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Essays on Frictional Labor Markets and Measurement

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by

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June 2018

The Dissertation of Christine Braun is approved.

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Essays on Frictional Labor Markets and Measurement

To my nephews, Lukas, Benni, and Leo for keeping me creative.

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> *"Our greatest weakness lies in giving up. The most certain way to succeed is always to try just one more time."*
>
> *Thomas A. Edison*

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Education

2018	Ph.D. in Economics *University of California, Santa Barbara*
2013	M.A. in Economics *University of California, Santa Barbara*
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Research Fields

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2017	UCSB Macroeconomics Workshop hosted by Finn Kydland (February), 4th Annual Macroeconomics and Business CYCLE Conference (May), Society of Economic Dynamics (June), WEAI Graduate Student Workshop (June), CERGE-EI (July), Workshop of Australasian Macroeconomics Society (August), Federal Reserve Bank of Kansas City (September), Vienna Macro Café (October)
2016	Midwest Economic Theory Meetings (April), UCI Macroeconomics Lunch (April, May), South West Search and Matching Workshop (May), Federal Reserve Bank of St. Louis (August), Midwest Macroeconomic Meetings (November)
2015	UCI Macroeconomics Grad Student Workshop (May), UCSB Macroeconomics Workshop hosted by Finn Kydland (May, November)

Teaching

Economics 140A	Introduction to Econometrics, Fall 2014, Winter 2015, Spring 2015
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Abstract

Essays on Frictional Labor Markets and Measurement

by

Christine Braun

This dissertation consists of three works which consider how frictional labor market models align with data, as well as how labor market data should be combined and used in applications of theoretical models. What unifies these essays is the underlying goal to further the consolidation of theoretical labor market models with empirical observations of worker and firm behavior in order to better understand and influence policy.

The first essay asks the question: How do changes in the minimum wage affect criminal activity? I answer this question by describing a frictional world in which a worker's criminal actions are linked to his labor market outcomes. The model is calibrated to match labor market outcomes and crime decisions of workers from the National Longitudinal Survey of Youth 1997, and shows that the relationship between the aggregate crime rate and the minimum wage is U-shaped. The results from the calibrated model as well as empirical evidence from county level crime data and state level minimum wage changes from 1995 to 2014 suggest that the crime minimizing minimum to median wage ratio for 16-19 year olds is 0.91. However, the welfare maximizing minimum to median wage ratio is 0.87, not equal to the crime minimizing value.

The second essay, joint with Ben Griffy, Bryan Engelhardt and Peter Rupert, asks the question: Is the arrival rate of a job independent of the wage that it pays? We answer this question by testing how, and to what extent, unemployment insurance changes the hazard rate of leaving unemployment across the wage distribution using a Mixed Proportional Hazard Competing Risk Model and data from the 1997 National Longitu-

dinal Survey of Youth. Controlling for worker characteristics we reject that job arrival rates are independent of the wages offered. We apply the results to several prominent job-search models and interpret how our findings are key to determining the efficacy of unemployment insurance.

Finally, the third essay, joint with Finn Kydland and Peter Rupert argues that not all hours are created equally. In this paper we present a method for adjusting aggregate hours to account for changes in the quality of hours worked. Average human capital has rapidly increased since 1980 as better educated cohorts enter the workforce and the baby boomers continue to work and gather experience. We construct an aggregate labor input series from 1979 to adjust for changes in the experience and education levels of the workforce using the Current Population Survey's Outgoing Rotation Groups. We show that a decrease in labor productivity beginning in 2004, the "productivity slowdown," is understated by 23 percentage points when using aggregate hours instead of labor input to calculate productivity, and that 80% of the average quarterly growth rate of labor productivity can be attributed to increases in education and experience since 2004.

Contents

Chapter 1

Crime and the Minimum Wage

1.1 Introduction

The minimum wage has once again made it to the front lines of political discussion in the United States. Both the Democratic and Republican party have come out in favor of substantial increases. An unprecedented number of cities have proposed legislation for higher local minimum wages and for the first time ever, a majority of states have minimum wages higher than the federal level. California and New York City have passed laws raising the minimum wage to $15 within a few years, bringing about some of the largest real increases since 1949. Economists have long debated the labor market effects of a minimum wage, dating back to Stigler (1946) who first drew attention to possible employment effects after a 21% erosion of the real wage floor induced a public outcry for a higher minimum. While nearly all of the arguments hinge on employment, in this paper I ask how changes in the minimum wage affect criminal activity? Given that the policy is primarily aimed at improving labor market conditions for young and unskilled workers, who are also most at risk in terms of criminