Δ Vacancy Rate	63.86	97.08	-41.35	35.75	50.52	-37.09

Table 1.5.: 1% increase in cost of search

	Baseline Value of Leisure			99% Baseline Value of Leisure		
	DMP	MJH	Full	DMP	MJH	Full
%Δ Unemp. Rate	1.39	-0.45	-16.18	1.09	1.20	-29.12
%Δ FT Rate	-0.12	0.04	0.23	0.04	-0.06	-0.10
%Δ PT Rate	-	-	17.07	-	-	19.11
%Δ MJH Rate	-	-15.86	-14.77	-	-10.28	-95.99
%Δ Vacancy Rate	-0.25	-6.12	-12.23	-0.08	-5.79	-10.66

Table 1.6.: 1% increase in cost of recruiting

	Baseline Value of Leisure			99% Baseline Value of Leisure		
	DMP	MJH	Full	DMP	MJH	Full
%Δ Unemp. Rate	2.27	0.56	-2.45	-2.00	-2.26	32.11
%Δ FT Rate	-0.20	-0.05	-0.03	0.07	0.11	-0.47
%Δ PT Rate	-	-	16.16	-	-	16.80
%Δ MJH Rate	-	-6.12	-1.83	-	9.17	-0.41
%Δ Vacancy Rate	-1.40	-3.42	-3.09	0.07	4.62	6.39

Table 1.7.: Parameters

Parameter	12/2001-12/2004	12/2007-6/2009
x_f	1	0.966
x_p	0.63	0.603
$\lambda_{f\to p}$	0.057	0.059
$\lambda_{p\to f}$	0.255	0.244
$\lambda_{f\to u}$	0.023	0.022
$\lambda_{pf\to p}$	0.037	0.035
$\lambda_{p\to u}$	0.046	0.045
$\lambda_{pp\to p}$	0.156	0.156
$\lambda_{fp\to f}$	0.191	0.177

Table 1.8.: Results for Recessionary Shock

	Baseline*			2007-2009)			
	DMP	Full	Data	DMP	Full	Data	Trough
Unemployment Rate	0.0810	0.0760	0.0764	0.0830	0.1024	0.0884	0.0930
FT Rate	0.9190	0.7579	0.7639	0.9170	0.7053	0.6902	0.6839
PT Rate	-	0.1661	0.1597	-	0.1923	0.1676	0.1702
MJH Rate	-	0.0407	0.0565	-	0.0012	0.0538	0.0529
%Δ RGDP	-	-	-	-0.220	-6.776	-1.689	-3.983

* Baseline corresponds to Dec. 2001 - Dec. 2004

2. DECOMPOSING THE SOCIETAL OPPORTUNITY COSTS OF PROPERTY CRIME

2.1 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.

[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.

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.

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

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

[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

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.

2.2 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.

2.3 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 (2.1). 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.

$$\max_{\substack{P_{t+1,i},\ K_{t+1,i},\ I_{t,i} \\ N_{t,i},\ C^m_{t,i},\ C^s_{t,i} \\ s^h_{t,i},\ s^y_{t,i}}} E_0 \sum_{t=1}^{\infty} \beta^t \Big\{ P_{t,i}\Big(\log(\sigma_i + C^m_{t,i} + b_2 C^s_{t,i}) + \chi_i \log(1 - N_{t,i} - b(s^h_{t,i} + s^y_{t,i}))\Big) \\ + (1 - P_{t,i}) log(\sigma_i \sigma + G_t)\Big\} \tag{2.1}$$

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 (2.2).

$$E_t\{P_{t+1,i} K_{t+1,i}\} = P_{t,i}[(1-d)K_{t,i} + I_{t,i}] \tag{2.2}$$

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 (2.3) 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 $G_{t,i}$.

$$C^m_{t,i} + I_{t,i} = (w_{t,i} N_{t,i} + R_t K_{t,i})(1 - f_{t,p})(1 - T_t)(1 - \tau^g - \tau^p) + G_{t,i}(1 - T_t) \tag{2.3}$$

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 (2.4).

$$C^s_{t,i} = (1-\rho^y_t)\big[a^y_{t,i}(s^y_{t,i})^\eta Y_t\big] + (1-\rho^h_t)\big[a^h_{t,i}(s^h_{t,i})^\eta V_t\big] \tag{2.4}$$

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 2.5

$$E_t\{P_{t+1,i}\} = P_{t,i} + \zeta(1-P_{t,i}) - (\rho^y_t + \rho^h_t)\theta_t(\sum_{i\in\{h,l\}} \phi_i C^s_{t,i})(s^y_{t,i} + s^h_{t,i})^\delta P_{t,i} \tag{2.5}$$

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 (2.5). 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.

$$\begin{aligned} V_t = {} & \phi_h P_{t,h}[(w_{t,h}N_{t,h} + R_t K_{t,h})(1-f_{t,p})(1-\tau^g-\tau^p) + G_{t,h}] \\ & + \phi_l P_{t,l}[(w_{t,l}N_{t,l} + R_t K_{t,l})(1-f_{t,p})(1-\tau^g-\tau^p) + G_{t,h}] \end{aligned} \tag{2.6}$$

[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.

$$T_t = (1 - \rho_t^h) \sum_{i \in \{h,l\}} \phi_i P_{t,i} a_{t,i}^h (s_{t,i}^h)^\eta \tag{2.7}$$

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 F.1 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 (2.9). It has no way of smoothing revenue over time by borrowing or lending.[7]

$$\text{Revenue}_t = [\phi_h P_{t,h}(w_{t,h}N_{t,h} + R_t K_{t,h}) + \phi_l P_{t,l}(w_{t,l}N_{t,l} + R_t K_{t,l})](\tau^g + \tau^p)(1 - f_{t,p}) \tag{2.8}$$

$$\text{Revenue}_t^p = f_{t,p} \sum_i \phi_i P_{t,i}(N_{t,i} w_{t,i} + K_{t,i} R_t) \tag{2.9}$$

$$= \frac{\tau_p}{\tau_p + \tau_g} \text{Revenue}_t \tag{2.10}$$

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

[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 F.2 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.

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

and capital is used to prevent theft. These resources are not used for firm production. Finally, police revenue transforms the probabilities of getting caught (2.11).

$$\rho_t^i = z_p \rho^i \Big(\sum_{i \in \{h,l\}} \sum_{j \in \{h,y\}} s_{t,i}^j \Big)^{-1} (\text{Revenue}_t^p)^{\eta_p} \tag{2.11}$$

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 (2.12).

$$\max_{\mathbb{H}_t, \mathbb{L}_t, \mathbb{K}_t} \quad Q_t(z_t) \mathbb{K}_t^{\alpha} \, \mathbb{H}_t^{\gamma} \, \mathbb{L}_t^{1-\alpha-\gamma} - R_t \mathbb{K}_t - w_{t,H} \mathbb{H}_t - w_{t,L} \mathbb{L}_t \tag{2.12}$$

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 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.

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

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

General Equilibrium

Equilibrium allocations are solved for by maximizing each household's utility (2.1) subject to constraints (2.5), (2.3), (2.4), and (2.2) such that $P_{t+1,i}$ $N_{t,i}$, $C^m_{t,i}$, $C^s_{t,i}$, $s^y_{t,i}$, $s^h_{t,i}$, $K_{t,i}$, and $I_{t,i} \geq 0$. The firm's problem (2.12) is solved for $\mathbb{K}_t$, $\mathbb{H}_t$, and $\mathbb{L}_t$ subject to (2.3). 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.

$$\mathbb{K}_t = (1 - f_{t,p})\phi_h P_{t,h} K_{t,h} + (1 - f_{t,p})\phi_l P_{t,l} K_{t,l} \tag{2.13}$$

$$\mathbb{H}_t = (1 - f_{t,p})\phi_h P_{t,h} N_{t,h} \tag{2.14}$$

$$\mathbb{L}_t = (1 - f_{t,p})\phi_l P_{t,l} N_{t,l} \tag{2.15}$$

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 (2.16).

$$\frac{\partial U_{t,i}(\cdot)}{\partial N_{t,i}} = w_{t,i}(1 - f_{t,p})(1 - T_t)(1 - \tau^g - \tau^p)\frac{\partial U_{t,i}(\cdot)}{\partial C^m_{t,i}} \tag{2.16}$$

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.

$$(1-\rho_t^y)a_{t,i}^y(s_{t,i}^y)^{\eta-1}Y_t = (1-\rho_t^h)a_{t,i}^h(s_{t,i}^h)^{\eta-1}V_t \tag{2.17}$$

Households must be indifferent between a little more time devoted to household theft and a little more time devoted to theft from firms in (2.17), 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 (E.1) in Appendix E. 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.

$$\frac{\partial U_{t,i}}{\partial C_{t,i}^m} = \beta E_t\Big\{\frac{\partial U_{t+1,i}}{\partial C_{t+1,i}^m}\big(R_{t+1}(1-f_{t+1,p})(1-T_{t+1})(1-\tau^g-\tau^p)+(1-d)\big)\Big\} \tag{2.18}$$

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 (2.3) and (2.4). Next period's non-incarcerated population is defined by flow equation (2.5) and the law of motion for capital (2.2) determines how the capital stock evolves.

Finally, solving for the firm's problem (2.12) yields three equations that pin down wages and the return on capital.

$$w_{t,H} = \gamma Q_t \mathbb{K}_t^{\alpha} \mathbb{H}_t^{\gamma-1} \mathbb{L}_t^{1-\alpha-\gamma} \tag{2.19}$$

$$w_{t,L} = (1-\alpha-\gamma) Q_t \mathbb{K}_t^{\alpha} \mathbb{H}_t^{\gamma-1} \mathbb{L}_t^{-\alpha-\gamma} \tag{2.20}$$

$$R_t = \alpha Q_t \mathbb{K}_t^{\alpha-1} \mathbb{H}_t^{\gamma} \mathbb{L}_t^{1-\alpha-\gamma} \tag{2.21}$$

Each wage (2.19) and (2.20) 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 (2.21) is determined by the marginal product of capital.

2.4 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 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 F.5 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 "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

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

minimize the sum of squared errors of the difference between the model generated impulse response functions (IRFs) and the IRFs from panel VAR. Table 2.2 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 2.2a and Table 2.3, 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 household types.

$$\text{Welfare} = \sum_{i \in \{h,l\}} \sum_{t=1}^{T} \beta^t \phi_i U_{t,i}(P_{t,i}, C_{t,i}^m, C_{t,i}^s, N_{t,i}, s_{t,i}^h, s_{t,i}^y, \mathbf{comp}_i) \tag{2.22}$$

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 $s_{i,t}^j$, but if there is $1 - x\%$ less crime, then I calculate CV using $s_{i,ss}^j$ for both before and after since I am taking control of $s_{i,t}^j$.

$$\sum_{t=1}^{T} \beta^t \phi_i \Big\{ U_{t,i}(P_{t,i}, C_{t,i}^m, C_{t,i}^s, N_{t,i}, s_{t,i}^h, s_{t,i}^y, \text{comp}_i^*) \\ - U_{t,i}(P_{t,i}^2, C_{t,i}^{m,2}, C_{t,i}^{s,2}, N_{t,i}^2, xs_{t,i}^h, xs_{t,i}^y) \Big\} = 0 \quad \forall i \in \{h, l\} \tag{2.23}$$

2.5 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 E.3 in Appendix F.4. 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.4. 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.

2.5.1 Welfare Analysis

Looking at Table 2.4, 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 2.3. 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.

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.

2.5.2 Decomposition

To get a sense of what drives my results, I individually fix several endogenous variables and compare the two environments as in Table 2.5. 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 E 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 2.5 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.

2.5.3 Policing

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

$$\sum_{t=1}^{T} \beta^t \phi_i \Big\{ U_{t,i}(\cdot, \bar{C}^s_i, \tau^{p,j}, \text{comp}^*_i) - U_{t,i}(\cdot, \bar{C}^s_i, \tau^{p*}, 0) \Big\} = 0 \ \ \forall i \in \{h, l\},\ j \in [\underline{\tau^p}\ \overline{\tau^p}] \tag{2.24}$$

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 2.4a and 2.4b, 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 F.6a and F.6b in Appendix F.4, 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 2.4a and 2.4b 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.

2.5.4 Transfers

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 if both households receive higher transfers without

[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."

raising taxes? Finally, what happens if households receive consumption transfers as opposed to income transfers?

The first row of Table 2.6 and Figure F.1 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 F.2 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 F.3 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 F.4 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 F.1 and F.4, 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 F.2 and F.3 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]

2.6 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. 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 trans-

[13]Figures E.1 and E.2 both show that property crime declines with increasing punishment.

fers 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.

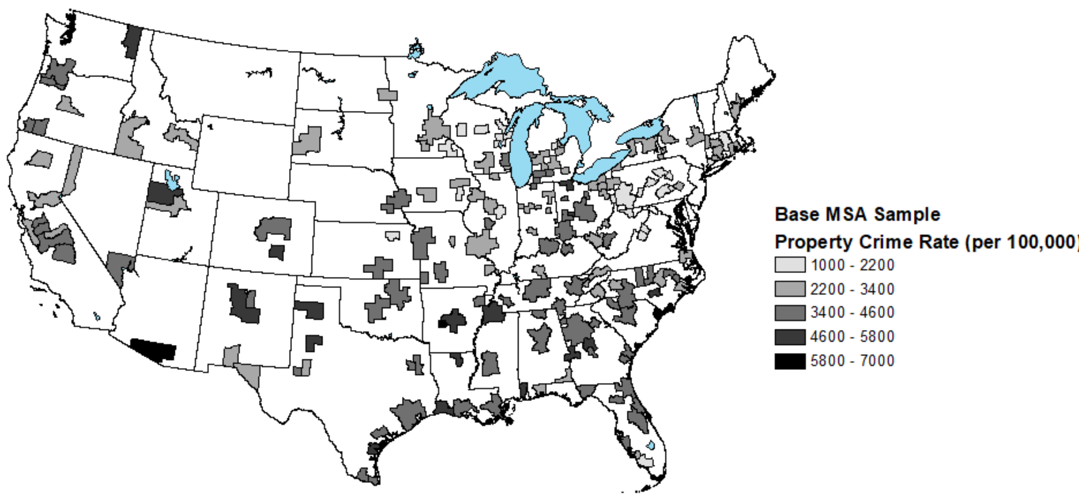


Figure 2.1.: Map of MSAs Used

Table 2.1.: Calibrated Parameters

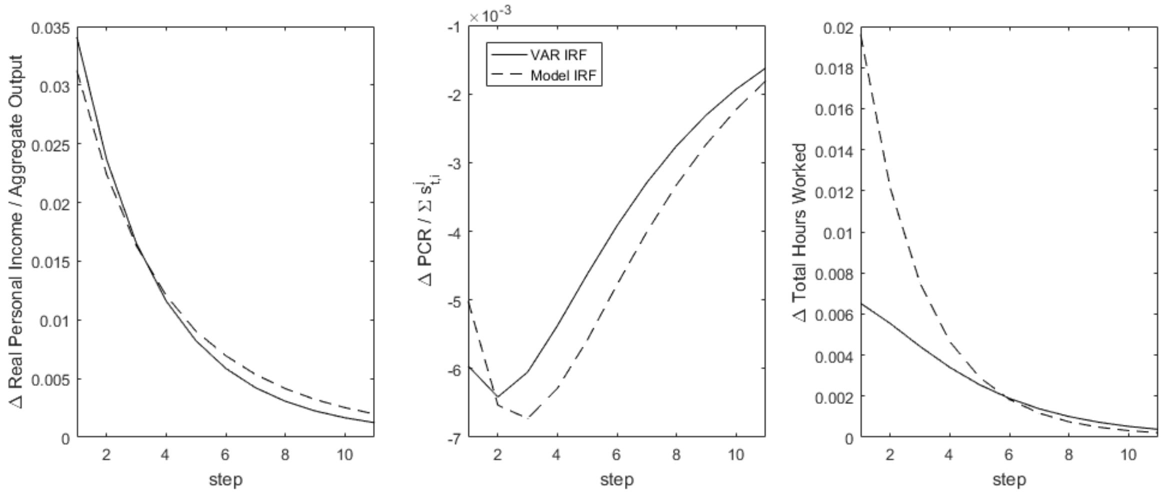
	Description	Value	Target
β	discount factor	0.97	3% return on 10-year T-bills
α	capital output share	0.33	capital expenditure share
ρ^h	probability of being caught stealing from HH	0.044	clearance data
ρ^y	probability of being caught stealing from firm	0.064	clearance data
ζ	probability of release from 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

Table 2.2.: 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

Table 2.3.: 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



(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 2.2.: Orthogonalized Shock to Real Personal Income per Capita

Figure 2.2a 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 2.2b shows the percent error for steps 1, 5, and 10 in Figure 2.2a.

Table 2.4.: 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 $0.99s^j_{i,ss}$. 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 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 F.3 and F.4

Figure 2.3.: Effect of Crime on Social Welfare

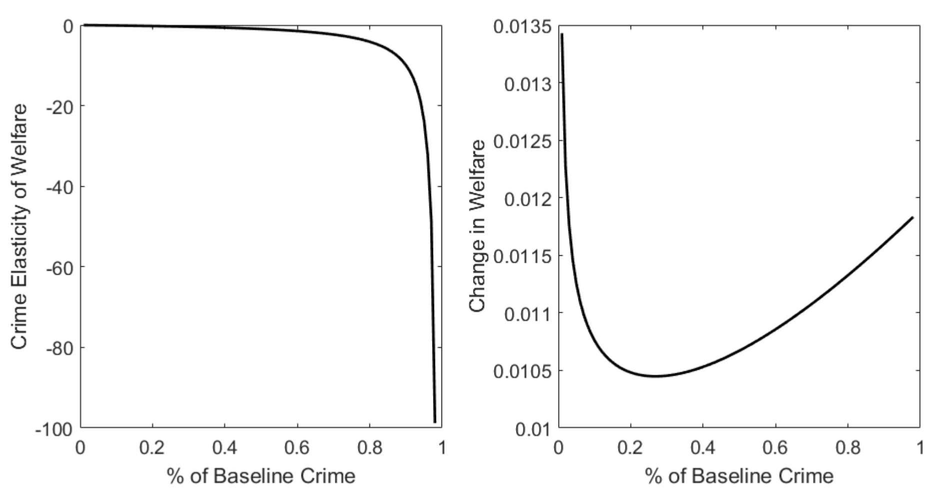


Table 2.5.: Comparison: CV and Output

	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 F.3.

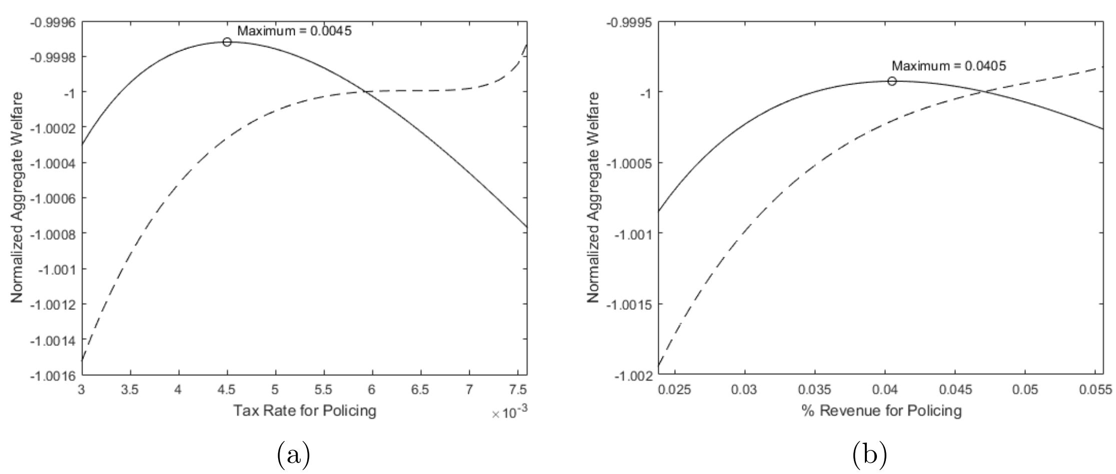


Figure 2.4.: Optimal Taxation for Policing

(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.

Table 2.6.: 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

3. ESTIMATING THE EFFECT OF PROPERTY CRIME ON INCOME: A SYSTEM GMM APPROACH

3.1 Introduction

Property crime imposes significant societal costs that far exceed the value of stolen property. While the value of reported stolen property in the U.S. is in the range of \$40-60 billion per year,[1] prevention, emotional damages, and changes in behavior can push the cost up to \$4 trillion for all crime categories.[2] While crime has declined in the U.S. beginning in the early 1990s, there still remains large regional variation in crime rates within the U.S. For instance, while the overall U.S. property crime rate has fallen 56% from 5,353.3 per 100,000 in 1980 to 2,362.2 in 2017, the Metropolitan Statistical Area (MSA) property crime rate ranges from 1108 to 8695 for the years 2002-2016. In addition, employment in protective services has remained fairly steady despite a downward trend in crime rates.[3] Employment in this sector takes workers away from producing real goods and services. While previous work suggests that property crime has a negative effect on income and output, estimates tend to be for developing nations and do not explore the differential effects of each category of property crime.

In this paper, I use system GMM to estimate the effect of property crime and its various subcategories on real personal income per capita in the U.S. The dataset consists of crime rates from the FBI's UCR, real personal income per capita

[1] The 2009 Global Retail Theft Barometer puts total retail theft at \$42.2 billion while the FBI's Uniform Crime Reports puts losses at \$13.6 billion.

[2] Anderson (1999) estimates the cost of all crime and prevention totals \$4 trillion.

[3] See Appendix G

from the Bureau of Economic Analysis (BEA), and demographics from the American Community Survey. In total, the dataset covers up to 181 MSAs from 2002 to 2016. My estimates put the cost of property crime at 5.9-13.3% of GDP. Within MSAs, a one standard deviation decrease in property crime causes a 0.9-1.9% increase in real income per capita. Breaking property crime into subcategories, I find statistically significant negative effects of larceny-theft, burglary, and motor vehicle theft with larceny-theft having the largest effect. Estimates for robbery are inconsistent, but mostly significant. Estimating the effect of all property crime subcategories together proves difficult due to collinearity, so these estimates are difficult to interpret.

This paper proceeds as follows. In Section 3.2, I discuss the relevant literature and how this paper contributes to the literature. Section 3.3 covers the data while section 3.4 discusses the model specification. Section 3.5 presents and discusses the primary results as well as additional results from the subcategories of property crime. Finally, section 3.6 contains concluding remarks.

3.2 Literature

The earliest body of literature exploring the effect of crime on economic outcomes are accounting studies. Anderson (1999) estimates the total annual cost of all forms of crime in the U.S. is up to $4 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), Collins (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. In addition, not much can be said about the marginal effect or cyclical effects of crime, nor can much be said about local effects. In this paper, I can explore the effect of property crime at the margin and see how time variation in crime rates within an MSA affect income.

The literature exploring the causal effect of property crime on economic outcomes utilizes time series econometrics. Narayan & Smyth (2004) test whether different categories of property crime granger cause male youth unemployment and male wages in Australia. They find support for fraud and motor vehicle theft granger causing both. Mauro & Carmeci (2007) build an overlapping generations model to generate a hypothesis regarding the relationship between crime, growth, and income. Using ARDL to estimate the effects in Italy, they find a negative effect of crime on income growth. At least four other papers use ARDL to estimate the effects of property crime on economic outcomes. Habibullah & Baharom (2008) conclude that armed robbery, daytime burglary, and motorcycle theft have a granger causal effect on economic conditions, 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. Detotto and Otranto (2010) find a small but significant decrease in economic growth due to crime with the effect being larger during recessions. One shortcoming of this paper is the use of sexual assault as an IV for crime. Sexual assualt has an ambiguous relationship with the business cycle[4], and it is not clear that sexual assault is necessarily correlated with property crime. Finally, Hazra & Cui (2018) find support for unemployment granger causing crime, but they find no support for crime causing economic outcomes in India. Two problem inherent to all these papers are the interpretation of coefficients and granger causality. Having lagged property crime

[4]Schneider, Harknett, & McLanahan (2016)

makes it hard to interpret the effect of today's property crime on today's income while granger causality still does not ensure causality. To get around these problems I use a system GMM approach instrumenting with deeper lags for income and property crime and excluding lags of property crime from the second stage.

Similar to my methodology, Goulas & Zervoyianni (2015) use system GMM to estimate the effect of crime on economic growth with a panel of 26 countries. Their results suggest that crime has a negative effect on economic growth when the economy is doing poorly, but little effect when the economy is doing well. Finally, 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.

Finally, the Macroeconomic literature provides some hypotheses of the effect of property crime on economic outcomes. Usher (1987) provides 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. Grossman & Kim (1995) suggest that poorer individuals are better off in an equilibrium where theft exists as opposed to one without theft. Overall, they suggest that property crime is detrimental to the economy.

3.3 Data

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 per capita personal income data from the Bureau of Economic Analysis (BEA), and the demographic characteristics from the American Community Survey (ACS). The unbalanced panel consists of 181 MSAs over 14 years. MSAs provide a reasonable connection between the markets for labor and crime.

Some MSA-year pairs are dropped due to overlap with other MSAs or missing observations. For instance, Detroit does not provide crime data at the MSA level for all years, so there are not enough continuous observations to utilize lags as instruments. In the case of New York City and Los Angeles, MSA boundaries change frequently making it hard to discern how to account for overlap. Despite dropping these MSAs and other, the data still retains substantial variation in crime levels and income as seen in Table E.1 and Figure 3.1.

While mean real personal income per capita (RPINC) is \$36,615 (2009 \$), the standard deviation is \$8219 with a range of \$89,103. Similarly, each crime rate shows large variation with the property crime rate (PCR) having a mean of 3430 per 100,000, a standard deviation of 1091, and a range of 7587. Despite losing a few MSAs when cleaning the data, a crime rate of 8695 in Hot Springs, AR is still the highest in the original sample. I can also explore separate catergories of PCR by breaking it into 4 separate categories: Larceny/Theft (LTR), Robbery, Burglary, and Motor Vehicle Theft (MVTR). Robbery and MVTR are escpially volatile across and within MSAs with $\sigma/\mu = 0.59$ and 0.69 respectively compared to across MSA PCR volatility of 0.32. Within MSA volatility is 0.05 and 0.06 for Robbery and MVTR respectively compared with 0.02 for PCR. As expected, volatility is higher across MSAs than within.

Finally, own children at home reflects the percentage of households with children at home multiplied by the number of children those households have. These values range from 23.2 to 61.7 with a mean of 42.1. The sample for this variable is smaller since the American Community Survey top codes some of the MSA names and only has MSA codes for 12 years of data as opposed to 14 for the rest of the variables. This is the most constraining variable for my estimation strategy.

3.4 Model Specification

The base specification for the econometric model has real personal income per capita (RPINC) as the dependent variable with the independent variables being the property crime rate (PCR), the first lag of RPINC, and other controls C.

$$\mathrm{RPINC}_{i,t} = \alpha + \beta \mathrm{RPINC}_{i,t-1} + \lambda \mathrm{PCR}_{i,t} + \delta C_{i,t} + \nu_i + \gamma_t + \varepsilon_{i,t} \tag{3.1}$$

One would expect that past realizations of income are going to affect today's income since past negative shocks to income can spill over to the next period via a reduction in capital accumulation or lower consumer sentiments that drive down wages overall regardless of skill level. In addition, past income is the best predictor of next periods income. For these reasons, I include the first lag of RPINC. Including the first lag creates endogeneity when the panel data is demeaned, so this must be accounted for otherwise the results will be biased.

$$\begin{aligned}\mathrm{RPINC}_{i,t} - \overline{\mathrm{RPINC}_i} = {} & \beta(\mathrm{RPINC}_{i,t-1} - \overline{\mathrm{RPINC}_i}) + \lambda(\mathrm{PCR}_{i,t} - \overline{\mathrm{PCR}_i}) \\ & + \delta(C_{i,t} - \overline{C_i}) + (\gamma_t - \overline{\gamma}) + (\varepsilon_{i,t} - \bar{\varepsilon}_i)\end{aligned} \tag{3.2}$$

In the equation above, the demeaned error term is correlated with both the demeaned dependent variable and the lag of the demeaned dependent variable. With small T ($T = 14$) and large N ($N = 181$), a dynamic panel data model should account for the endogeneity problem. For this paper, I use the system GMM estimator proposed by Arellano & Bover (1995) and Blundell & Bond (1998). The advantage of this estimator over difference GMM is two-fold. First, lagged levels are generally poor instruments for differences when the variable follows a random walk. RPINC likely follows an AR process with an error term that follows a random walk. This poses a potential problem for using the levels as instruments. Second, system GMM utilizes the most information contained in the data by using both the lag difference and lag levels as instruments.

Lags 3 and older are used as instruments since the null hypothesis that there is no correlation between $(\varepsilon_{i,t-1} - \varepsilon_{i,t-2})$ and $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$ are rejected, but the null for the AR(3) test is not rejected. This implies the GMM-style instruments for the lagged dependent variable and the endogenous independent variable will consist of blocks taking the form

$$Z_i = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ y_{i,1} & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & y_{i,2} & y_{i,1} & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & y_{i,3} & y_{i,2} & y_{i,1} & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \text{ or, collapsed, } \begin{bmatrix} 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & \dots \\ y_{i,1} & 0 & 0 & \dots \\ y_{i,2} & y_{i,1} & 0 & \dots \\ y_{i,3} & y_{i,2} & y_{i,1} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

for the difference equation and the form

$$W_i = \begin{bmatrix} 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & \dots \\ \Delta w_{i,3} & 0 & 0 & \dots \\ 0 & \Delta w_{i,4} & 0 & \dots \\ 0 & 0 & \Delta w_{i,5} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \text{ or, collapsed, } \begin{bmatrix} 0 \\ 0 \\ \Delta w_{i,3} \\ \Delta w_{i,4} \\ \Delta w_{i,5} \\ \vdots \end{bmatrix}$$

for the level equation. Collapsing the instrument set is one way to limit the number of instruments by creating only one instrument per time period instead of one instead of one per time period and lag available.

$$\mathbf{Z} = \begin{bmatrix} Z_1^Y & Z_1^X & \Delta t05 & \dots & \Delta t15 & \Delta C_1 \\ Z_2^Y & Z_2^X & \Delta t05 & \dots & \Delta t15 & \Delta C_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ Z_N^Y & Z_N^X & \Delta t05 & \dots & \Delta t15 & \Delta C_N \end{bmatrix}, \mathbf{W} = \begin{bmatrix} W_1^Y & W_1^X & t05 & \dots & t15 & C_1 \\ W_2^Y & W_2^X & t05 & \dots & t15 & C_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ W_N^Y & W_N^X & t05 & \dots & t15 & C_N \end{bmatrix}$$

These blocks are then stacked into matrix $\mathbf{Z}$ for the difference equation and $\mathbf{W}$ for the level equation. In the case of $\mathbf{Z}$, each block Z_i is stacked on top of the other with the instruments for Y and X stacked next to each other. In addition to the GMM-style instruments, standard instruments are included for the exogenous variable ΔC_i as well as dummies for the first difference in time Δt in stacked columns. A similar structure follows for the level equation, the instrument set $\mathbf{W}$ stacks W_i instead of Z_i and includes standard instruments for the exogenous variable C_i and dummies for each time period t.

The last and biggest problem to deal with is the issue of causality. The empirical literature suggests a negative causal effect of economic outcomes on crime,[5] so I must rule this effect out when trying to estimate the causal effect of crime on income, otherwise the results will be biased. There are two key assumptions required to infer causality. First, crime today causes income today, $X_{i,t} \rightarrow Y_{i,t}$, and income yesterday causes crime today, $Y_{i,t-1} \rightarrow X_{i,t}$, but crime yesterday does not cause income today, $X_{i,t-1} \rightarrow Y_{i,t}$. In essence, people observe their past realization of income and form expectations about income today when choosing how much crime to commit today. Simulations from Allison, Williams, & Benito-Morales (2017) suggest that system GMM should sufficiently control for reverse causality with lagged crime left out of the equation. Second, past realizations of X and Y are not correlated with today's shocks which allows them to be used as instrumental variables. Using the third lag and higher as instruments should provide strong correlation between the lags, income, and crime.

Finally, at first glance it appears that this model contradicts the Chapter 2 by excluding lagged property crime from the equation and using the lags of property crime as instruments. In a dynamic stochastic general equilibrium model, lagged

[5]There is a substantial literature suggesting that economic outcomes have a a causal effect on crime. Chiricos (1987), Raphael & Winter-Ebmer (2001), Gould, Weinber, & Mustard (2002), Corman & Mocan (2005), Machin & Meghir (2004), Freedman & Owens (2016), Yang (2017), and Dix-Carneiro, Soares, & Ulyssea (2018) all find some support for various outcomes ranging from income shocks to employment shocks having a negative causal relationship with property crime and crime in general.

crime will have an effect on today's income which means that using it as an instrument will bias the results since it is correlated with the error term for today $E(PCR_{i,t-1}u_{i,t}) \neq 0$. To address this contradiction, I show that lagged crime in Chapter 2 only has an effect through its effect on state variables and today's crime. In addition, I show that the point estimate from excluding property crime as an instrument still results in a significant estimate that is within the original range of point estimates. Finally, I show that including lagged property crime in a VAR model results in a significant point estimate that is larger in magnitude.

First, I take the simulated data from the model and run a simple VAR with one lag. The results suggest that property crime does not granger cause today's income in the DSGE model, but it is highly correlated with itself, so it is a valid instrument for past property crime without interfering with the estimate for today's income. Given that everything is interrelated in the model, I conclude that the effect of lagged property crime is through its effect on other state variables, lagged income and today's crime. I also run system GMM with property crime treated as an exogenous variable. This would imply that lagged property crime is not a good instrument for property crime and income due to its effect on today's income. The point estimate is -0.0633 which is still large and significant. It is lower than the largest estimate of -0.133, but still larger than my lower bound estimate of -0.0593. Finally, I revisit the VAR from the Chapter 1 and find that the contemporary effect of today's crime on income is -0.175 which is significant and larger than the largest estimate from system GMM. Overall, I conclude that the effect of lagged property crime is through its effect on other state variables, lagged income and today's crime. Intuitively, physical and human capital accumulation may be affected by past crime which in turn has an effect on today's crime and income, but the channel is indirect. As long as today's crime is controlled for, then the results should not be biased.

In addition, using deeper lags should diminish the potential bias and the results presented here should be less biased than a standard OLS approach.

3.5 Results

Running system GMM on the data generates statistically significant results as seen in Table E.3. The baseline results in column 1 do not suggest any significant effect of PCR on RPINC; however, once we control for ”own children at home” (living with parents), the coefficient becomes significant with a value ranging from -0.0593 to -0.133. The reason why we control for the population of ”own children at home” is that they are counted in the measure of per capita, but are likely not contributing to income. In addition, the likelihood of committing property crime decreases with age, so having a young population is correlated with higher crime. The coefficient for PCR suggest that a 1 standard deviation change in PCR within a given MSA would result in per capita income decreasing by 0.862% - 1.935%. Finally, if 100% of property crime disappeared, real personal income per capita would increase by 5.9 - 13.3%.

There are three additional concerns regarding estimating the model using system GMM. First, Roodman (2009a) shows how instrument proliferation can bias results in a number of ways. Having too many instruments can overfit the endogenous variables in the first stage generating bias in the direction of the OLS result, lead to a singular weighting matrix, bias standard errors (corrected with Windmeijer (2005) standard errors), and weaken the Hansen test for instrument validity. One way of limiting the number of instruments is to limit the number of lags. If I limit the number of lags used as GMM-style instruments in columns 5 so that only the 3rd lag is used, the estimate for PCR is -0.0681. While this is a step in the right direction, Roodman argues that collapsing the instrument set conveys more information while limiting the instrument count. Doing this brings the instrument count down from 162 to 26 and results in the estimate increasing in magnitude to -0.133 as seen in column 6. It also reduces the p-value for the Hansen test from 0.897 to 0.199. While a higher p-value is not necessarily bad, it does suggest that the estimated model has too many instruments.

Second, the model shows a unit root as evidenced by the point estimates for lagged RPINC being close to one. This biases all test statistics as the asymptotic distribution of the statistics is unknown. Any conclusions drawn in the presence of a unit root may be biased. Fortunately, limiting the number of instruments gets rid of this problem with the coefficient being reduced to 0.867. I also exclude the level instruments and find the point estimate for property crime declines, but still remains large at -0.105.

Finally, there is the question of weak instruments which is especially problematic for level instruments. Focusing only on difference GMM results in column 4, the results are actually close to the collapse results with an estimate of -0.119 and the unit root is not present either suggesting that weak instruments are likely not a problem especially for system GMM.

To control for potential non-linear responses depending on the size of the MSA, I weight the model with the labor force size as well as running the model excluding the 5% smallest and largest MSAs. Performing this size check on the baseline estimate results in the estimate declining in magnitude to -0.0347 and -0.0592 in columns 7 and 9 respectively, so there may be some effects from labor force size, but it is not being driven by the extremes. Applying this size check to the collapse result, the estimates move in different directions. Weighting by labor force size increases the estimate in magnitude to -0.148 while excluding the extreme MSAs decreases the estimate in magnitude to -0.119. Across all these checks, the estimates remain consistent and significant. Placing a lower bound on the estimate still implies that reducing property crime by 100% would increase real income per capita by 3.5%, but the primary estimate using the collapse command suggests that real income per capita would increase by 13.3%.

Looking at the individual subcategories of property crime should provide some useful information about what is driving our main result. Property crime can be broken into larceny-theft, burglary, robbery, and motor vehicle theft. First, I consider larceny-theft. Focusing on column 6 of Table 3.3, a 1% reduction in larceny-theft (LTR) would result in a 0.179% increase in RPINC. This estimate is significant at the 5% level. Significance is retained in columns 8 and 10 when the results are weighted by the labor force size and when large and small MSAs are left out. In both cases, the estimated coefficient on LTR drops from -0.179 to -0.083 and -0.149 respectively. Significance is increased in the case of weighting, but weakened when the sample is restricted. Larceny-theft having a large effect is intuitive. It has a large effect on firms relative to other categories, so it can affect how many workers they hire, how much they pay their workers, and how many of their workers are being used for loss prevention. Each of these can result in crime having a negative effect on real income.

Burglary also appears to be a significant driver of the effect of property crime on income. Looking at columns 5, 6, 8, and 10 of Table 3.4, the coefficient estimate ranges from -0.0427 in column 8 to -0.110 in column 6. In each of these cases, the instrument set is collapsed providing the the most robust result/ These estimates suggest that, on average, a 1 standard deviation decrease in Burglary within an MSA increases RPINC by 0.74-1.91%. Again, the large effect of burglary is intuitive as it has the largest direct effect on household behavior. Burglary includes breaking and entering into someones home and stealing from their homes. This encourages households to invest in security which is not an efficient use of resources. It also encourages households to purchase replacement goods which also an inefficient use of resources. These combine to encourage firms to produce goods and services using resources that could be more productive elsewhere in the absence of crime.

Robbery does not appear to be a significant driver of the primary result. Column 5 of Table G.1 suggests that robbery is not significant even if the estimated coefficient is -0.053. Restricting the sample size has no effect on significance, but weighting by the labor force size makes the results significant at the 0.01 level with an estimate of -0.0797. This would imply that a 1 standard deviation decrease in robbery increases RPINC by an average of 1.623% across MSAs. Overall though, the results do not appear to be very robust. This likely stems from the nature of robbery. Since the victim has to be present, it is more likely that robbery occurs person-to-person on the streets. This can be prevented by avoiding certain locations in a MSA. At a neighborhood level, there is likely to be a strong negative effect, but at a MSA or county level, the effect is not likely to be identifiable in a significant way.

Finally, motor vehicle theft appears to be a significant driver of the primary result as well with the estimates ranging from -0.042 in column 9 of Table G.2 to -0.060 in column 5. These results are smaller, but still suggest that a 1 standard deviation decrease in the MVTR would increase RPINC by up to 1.97% on average. Given that these coefficient estimates are small relative to the property crime estimates, motor vehicle theft is not a large driver of the main result. Since car insurance is fairly common, motor vehicle theft has a limited impact on individuals even if it requires insurers use resources that could be put towards other more productive uses in the absence of crime. This causes the overall magnitude of the effect to decline.

Larceny-theft and Burglary seem to be the largest drivers with motor vehicle theft having a significant, but smaller effect. While putting all subcategories in the same regression could provide useful information about what is driving the results, in practice the results are highly volatile and unreliable due to the high degree of correlation (0.52-0.72) across the different subcategories. I would likely need instruments that correlate with only one subcategory, but not the others. Unfortunately, this has not proven fruitful.

3.6 Conclusion

Using system GMM to estimate the effect of property crime (PCR) on real personal income per capita (RPINC) suggests that property crime reduces RPINC by 13.3% which works out to about $2.8 trillion dollars as of the fourth quarter of 2018. At the household level, this means that RPINC is reduced by an average of $4,869. Estimating the effect of property crime on real personal income per capita hinges on two key assumptions. First, that causality is identified via the use of lags as instruments and that the instruments themselves are valid. If the assumptions regarding the mechanism of causality are believed, then causality should be established as well. For this paper, lags of changes in income per capita are likely good predictors of income per capita, but not necessarily current property crime rates. This should rule out the potential for reverse causality biasing the primary results. Establishing that the instruments are valid hinges on reducing the number of instruments. Collapsing the instrument set brings the total number of instruments down from 162 to 26 while bringing the p-value for the Hansen test for over-identifying restrictions down from 0.897 to 0.199. While a higher p-value is not necessarily bad, it does suggest that the estimated model has too many instruments.

Exploring the different subcategories of property crime suggests that larceny-theft and burglary are the most significant drivers of the overall effect with motor vehicle theft being significant, but small and estimates for robbery being unstable.

Intuitively, larceny-theft and burglary should be the most impactful. First, larceny-theft affects businesses the most which can effect how many workers firms can hire, how much they pay those workers, and how many workers are used for loss prevention instead of producing real output. Burglary effects people at home which can affect their emotional well-being, encourage them to invest in security which is not contributing to real output, and forces them to purchase replacement items instead of purchasing what would make them the most well off. Robbery on the other hand can be avoided by avoiding certain areas and usually only causes emotional and monetary damage which can be mitigated by using credit cards and debit cards. I would expect that the effect of robbery is substantial at a neighborhood level, but at an MSA level, it is harder to identify. Finally, motor vehicle theft is common, but more easily remedied as it is harder to hide a car forever and insurance is available to cover losses.

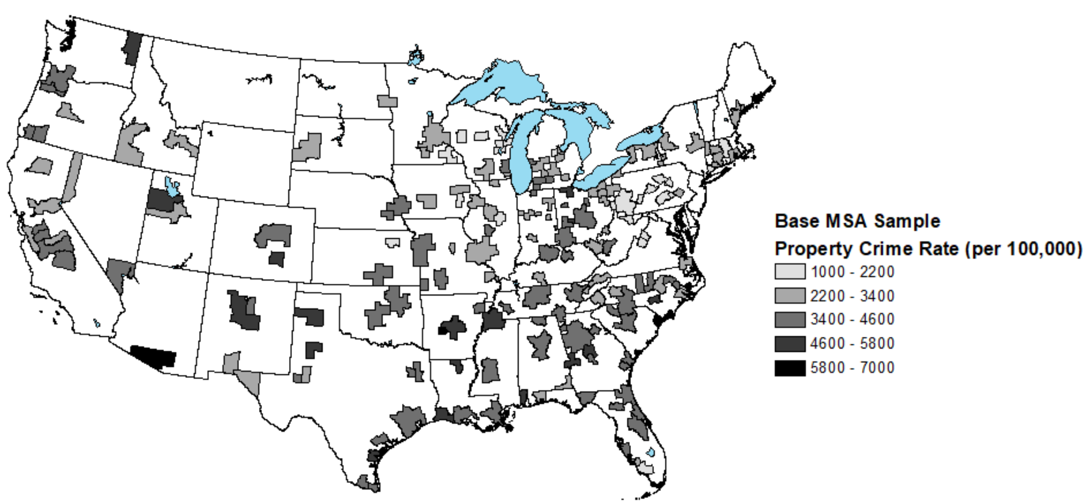


Figure 3.1.: Map of MSAs Used

This map shows which MSAs are included in the sample as well as variation in the mean property crime rate across MSAs. MSAs are binned and shaded according to the property crime rate. The higher the crime rate bin, the darker the shading.

Table 3.1.: Summary Statistics

Variable	Obs	MSAs	Years	Mean	Std. Dev.	Min	Max
Real Personal Income per Capita	2180	181	14	36,615	8219	18,489	107,592
Property Crime Rate	2133	181	14	3430	1091	1108	8695
Larceny/Theft Rate	2156	181	14	2378	723.8	854.7	5459
Robbery	2180	181	14	105.0	61.5	3.6	458.5
Burglary	2163	181	14	789.2	337.0	158.7	2859
Motor Vehicle Theft	2171	181	14	264.3	181.7	15.5	1409
Labor Force (100,000s)	2180	181	14	6.0	7.6	0.5	45.3
Own Children at Home ($\% \cdot n$)	1333	159	12	42.1	4.7	23.2	61.7

Real personal income per capita is denoted in 2009 \$. All crime rates are denoted per 100,000 persons. Finally, own children at home reflects the percentage of households with children at home times the number of children they have at home.

Table 3.2.: Blundell-Bond Estimates for Property Crime Rate

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) no level equation	(5) lag(2 2)	(6) lag(6 .) collapse	(7) LF weight	(8) LF weight collapse	(9) percentile	(10) percentile collapse
log(RPINC$_{i,t-1}$)	1.046***	1.028***	1.033***	0.732***	1.070***	0.867***	1.013***	0.933***	1.024***	0.971***
	(0.019)	(0.018)	(0.017)	(0.104)	(0.026)	(0.259)	(0.015)	(0.115)	(0.031)	(0.174)
log(PCR$_{i,t}$)	-0.032	-0.059***	-0.058***	-0.119***	-0.068***	-0.133**	-0.035***	-0.148***	-0.059***	-0.119***
	(0.023)	(0.015)	(0.014)	(0.017)	(0.010)	(0.057)	(0.010)	(0.031)	(0.012)	(0.036)
Own Children at Home		0.143***	0.111	0.170***	-0.008	-0.031	0.074**	0.151	0.144***	0.102
		(0.043)	(0.083)	(0.057)	(0.060)	(0.277)	(0.035)	(0.103)	(0.050)	(0.202)
Constant	-0.199	0.147	0.091		-0.238	2.492	0.130	1.846	0.183	1.236
	(0.262)	(0.186)	(0.195)		(0.306)	(3.214)	(0.199)	(1.414)	(0.306)	(2.146)
Observations	1,864	1,224	1,224	1,037	1,224	1,224	1,224	1,224	1,175	1,175
Number of geoFIPS	180	141	141	135	141	141	141	141	135	135
Instruments	166	162	162	139	52	26	161	25	161	25
AB test for AR(2)	0.0825	0.118	0.119	0.075	0.121	0.161	0.108	0.172	0.123	0.176
AB test for AR(3)	0.800	0.557	0.555	0.148	0.562	0.534	0.456	0.928	0.505	0.478
Hansen test	0.273	0.897	0.887	0.650	0.166	0.199	0.847	0.693	0.931	0.285
%Δ RPINC wrt 1 std Δ PCR	-0.468	-0.862	-0.845	-1.728	-0.989	-1.935	-0.505	-2.150	-0.866	-1.746

Windmeijer robust standard errors clustered at the MSA level are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.3.: Blundell-Bond Estimates for Larceny-Theft Rate

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) lag(2 6)	(5) lag(3 7)	(6) collapse (6 .)	(7) LF weight	(8) LF weight collapse	(9) percentile	(10) percentile collapse	(11) no level equation
$\log(\text{RPINC}_{i,t-1})$	1.043***	1.033***	1.036***	1.049***	1.030***	0.515	1.019***	1.045***	1.027	0.893**	0.746***
	(0.015)	(0.033)	(0.014)	(0.020)	(0.022)	(0.383)	(0.036)	(0.053)	(5.799)	(0.358)	(0.082)
$\log(\text{LTR}_{i,t})$	-0.012	-0.032	-0.034***	-0.042***	0.025	-0.179**	-0.030**	-0.083***	-0.050	-0.149*	-0.102***
	(0.017)	(0.023)	(0.012)	(0.012)	(0.028)	(0.082)	(0.014)	(0.021)	(7.848)	(0.088)	(0.022)
Own Children at Home		0.111	0.110*	0.118***	0.045	-0.307	0.066	0.081	0.121	0.060	-0.003
		(0.116)	(0.058)	(0.039)	(0.030)	(0.319)	(0.082)	(0.066)	(26.30)	(0.299)	(0.062)
Constant	-0.275	-0.122	-0.138	-0.220	-0.492	6.611	0.029	0.149	0.065	2.261	
	(0.216)	(0.289)	(0.164)	(0.233)	(0.406)	(4.708)	(0.441)	(0.670)	(115.6)	(4.517)	
Observations	1,884	1,238	1,238	1,238	1,238	1,238	1,238	1,238	1,189	1,189	1,059
Number of geoFIPS	180	141	141	141	141	141	141	141	135	135	135
Instruments	166	163	163	121	111	27	161	33	162	26	140
AB test for AR(2)	0.0753	0.107	0.104	0.110	0.0983	0.339	0.0817	0.132	0.902	0.251	0.165
AB test for AR(3)	0.911	0.689	0.694	0.684	0.741	0.606	0.176	0.322	0.869	0.500	0.598
Hansen test	0.336	0.906	0.931	0.215	0.135	0.834	0.781	0.203	0.302	0.441	0.647
%ΔRPINC wrt 1 std ΔLTR	-0.281	-0.441	-0.468	-0.576	0.342	-2.471	-0.416	-1.145	-0.686	-2.058	-1.406

Windmeijer robust standard errors clustered at the MSA level are reported in parentheses

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

Table 3.4.: Blundell-Bond Estimates for Burglary Rate

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) lag(2 5)	(5) collapse (4 .)	(6) collapse (5 .)	(7) LF weight	(8) LF weight collapse	(9) percentile	(10) percentile collapse	(11) no level equation
$\log(\text{RPINC}_{i,t-1})$	1.053***	1.031***	1.037***	1.049***	0.780***	0.589**	1.014***	0.990***	1.030***	0.978***	0.752***
	(0.018)	(0.016)	(0.017)	(0.017)	(0.081)	(0.240)	(0.033)	(0.043)	(0.017)	(0.053)	(0.010)
$\log(\text{Burglary}_{i,t})$	-0.010	-0.033***	-0.035***	-0.046***	-0.094***	-0.110***	-0.017*	-0.043***	-0.032***	-0.070***	-0.087***
	(0.013)	(0.010)	(0.011)	(0.013)	(0.015)	(0.028)	(0.010)	(0.008)	(0.011)	(0.013)	(0.013)
Own Children at Home		0.102***	0.031	0.120***	-0.094	-0.285	0.072	0.081**	0.103***	0.099	-0.024
		(0.034)	(0.062)	(0.044)	(0.128)	(0.269)	(0.053)	(0.039)	(0.035)	(0.066)	(0.066)
Constant	-0.470**	-0.136	-0.155	-0.245	2.974***	5.167*	-0.038	0.377	-0.132	0.667	
	(0.203)	(0.175)	(0.189)	(0.207)	(0.939)	(2.744)	(0.394)	(0.488)	(0.188)	(0.640)	
Observations	1,893	1,250	1,250	1,250	1,250	1,250	1,250	1,250	1,200	1,200	1,072
Number of geoFIPS	180	141	141	141	141	141	141	141	135	135	137
Instruments	166	163	163	107	31	29	163	35	163	35	140
AB test for AR(2)	0.0726	0.0816	0.0845	0.0843	0.0957	0.143	0.104	0.0882	0.0873	0.0882	0.092
AB test for AR(3)	0.855	0.665	0.660	0.669	0.711	0.764	0.400	0.375	0.602	0.616	0.708
Hansen test	0.323	0.844	0.830	0.103	0.103	0.591	0.928	0.336	0.933	0.153	0.471
$\%\Delta$RPINC wrt 1 std ΔBurglary	-0.176	-0.570	-0.604	-0.804	-1.626	-1.914	-0.302	-0.740	-0.565	-1.218	-1.509

Windmeijer robust standard errors clustered at the MSA level are reported in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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A. Worker Flow Derivation

Worker flows were calculated using the Current Population Survey (IPUMS-CPS). Starting in 1994, the CPS started asking questions regarding multiple job holdings. In particular, they started asking individuals if they worked more than one job in the prior week, and if so, how many. The survey also asks about an individuals work history. Particularly useful for me, they ask whether the individual is unemployed, part-time or full-time for economic or non-economic reasons, or if they are not part of the labor force. Combining these questions gives me a reasonable way to measure the fraction of workers in each employment state and the transitions between.

The data is not without shortcomings though. Data from 1995 showed much more fluctuation in the number of individuals in each sample month, so I have elected to drop the years 1994 and 1995.[1] In addition, I have elected to keep only those individuals between the ages of 25 and 54.[2] This way I can minimize transitions from being in school to working and from working into early retirement. Thus, my sample consists of all individuals between the ages of 25 and 54 who were sampled between January 1996 and December 2014

Once I have calculated the weighted sums of individuals in each state and moving between each state, I can calculate the probability of a worker moving from one state to another. This probability is denoted by

$$f_{t,i\to j} = \frac{M_{t,i\to j}}{M_{t-1,i}}$$

[1] Individuals are surveyed for 4 months, then ignored for 8 months, and re-surveyed for 4 months. Sample months are labeled 1-8 to represent the 8 total months that individuals get sampled

[2] Similar to Shimer (2012)

where t is the current time period, $t-1$ is the previous time period, i is the previous state of employment, j is the current state of employment, and M is the mass of workers in a given state. Once I have this probability, I can back out the Poisson rate using the equation $Pr(X < x) = f_{t,i \to j} = 1 - e^{-\lambda_{t,i \to j} x}$. Setting $x = 1$, I can solve for the Poisson arrival rate

$$\lambda_{t,i \to j} = -ln(1 - f_{t,i \to j})$$

Once these rates are calculated, I apply a HP filter to the data in order to extract the underlying trend.

B. Part-Time and Full-Time Employment

In order to get a better understanding of the choices that workers are making, I consider a simplified framework with workers and firms restricted to either one part-time job or one full-time job. The worker's goal is to receive a job offer for either a part-time or full-time job, but receiving more than one job offer is no more valuable than receiving only one.

B.1 Environment

Consider a discrete time job search model where time goes on forever. There is a continuum of infinitely lived, risk-neutral workers with lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t y_t$$

where y_t is the worker's instantaneous income at time t and $\beta \in (0,1)$ is the discount factor.

Workers can be in one of 3 states: unemployed, employed part-time, or employed full-time. Each worker is endowed with 40 hours of time with a part-time job requiring 20 hours and a full-time job requiring 40 hours. While unemployed, workers are assumed to always be searching for a job, but can choose the intensity with which they search for part-time work (s_p) or full-time work (s_f), however, they must pay weakly convex search cost $\sigma(s_p, s_f)$. Search intensity can be thought of as some measure of the number of applications a worker sends out as well as the quality of each application such that search intensity $\{s_f, s_p\} \in \mathbb{R}$. Searching with intensity $s_i = 0$ is equivalent to not searching at all. Unemployed workers receive value of leisure z while employed workers receive wage w_i with $i \in \{f, p\}$. There is one type of firm that can be in one of 3 states: vacant, employing a part-time worker, or employing a full-time worker. Firms can post vacancies v and choose whether to recruit to full-time workers (a_f) or part-time workers ($a_p = 1 - a_f$) while paying weakly convex recruiting cost $C(a_p, a_f)$. Firms that hire a worker of type i receive output p_i and pay wage w_i.

Having variable search intensity and recruiting intensity is an important component in this model for two primary reasons. First, empirical results show that workers do not search in the same manner for every type of job nor do they search in the same manner when employed and unemployed. Workers use different methods of search as well as choosing different search hours depending on the type of job they are searching for and their current job status (Holzer (1988), Pissarides & Wadsworth (1994), Aguiar, Hurst, & Karabarbounis (2013), Faberman et al. (2016)). Thus, it is important that workers in this model be able to change their search intensity according to their current employment status and desired job rather than being stuck searching with the same intensity across all jobs. Likewise, firms do not recruit for full-time and part-time positions in the same manner or the same quantity(Russo, Gorter, & Schettkat (2001)). Likewise, they recruit to workers differently depending on their current employment status (Faberman et al. (2016)). In Section 3.5, I show the importance of this margin. Without the intensive margin of search and recruiting, the results look dramatically different.

Workers and firms are matched pairwise according to two CRTS matching functions, one for full-time jobs and one for part-time jobs. The matching function depends on the effective mass of firms ($a_i v$) and the effective mass of workers ($s_i u$).

The rate at which matches of type $i \in \{f, p\}$ are formed between a firm and worker is given by

$$m_i(\bar{s}_i u, a_i v)$$

where the effective mass of workers depends on average search intensity over all workers $\bar{s}_i$. The probability that any one unit of search intensity results in a job offer is:

$$\mu_i(\theta_i) = m_i(1, \theta_i) = \frac{m_i(\bar{s}_i u, a_i v)}{\bar{s}_i u}$$

where θ_i represents market tightness. Given market tightness, an individual worker who chooses to search with intensity s_i has individual matching probability

$$q_i(\theta_i, s_i) = 1 - \big(1 - \mu_i(\theta_i)\big)^{s_i}$$

which is the probability that a worker receives at least one job offer resulting from their search effort. At this point it is worth noting that in equilibrium, $\bar{s}_i = s_i$ since all workers are homogeneous. This matching probability has some important properties. First, as an individual worker increases their search intensity s_i, they increase the probability that they match with a firm, but all workers are homogeneous, aggregate search intensity $\bar{s}_i$ will increase which results in a lower probability that any one unit of search intensity produces a job offer such that the individuals matching probability falls as well resulting in an ambiguous response. Because the measure of workers who match in a given period is $uq_i(\theta_i)$, the probability that a firm's vacancy is filled is

$$p_i(\theta_i, \bar{s}_i) = \frac{q_i(\theta_i, \bar{s}_i)}{\theta_i \bar{s}_i}$$

which does not depend on the individual level of search intensity. After a worker and firm match, they both face some exogenous probability λ_i that the job is destroyed which depends on the type of job.

B.2 Equilibrium

At the beginning of each period, workers and firms find out if they matched. If a worker matches with a part-time firm, they agree with the firm on the part-time wage. If they match with a full-time firm, they agree with the firm on the full-time wage. The worker receives the corresponding wage and the firm receives the corresponding final value of output and pays the corresponding wage. If a worker remains unemployed, they receive the instantaneous value of leisure and choose their search intensity and pay some search cost. If a firm remains vacant, they choose their recruiting intensity and pay some recruiting cost.

B.3 Firm's Problem

Firms start by posting a vacancy and choosing recruiting intensity $a_p = 1 - a_f$ for part-time jobs and recruiting intensity a_f for full-time jobs. Firms choose their recruiting intensity to maximize flow value

$$V = \max_{a_f} \Big\{ - C(a_p, a_f) + \beta V + \beta p_f(\theta_f, \bar{s}_f)[J_f - V] + \beta p_p(\theta_p, \bar{s}_p)[J_p - V] \Big\} \tag{B.1}$$

where they pay recruiting cost $C(a_p, a_f)$ and match with a part-time worker with probability $p_p(\theta_p, \bar{s}_p)$ and with a full-time worker with probability $\beta p_f(\theta_f, \bar{s}_f)$. If they match with a worker of type $i \in \{f, p\}$, they receive flow value

$$J_i = x_i - w_i + \beta J_i + \beta \lambda_i [V - J_i] \tag{B.2}$$

where instantaneous income is the value of output x_i and instantaneous cost is wage w_i. They also face some risk that the job is destroyed with probability λ_i in which case they choose whether to open a vacancy. Because the goods market is perfectly competitive, firms will post vacancies until the flow value of posting an additional vacancy $V = 0$ in equilibrium.

The choice of recruiting intensity for full-time workers a_f is given by equation (B.3).

$$\frac{\partial C}{\partial a_f} = \beta\Big[\frac{\partial p_f(\theta_f, \bar{s}_f)}{\partial a_f}\Big(\frac{x_f - w_f(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\alpha_f}\Big) + \frac{\partial p_p(\theta_p, \bar{s}_p)}{\partial a_f}\Big(\frac{x_p - w_p(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\alpha_p}\Big)\Big]$$
$$- \Big[\frac{\partial w_f(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\partial a_f}\Big(\frac{p_f(\theta_f, \bar{s_f})}{\alpha_f}\Big) + \frac{\partial w_p(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\partial a_f}\Big(\frac{p_p(\theta_p, \bar{s_p})}{\alpha_p}\Big)\Big] \quad \text{(B.3)}$$

The LHS denotes the direct cost of increasing recruiting intensity a_f while the RHS denotes the indirect gains and costs that increased recruiting has on matching probabilities and wages. First, increased recruiting intensity a_f increases the full-time matching probability for a firm while decreasing the part-time matching probability since $a_p = 1 - a_f$. In addition, increased recruiting intensity a_f increases the wage w_f that the firm pays to a full-time worker while decreasing the wage w_p that they pay to a part-time workers.

B.4 Worker's Problem

Unemployed workers receive some value of leisure z and choose their search intensity for part-time and full-time employment in order to maximize the flow value

$$U = \max_{s_f, s_p} \Big\{ z\big(1 - h(s_p + s_f)^\nu\big) + \beta\big(U + q_f(\theta_f, s_f)[E_f - U] + q_p(\theta_p, s_p)[E_p - U]\big)\Big\} \quad \text{(B.4)}$$

where they pay search cost $zh(s_p + s_f)^\nu$. Their choice of search intensity affects the probability that they match with a firm for a part-time job with probability $q_p(\theta_p, s_p)$ or for a full-time job with probability $q_f(\theta_f, s_f)$. If a worker matches with a firm of type $i \in \{f, p\}$, they receive flow value

$$E_i = w_i + \beta E_i + \beta\lambda_i[U - E_i] \tag{B.5}$$

where wage w_i is their instantaneous income and they face some risk that the job is destroyed with probability λ_i in which case they become unemployed.

The choice of search intensity for employment of type $i \in \{f, p\}$ is given by

$$(\Omega_{si} + \Omega_{wi})\Delta_1 + \Omega_{qi}\Delta_2 = \beta(B_{qi} + B_{wi})\Delta_1 \tag{B.6}$$

where the left-hand side of this equation corresponds to the cost of increasing search intensity s_i while the right-hand side corresponds to the benefits from increasing search intensity s_i. Workers must pay both direct and indirect cost that result from their choice. First, they pay cost

$$\Omega_{si} = \alpha_f\alpha_p z\nu h(s_p + s_f)^{\nu-1}$$

which corresponds to the direct marginal cost of changing their search intensity. The term $\alpha_i = 1 - \beta(1 - \lambda_i)$ is the discount term for a firm of type i and $\sigma = z\big(1 - h(s_p + s_f)^\nu\big)$ is the cost of search intensity. Second, any increase in search intensity s_i will decrease the wage w_i, so the worker pays indirect cost

$$\Omega_{wi} = -\beta\alpha_{-i}q_i(\theta_i, \bar{s}_i)\frac{\partial w_i(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\partial s_i}$$

which results from a decrease in market tightness. This is similar to the result from the canonical DMP model wherein falling market tightness reduces the wage. Both of these costs are discounted by the discount term Δ_1.

$$\Delta_1 = \alpha_f \alpha_p + \beta \sum_i \alpha_{-i} q_i(\theta_i, \bar{s}_i)$$

Finally, The worker pays discounted indirect cost

$$\Omega_{qi} \Delta_2 = \left[\beta \alpha_{-i} \frac{\partial q_i(\theta_i, \bar{s}_i)}{\partial s_i}\right] \left[\alpha_f \alpha_p \sigma(\boldsymbol{s}) + \beta \sum_i \alpha_{-i} q_i(\theta_i, \bar{s}_i) w_i(\boldsymbol{\theta}, \bar{\boldsymbol{s}})\right]$$

which results from an increase in the discount term for the value of being unemployed. This means that an increase in search intensity s_i increases q_i which increases the denominator of the flow value of being unemployed U resulting in a decrease in U. In addition to these costs, an unemployed worker can benefit from increasing search intensity s_i as seen on the RHS of equation (B.6). First, workers get direct benefit

$$B_{qi} = \alpha_{-i} \frac{\partial q_i(\theta_i, \bar{s}_i)}{\partial s_i} w_i(\boldsymbol{\theta}, \bar{\boldsymbol{s}})$$

which comes from an increase in the probability of matching with a firm resulting from an increase in search intensity s_i. Second, workers receive indirect benefit

$$B_{wi} = \alpha_i q_{-i}(\theta_{-i}, \bar{s}_{-i}) \frac{\partial w_{-i}(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\partial s_i}$$

from an increase in the wage for the other type of job $-i$. As a worker increases search intensity s_i holding s_{-i} constant, a higher wage must be paid in order for workers to be willing to work a job of type $-i$. Both of these benefits are discounted at rate $\beta\Delta_1$.

B.5 Wage Determination

When a worker-firm match is formed, they bargain over the wage which reduces to the axiomatic Nash Bargaining solution. Workers and firms have full information about each other and the worker has bargaining power γ while the firm has bargaining power $1-\gamma$. Thus the wage for a job of type $i \in \{f, p\}$ is determined by

$$w_i = \text{argmax}(E_i - U)^{\gamma}(J_i - V)^{1-\gamma} \tag{B.7}$$

which yields a system of two equations which can be solved for wages w_p and w_f as in equation (B.8). It is important to note that neither wage can be independently determined. They depend on each other.

$$w_i = \frac{\Big(\gamma x_i + \frac{(1-\gamma)\alpha_i z(1-h(s_p+s_f)^{\nu})}{\alpha_i+\beta q_i}\Big) + \Big(\gamma x_{-i} + \frac{(1-\gamma)\alpha_{-i} z(1-h(s_p+s_f)^{\nu})}{\alpha_{-i}+\beta q_{-i}}\Big)\Big(\frac{(1-\gamma)\beta q_{-i}}{\alpha_{-i}+\beta q_{-i}}\Big)}{1-(\alpha_i+\beta q_i)(\alpha_{-i}+\beta q_{-i})} \tag{B.8}$$

The wage for a job of type i depends not only on the surplus generated from creating a job of type i, but also on the surplus generated from creating a job of type $-i$. Assuming $x_f > x_p$ implies that as x_p increases, both wages w_p and w_f will increase.

B.6 Steady-State

Definition B.6.1 *The steady-state equilibrium consists of a list (u, l_f, v, a_f, w_f, w_p, s_f, s_p) that solves the unemployment flow equation*

$$m_p(\bar{s}_p u, a_p v) + m_f(\bar{s}_f u, a_f v) = \lambda_f l_f + \lambda_p(1-u-l_f), \tag{B.9}$$

the full-time employment flow equation

$$m_f(\bar{s}_f u, a_f v) = \lambda_f l_f, \tag{B.10}$$

the job creation condition for vacancies

$$c = \beta p_f(\theta_f, \bar{s}_f)\Big(\frac{x_f - w_f(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\alpha_f}\Big) + \beta p_p(\theta_p, \bar{s}_p)\Big(\frac{x_p - w_p(\boldsymbol{\theta}, \bar{\boldsymbol{s}})}{\alpha_p}\Big), \tag{B.11}$$

the firm's recruiting intensity maximization equation (B.3), two wage setting conditions (B.8), and the worker's two search intensity maximization equations (B.6).

B.7 Numerical Examples

To illustrate how the model works in this simplified environment, I parameterize the model and perform some comparative statics assuming a time period of one month. First, the elasticity of the search cost function is $\nu = 1$, the value of leisure is $z = 1$, the cost of recruiting is fixed at $c = 0.1x_f$, and the discount factor is $\beta = 0.995$. For worker's and firms, the full-time and part-time job destruction rates are $lambda_f = 0.04$ and $lambda_p = 0.08$ respectively, the probability of matching is $\mu_i = \theta_i(1 - e^{-1/\theta_i})$, and worker's bargaining power is $\gamma = 0.5$. The final value of output for full-time workers is $x_f = 1.6$ while the final value of output for part-time workers follows a Cobb-Douglas production function with a labor-income share of 2/3 so that $x_p = x_f(0.5)^{2/3} = 1.01$. Finally, the marginal cost of search $h = 0.001$.

The results shown in Table B.1 line up well with the observed data with an unemployment rate of 7%, a full-time employment rate of 70%, and a part-time employment rate of 23%. There are a few things that are unusual. First, search effort for part-time employment is 12 times as large as search effort for full-time employment which is not empirically consistent with observations that suggest part-time search effort is lower than full-time search effort. One of the properties of the matching function is that as vacancies fall, search effort rises. Since firms are only recruiting for part-time workers with intensity $a_p = 0.174$, workers are induced to search harder

Table B.1.: Numerical Elasticities

	u	l_f	l_p	s_f	s_p	v	a_f	a_p	w_f	w_p
Baseline	0.071	0.698	0.231	0.183	2.227	0.115	0.826	0.174	1.279	1.186
h	0.002	−0.000	−0.000	−0.008	−0.006	0.007	0.002	−0.008	−0.001	−0.001
z	−0.995	0.232	−0.396	5.282	7.433	−2.354	−0.635	3.022	0.369	0.425
λ_f	0.746	−0.222	0.442	0.562	0.540	−0.015	−0.097	0.462	0.011	−0.004
λ_p	0.167	0.055	−0.219	0.033	−0.979	−0.125	−0.194	0.922	0.107	0.136
γ	1.628	−0.667	1.517	−2.098	−2.646	−1.260	−0.607	2.888	0.347	−0.065
x_f	1.649	0.001	−0.512	−3.274	−2.153	2.461	0.597	−2.838	0.272	0.041
x_p	−0.421	−0.167	0.636	0.371	−1.737	−0.015	−0.132	0.626	0.377	0.599

for part-time employment than full-time employment. This suggests that separable cost of search may be needed. Second, the wage for part-time workers is higher than the final value of output for part-time workers. This is likely due to the high value of leisure and firms willingness to take a smaller loss from employing a part-time worker as opposed to continuing to post a vacancy.

Perturbing the model generates some interesting results as well. First, increased marginal cost of search h has a limited effect, but unemployment increases while both part-time and full-time employment decrease as expected. In addition, workers search with less intensity since the cost of search is higher. Second, increasing the full-time job destruction rate λ_f results in increased unemployment, increased part-time employment, and decreased full-time employment. It also results in increased search effort for both part-time and full-time employment. This result aligns with Aguiar, Hurst, and Karabarbounis (2013) who find that the value of leisure is lower in bad economic conditions and search intensity is higher. Third, increasing the part-time job destruction rate λ_p leads to similar results with increased unemployment, increased full-time employment and decreased part-time employment. Interestingly, search intensity increases for full-time employment, but decreases for part-time employment. This is likely due to the dominating effect that full-time employment exerts in the model. Finally, if the value of leisure z is increased, the unemployment rate decreases due to a large increase in search effort. Interestingly, part-time employment decreases while full-time employment increases even with increased firm recruiting for part-time workers. I posit that this stems from the higher job destruction rate for part-time employment compared to full-time employment.

There are some very inconsistent result. First, increasing the full-time final value of output x_f results in higher unemployment even if the full-time employment rate increases. This is inconsistent with the prior literature and largely stems from a large decrease in search effort by workers; however, increasing the part-time final value of output x_p results in decreased unemployment and full-time employment, but higher part-time employment as one would expect. If both are increased proportionally, then the full-time effect dominates the part-time effect resulting in higher unemployment. Even though both wages increase, the response from search effort induces a decrease in unemployment. Scheduling costs, which are analogous to an increase in the final value of output for a firm, are one interesting theory as to why part-time employment has risen in recent years. With more efficient scheduling, part-time employment can become more valuable as it allows firms greater scheduling flexibility. As an example consider the case of n 160 hour blocks that need to be filled. You could fill each block with one full-time worker who work 160 hours per month or two part-time workers who work 80 hours each. This means that an employer has $n!$ ways to fill these blocks with full-time workers or $(2n)!$ ways with part-time workers. It is fairly obvious to see that the number of ways a block can be filled with part-time workers is growing at a much faster rate than for full-time workers which implies that there may be lower scheduling costs associated with part-time workers and any decrease in part-time costs could have a disproportionate impact. In the context of the model, a decrease in scheduling costs is associated with a higher final value of output and higher part-time employment which would be consistent with the scheduling cost theory.

Without multiple job holdings, the model is fairly consistent with the data even without calibrating the model. When workers and firms have a choice between full-time and part-time employment, their search intensity and recruiting intensity depend not only on the direct and indirect costs and benefits of searching/recruiting for a given type of job, but also the indirect costs and benefits for the other type of job. If the two types of jobs are identical in every way, then the problem reduces to the standard DMP model, so it is relatively tractable. When workers and firms have the option to hold multiple jobs, their search intensity and recruiting intensity depend not only on the direct and indirect costs and benefits of searching/recruiting for a given type of job, but also the indirect costs and benefits for the other type of job. Even if the two types of jobs are identical in every way, the problem does not reduce to the standard DMP model unless multiple job holdings is turned off entirely.

One final observation regards the relationship between the unemployment rate and the full-time rate. As can be seen in Table B.1, the unemployment rate u and the full-time rate l_f usually move in opposite directions. A natural question to ask is under what conditions, the relationship switches as it does when perturbing λ_p and x_p.

Proposition B.7.1 *So long as the following condition holds, the full-time rate will always move in the opposite direction of the unemployment rate:*

$$\frac{\lambda_f - \lambda_p - u\Big[\Big(\frac{\partial q_f}{\partial v} + \frac{\partial q_p}{\partial v}\Big)\frac{\mathrm{d}v}{\mathrm{d}l_f} + \Big(\frac{\partial q_f}{\partial a_f} + \frac{\partial q_p}{\partial a_f}\Big)\frac{\mathrm{d}a_f}{\mathrm{d}l_f} + \Big(\frac{\partial q_f}{\partial s_f}\Big)\frac{\mathrm{d}s_f}{\mathrm{d}l_f} + \Big(\frac{\partial q_p}{\partial s_p}\Big)\frac{\mathrm{d}s_p}{\mathrm{d}l_f}\Big]}{\lambda_p + q_p + q_f + u\Big(\frac{\partial q_f}{\partial u} + \frac{\partial q_p}{\partial u}\Big)} < 0$$

The derivation for Proposition B.7.1 is provided in Appendix C. As soon as the gains to matching are positive for an increased unemployment rate, the full-time employment rate and unemployment rate will begin to move in the same direction. This switching is most obvious for changes in λ_p for which u and l_f begin to move in the same direction. This becomes apparent again when both search intensities drop and vacancies rise as it does for a change in x_p. This causes the gains from higher unemployment to increase.

To remedy some of the inconsistencies described above, I consider the case of multiple job holdings in addition to part-time employment. Multiple job holdings is particularly relevant when considering part-time employment as part-time workers are more likely to have multiple jobs and the option of additional employment increases the flow value of being a part-time worker. For instance, if being a full-time worker becomes more valuable, then fewer workers will be employed part-time, but with multiple job holdings, the value of being a part-time worker also increases as they have the option of working a secondary full-time job. This mutes dampens the response of part-time employment. Finally, I consider the case of separable search cost with the cost of search being allowed to vary depending on the type of job a worker is searching for.

B.8 Uniqueness

Given that workers can hold more than one job and firms can recruit more than one type of worker, it is not clear that there will be a unique solution. Consider the job creation curve and wage setting curve that relate how the vacancy rate and wage are related. Since there are two wages, the wage setting curve could be non-monotonic or upward sloping which would result in more than one equilibrium.

Proposition B.8.1 *If the following conditions hold, then there exist a unique triplet (v,w_1,w_2) for the vacancy rate and both wages such that there exist a unique steady-state equilibrium for the above problem.*

$$q_2 < \frac{1}{\beta} \tag{B.12}$$

$$\begin{aligned}\alpha_1\alpha_2 C(a_1)\big[\alpha_2\frac{\partial p_1}{\partial v} + \beta\lambda_1\frac{\partial p_2}{\partial v}\big] > x\big[\beta\lambda_1(\lambda_1 p_2 - \beta\lambda_1 p_2) - p_1\alpha_1\alpha_2\big]\frac{\partial p_2}{\partial v}\\ + x\big[p_2\alpha_1\alpha_2\big]\frac{\partial p_1}{\partial v} - w_2\big[p_2\beta\lambda_1\alpha_1\big]\frac{\partial p_2}{\partial v}\\ + w_2\alpha_1\big[p_1\alpha_2 + \beta\lambda_1 p_2 + p_2\alpha_2\big]\frac{\partial p_1}{\partial v}\end{aligned} \tag{B.13}$$

$$\alpha_1 C(a_1)\frac{\partial p_2}{\partial v} > \beta(x - w_1)\Big(p_2\frac{\partial p_1}{\partial v} - p_1\frac{\partial p_2}{\partial v}\Big) \tag{B.14}$$

$$0 < \beta\Big[\frac{(1-\gamma)\beta\lambda_1(w_1 + \sigma_2 - \sigma_1)}{(1 - \beta + \beta\lambda_1 + \beta q_1)^2}\Big]\frac{\partial q_1}{\partial v} \tag{B.15}$$

The proof for this proposition is given below. Essentially, it must be shown that the wage setting curves cross the job creation curve at only one point regardless of whether the two curves are both upward sloping. It is not enough to show that the two curves are monotonically moving in opposite directions since the two curves are allowed to do so given the other wage and recruiting intensity. As such, a continuum of solutions can also be ruled out.

Proof Given w_2, (1.11) can be plugged into (1.15) to form a single equation in terms of v. Similarly, given w_1, (1.12) can be plugged into (1.15) to form another equation in terms of v. Since the job creation condition is set equal to zero, it follows that

$$f(v) = h(v) + g(v) = 0$$

is an implicit function defined in terms of v. In order for a unique solution to exist, there must be a unique optimum that satisfies:

$$f'(v) = h'(v) + g'(v) = 0$$

As long as $h'(v) = -g'(v)$, a unique optimum exist. ■

C. Derivation of Proposition B.7.1

Proof Fully differentiating the unemployment flow equation, we get:

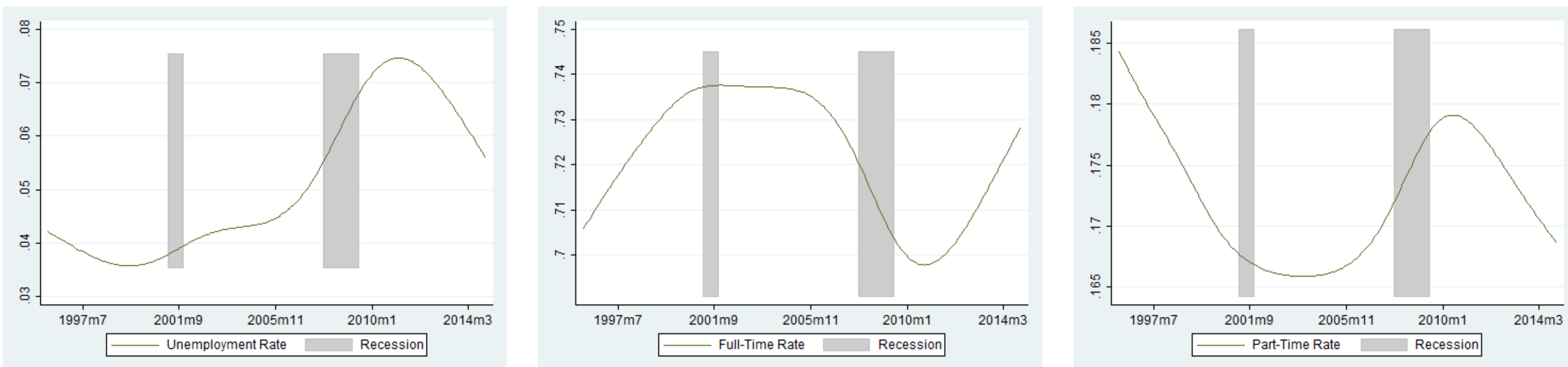
$$du(q_f + q_p + \lambda_p) = (\lambda_f - \lambda - p)dl_f - u\Big(\frac{\partial q_f}{\partial u}du + \frac{\partial q_f}{\partial v}dv + \frac{\partial q_f}{\partial a_f}da_f + \frac{\partial q_f}{\partial s_f}ds_f\Big)$$
$$- u\Big(\frac{\partial q_p}{\partial u}du + \frac{\partial q_p}{\partial v}dv + \frac{\partial q_p}{\partial a_f}da_f + \frac{\partial q_p}{\partial s_p}ds_p\Big)$$

which can be rearranged as

$$\frac{\mathrm{d}u}{\mathrm{d}l_f} = \frac{\lambda_f - \lambda_p - u\Big[\Big(\frac{\partial q_f}{\partial v} + \frac{\partial q_p}{\partial v}\Big)\frac{\mathrm{d}v}{\mathrm{d}l_f} + \Big(\frac{\partial q_f}{\partial a_f} + \frac{\partial q_p}{\partial a_f}\Big)\frac{\mathrm{d}a_f}{\mathrm{d}l_f} + \Big(\frac{\partial q_f}{\partial s_f}\Big)\frac{\mathrm{d}s_f}{\mathrm{d}l_f} + \Big(\frac{\partial q_p}{\partial s_p}\Big)\frac{\mathrm{d}s_p}{\mathrm{d}l_f}\Big]}{\lambda_p + q_p + q_f + u\Big(\frac{\partial q_f}{\partial u} + \frac{\partial q_p}{\partial u}\Big)}$$

■

D. Tables and Figures



(a) U Rate

(b) FT Rate

(c) PT Rate

Figure D.1.: Employment Rates

Table D.1.: Descriptive Statistics – Non-Recession*

Employment Status	Percent of Population	Millions of Persons	Flow Into	Percent	Millions of Persons	Hazard Rate
U	7.6	7.4	FT	20.5	1.5	1.6
			PT	9.1	0.7	2.4
			U	70.4	5.2	0.4
FT	70.7	64.2	PT	5.7	3.7	2.9
			FT / PT	0.9	0.6	4.7
			U	2.3	1.5	3.8
			FT	91.1	58.4	0.1
PT	16.0	14.8	FT	25.5	3.8	1.4
			FT / PT	0.9	0.1	4.7
			Dual PT	0.6	0.1	5.1
			U	4.6	0.7	3.1
			PT	68.4	10.1	0.4
FT / PT	4.7	4.3	FT	19.1	0.8	1.7
			PT	3.7	0.2	3.3
			FT / PT	77.2	3.3	0.3
Dual PT	0.8	0.7	PT	15.6	0.1	1.9
			Dual PT	84.4	0.6	0.2

*Average calculated using HP-filtered monthly CPS data from December 2001 to December 2004

Table D.2.: Jointly Calibrated Parameters

Parameter	2001-2004*	2015-2016*	New Target
b	0.9668	0.9568	$a_s v/u = 0.88$
c	0.3418	0.6130	Total cost of recruiting = 0.3203
h_f	0.0432	0.0464	$q_{uf} = 0.1773$
h_p	0.0040	0.0053	$q_{up} = 0.0873$
H_f	7784.1	8067.5	$q_{fp} = 0.0073$
H_p	1346.5	1348.9	$q_{pf} = 0.0066$
C	0.2929	0.2022	$q_{pp} = 0.0054$

* Time periods correspond to Dec. 2001 - Dec. 2004 and Jan. 2015 - Dec. 2016.

E. Additional Equations, Tables, and Figures for Chapter 2

E.1 Additional Equations

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

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

$$U_{t,i} = \log(\sigma_i + C^m_{t,i} + b_2 C^s_{t,i}) + \chi_i \log(1 - N_{t,i} - (s^h_{t,i} + s^y_{t,i}))$$
$$U^0_{t,i} = \log(\sigma_i\sigma + G_t)$$

E.2 Summary Statistics and Regressions

Table E.1.: 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

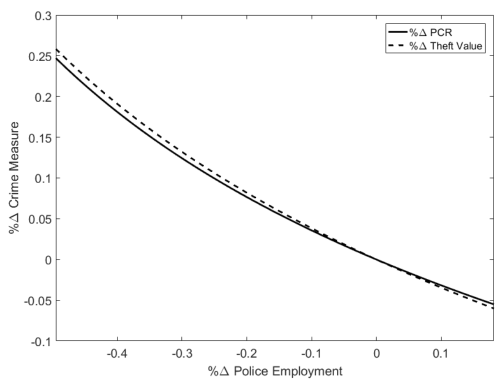


Figure E.1.: Effect of Policing on Property Crime

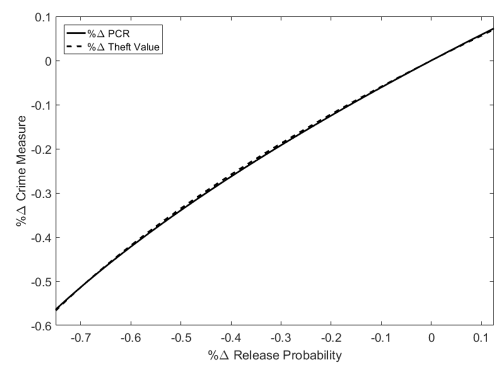


Figure E.2.: Effect of Release Probability on Property Crime

Table E.2.: 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

Table E.3.: 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

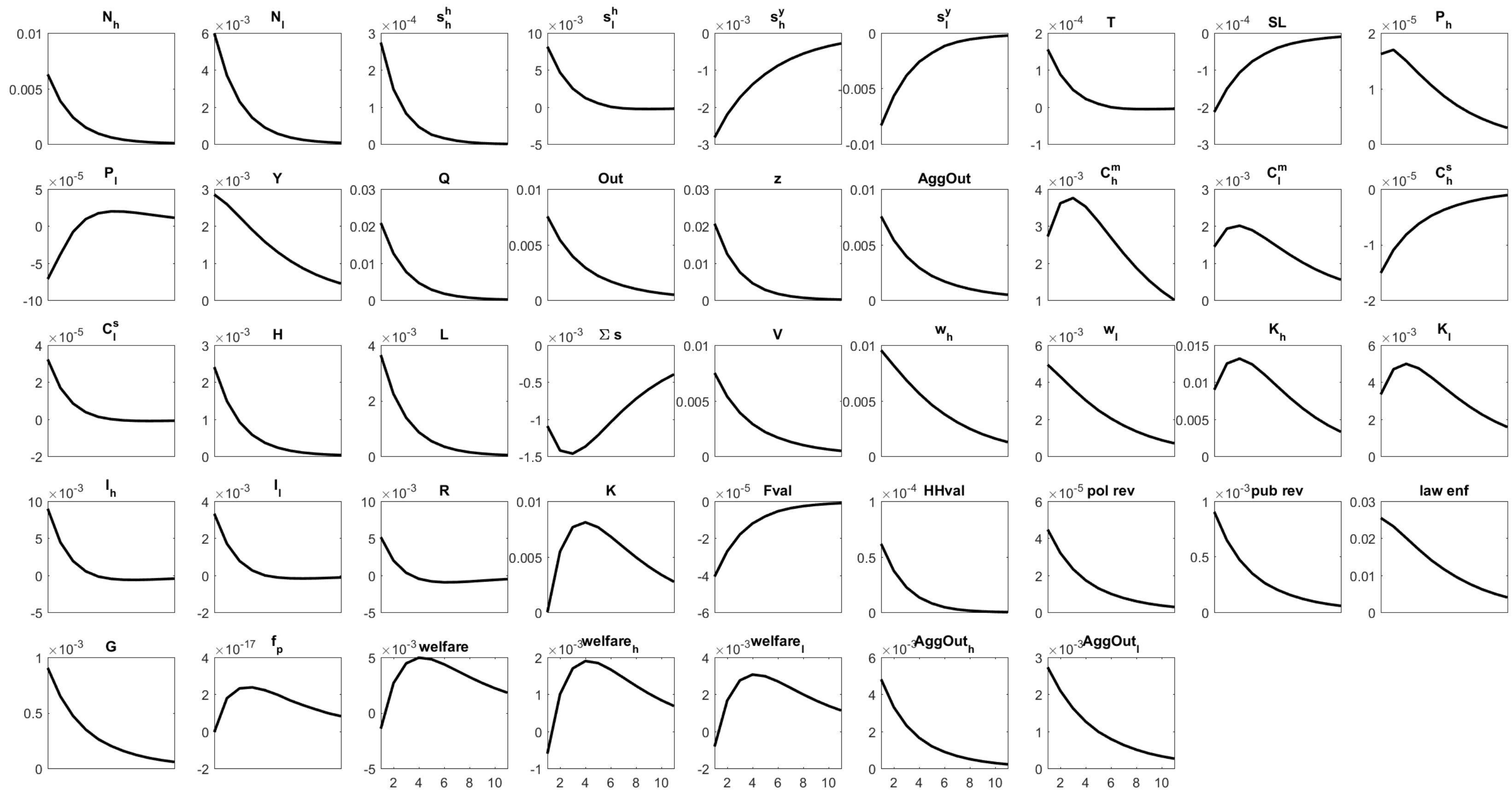


Figure E.3.: Orthogonalized shock to TFP

F. Robustness Checks for Chapter 2

F.1 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.

$$T_{t,l} = 1.2T_{t,h} \tag{F.1}$$

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.

$$\frac{\partial U_{t,i}}{\partial C^m_{t,i}} = \beta E_t \Big\{ \frac{\partial U_{t+1,i}}{\partial C^m_{t+1,i}} \big(R_{t+1,i}(1 - f_{t+1,p})(1 - T_{t+1,i})(1 - \tau^g - \tau^p) + (1 - d) \big) \Big\} \tag{F.2}$$

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 $(1 - \kappa)\alpha$

$$\max_{\mathbb{H}_t, \mathbb{L}_t, \mathbb{K}_{t,h}, \mathbb{K}_{t,l}} \quad Q_t(z_t) \mathbb{K}^{\kappa\alpha}_{t,h} \, \mathbb{K}^{(1-\kappa)\alpha}_{t,l} \, \mathbb{H}^{\gamma}_t \, \mathbb{L}^{1-\alpha-\gamma}_t - R_{t,h}\mathbb{K}_{t,h} - R_{t,l}\mathbb{K}_{t,l} - w_{t,H}\mathbb{H}_t - w_{t,L}\mathbb{L}_t \tag{F.3}$$

Calibration for the model with unequal burden mirrors that of the baseline with the addition of κ as seen in Table F.1. 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.

Table F.1.: 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	$\mathbb{K}_{t,h}/\mathbb{K}_{t,l} = 3$

As seen in Table F.2, 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 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 F.2.: 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.

F.2 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,

$$\mathsf{G}_t = \tau^g \sum_i \phi_i P_{t,i}\big[(w_{t,i}N_{t,i} + R_t K_{t,i})\big](1 - f_{t,p})(1 - T_t) - (1 + r_{t-1})\mathsf{D}_t + \mathsf{D}_{t+1} \quad \text{(F.4)}$$

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

$$\frac{\mathsf{G}}{\mathsf{Y}} = \tau^g \frac{\sum_i \phi_i P_i\big[(w_i N_i + RK_i)\big](1 - f_p)(1 - T)}{\mathsf{Y}} - r\frac{\mathsf{D}}{\mathsf{Y}} \quad \text{(F.5)}$$

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.

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

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

Table F.3.: 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.

F.3 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 average.

$$\sum_{i\in\{h,l\}} \sum_{t=1}^{T} \beta^t \phi_i \Big\{ U_{t,i}(P_{t,i}, C^m_{t,i}, C^s_{t,i}, N_{t,i}, s^h_{t,i}, s^y_{t,i}, \text{comp}^*) - U_{t,i}(P^2_{t,i}, C^{m,2}_{t,i}, C^{s,2}_{t,i}, N^2_{t,i}, xs^h_{t,i}, xs^y_{t,i}) \Big\} = 0 \tag{F.6}$$

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 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

Table F.4.: 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.

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.4 Robustness

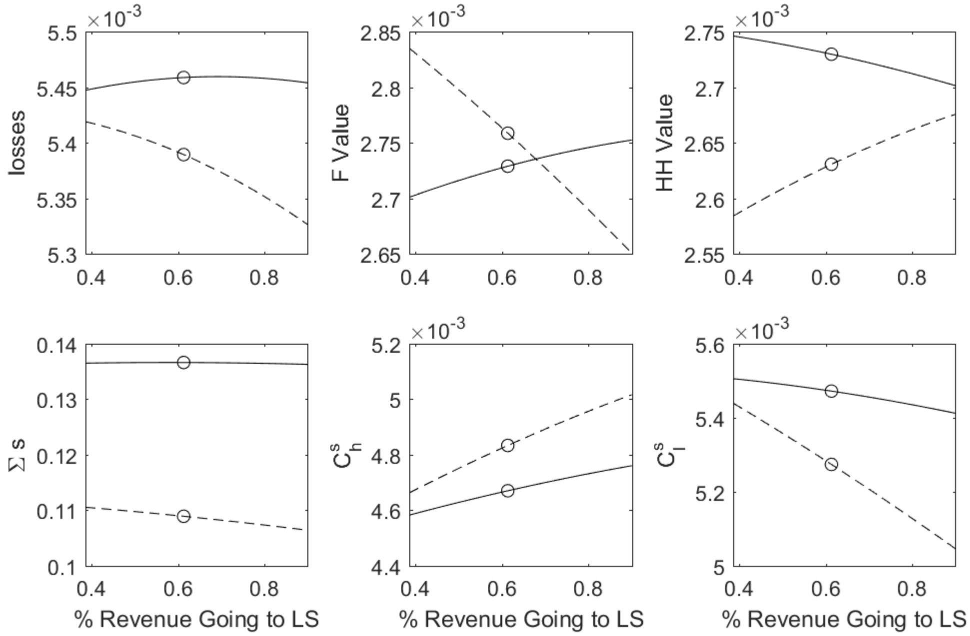


Figure F.1.: Transfers to LS Workers (Revenue Clearing)

Figure F.1 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.

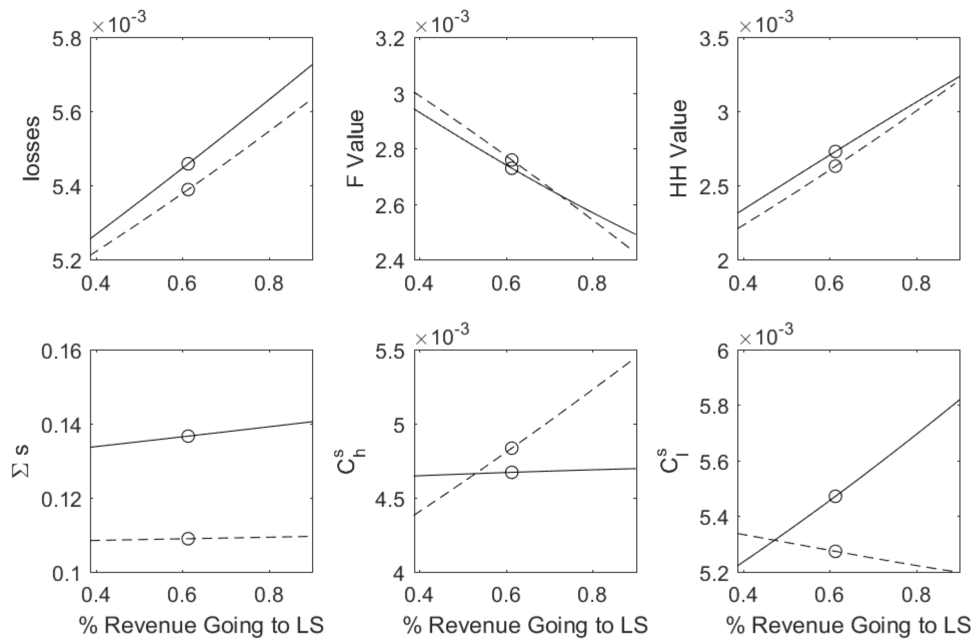


Figure F.2.: Transfers to LS Workers (Fixed HS Transfers)

Figure F.2 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.

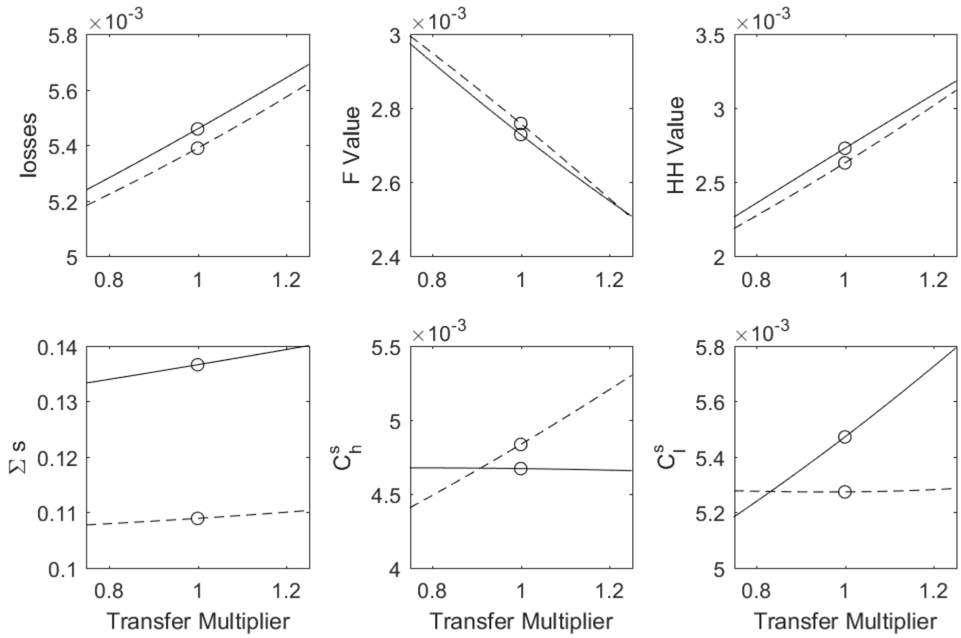


Figure F.3.: Transfer Multiplier

Figure F.3 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.

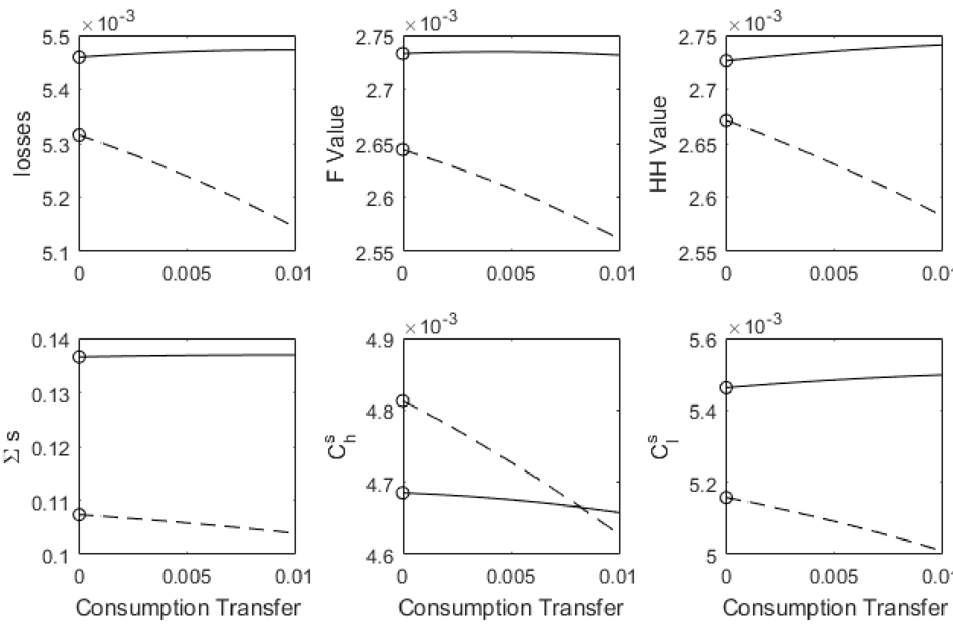


Figure F.4.: Consumption Transfer

Figure F.3 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 F.5.: 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

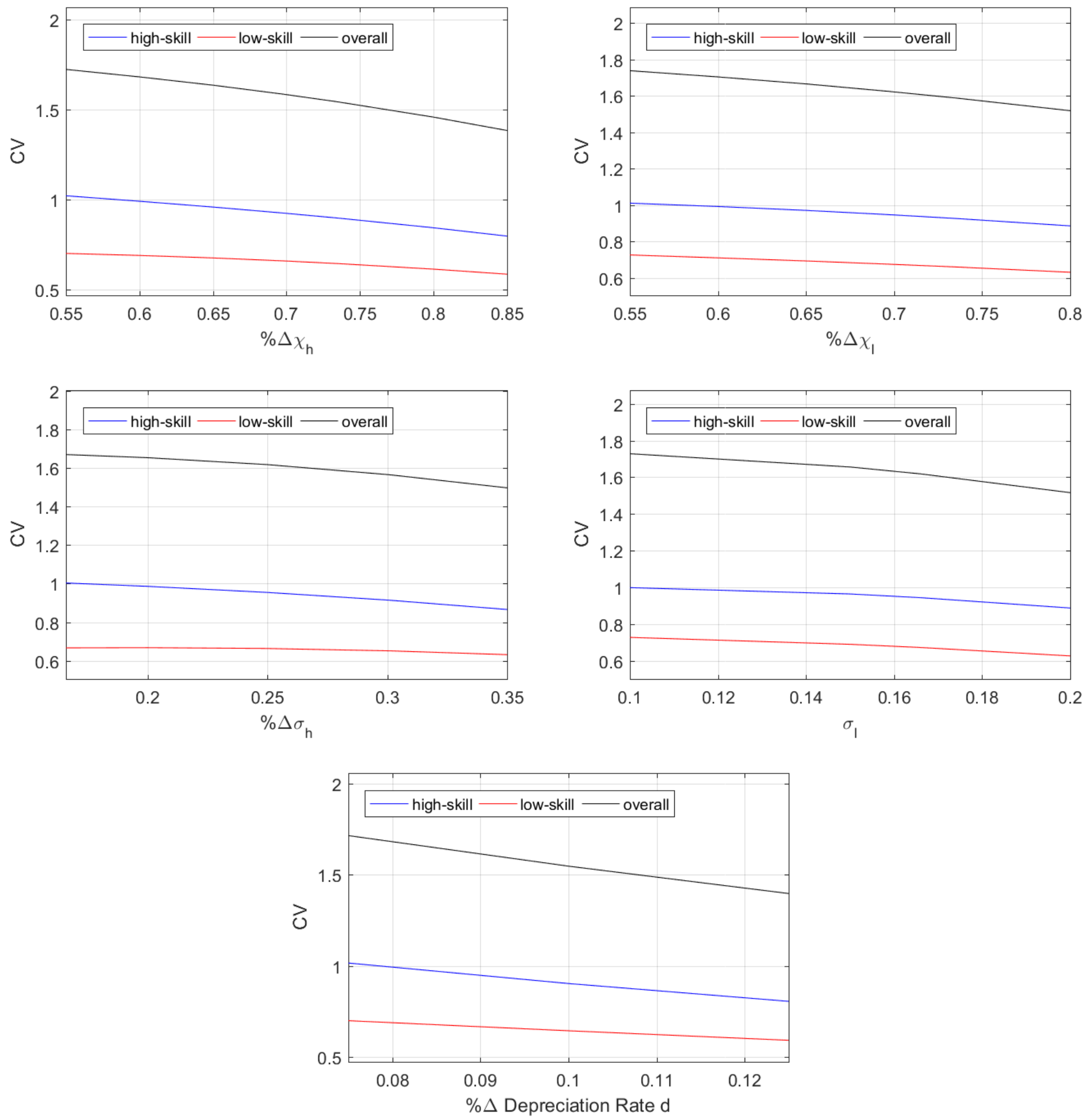
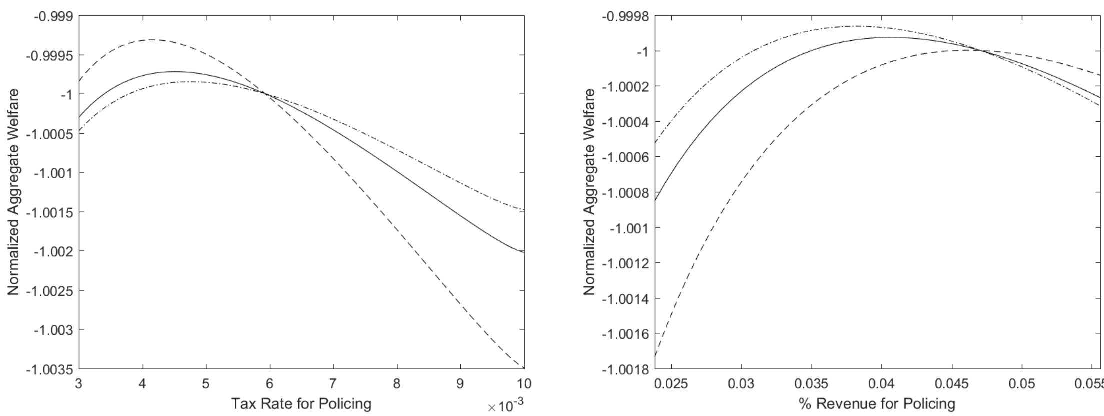


Figure F.5.: Robustness of CV to Changes in Baseline Parameterization



(a) (b)

Figure F.6.: 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.

G. Additional Tables and Figures for Chapter 3

Table G.1.: Blundell-Bond Estimates for Robbery Rate

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) lag(2 5)	(5) collapse (6 .)	(6) LF weight	(7) LF weight collapse	(8) percentile	(9) percentile collapse	(10) no level equation
log(RPINC$_{i,t-1}$)	1.059***	1.049***	1.054***	1.075***	1.209***	1.048***	1.006***	1.046***	1.165***	0.880***
	(0.017)	(0.014)	(0.015)	(0.016)	(0.222)	(0.018)	(0.046)	(0.071)	(0.206)	(0.128)
log(Robbery$_{i,t}$)	-0.015	-0.024***	-0.024***	-0.031**	-0.053	-0.016**	-0.080***	-0.026***	-0.0666	-0.061***
	(0.011)	(0.008)	(0.008)	(0.012)	(0.043)	(0.007)	(0.017)	(0.006)	(0.043)	(0.013)
Own Children at Home		0.118***	0.040	0.129***	0.177	0.082**	0.148**	0.122	0.146	-0.066
		(0.031)	(0.054)	(0.041)	(0.339)	(0.037)	(0.074)	(0.121)	(0.333)	(0.072)
Constant	-0.529***	-0.439***	-0.452***	-0.681***	-2.007	-0.453**	0.260	-0.392	-1.465	
	(0.182)	(0.167)	(0.166)	(0.196)	(2.594)	(0.181)	(0.507)	(0.770)	(2.412)	
Observations	1,908	1,260	1,260	1,260	1,260	1,260	1,260	1,210	1,210	1,088
Number of geoFIPS	180	141	141	141	141	141	141	135	135	137
Instruments	166	162	162	106	26	162	32	162	26	139
AB test for AR(2)	0.0679	0.0812	0.0819	0.0833	0.0950	0.0663	0.118	0.0914	0.118	0.129
AB test for AR(3)	0.901	0.655	0.656	0.641	0.614	0.159	0.278	0.591	0.531	0.576
Hansen test	0.315	0.825	0.851	0.0648	0.238	0.796	0.119	0.908	0.462	0.393
%ΔRPINC wrt 1 std ΔRobbery	-0.322	-0.480	-0.486	-0.636	-1.077	-0.318	-1.623	-0.532	-1.362	-1.239

Windmeijer robust standard errors clustered at the MSA level are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G.2.: Blundell-Bond Estimates for Motor Vehicle Theft Rate

VARIABLES	(1) baseline	(2) baseline	(3) diff	(4) lag(2 2)	(5) collapse (5 .)	(6) LF weight	(7) LF weight collapse	(8) percentile	(9) percentile collapse	(10) no level equation
$\log(\text{RPINC}_{i,t-1})$	1.060***	1.053***	1.055***	1.094***	0.867***	1.023***	1.054***	1.043***	1.159***	0.737***
	(0.017)	(0.015)	(0.016)	(0.020)	(0.132)	(0.021)	(0.092)	(0.017)	(0.069)	(0.088)
$\log(\text{MVTR}_{i,t})$	0.005	-0.016***	-0.014***	-0.031***	-0.060***	0.012	-0.048**	-0.014**	-0.042***	-0.051***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.017)	(0.010)	(0.023)	(0.006)	(0.015)	(0.008)
Own Children at Home		0.150***	0.075	0.246***	0.111	0.048	0.215**	0.137***	0.308**	-0.058
		(0.034)	(0.062)	(0.061)	(0.218)	(0.037)	(0.084)	(0.034)	(0.134)	(0.077)
Constant	-0.642***	-0.518***	-0.510***	-0.902***	1.693	-0.298	-0.382	-0.418**	-1.558**	
	(0.173)	(0.164)	(0.176)	(0.212)	(1.474)	(0.212)	(0.976)	(0.186)	(0.767)	()
Observations	1,900	1,253	1,253	1,253	1,253	1,253	1,253	1,203	1,203	1,077
Number of geoFIPS	180	141	141	141	141	141	141	135	135	137
Instruments	166	163	163	53	29	163	27	162	26	140
AB test for AR(2)	0.0747	0.0887	0.0926	0.0889	0.0693	0.0955	0.0301	0.105	0.0990	0.087
AB test for AR(3)	0.876	0.633	0.629	0.664	0.720	0.129	0.182	0.562	0.615	0.731
Hansen test	0.362	0.881	0.874	0.171	0.351	0.846	0.111	0.916	0.103	0.526
%ΔRPINC wrt 1 std ΔMVTR	0.158	-0.509	-0.471	-1.002	-1.972	0.383	-1.581	-0.453	-1.383	-1.661

Windmeijer robust standard errors clustered at the MSA level are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

G.1 Occupational Employment Statistics

When considering the effect that crime has on the economy, loss prevention and policing come to mind as a deterrent. If firms expect that more crime will be committed during recessions or when income is low, they might hire more protective services such as loss prevention and security. To get an idea of whether this is happening, I look at employment data from the Occupational Employment Statistics data set. Figure G.1 shows the percent change in employment by major occupational group by year from 2002 to 2016. There are few key patterns that emerge. First, many of the occupations in the bottom two rows show a decrease in employment during the recession, especially between 2007 and 2008. Many of the occupations in the top three rows show positive employment growth, but between 2008 and 2009, employment growth shrinks, not necessarily going negative. There are some outliers of course. First, services such as healthcare, education, and community/social services stay pretty level. This make sense as these services are necessary and often funded by the government. Protective services on the other hand see a sharp uptick in the first year of the recession and then levels off. Importantly, employment growth in protective services never decreases while employment growth for sales decreases throughout the recession. These two facts suggest that firms may be responding to increased crime during recessions, but given the small sample, it is hard to say.

I also consider percent change in total firm expenditure on each major occupational group. Looking at the percent change in expenditure on sales occupations in the fourth row of Rigure G.2, it appears that expenditure starts slowing at the beginning of the recession and then starts decreasing towards the end. On the other hand, expenditure on protective services see a 6-7% increase at the beginning of the recession and keep growing at about 5% throughout the recession. It does not begin to taper until the end. Combined with the previous evidence on employment, this result further supports that hypothesis that firms respond to crime. While it is not completely convincing, it appears to be plausible.

Figure G.1.: Percent Change in Employment by Occupation

Figure G.2.: Percent Change in Expenditure by Occupation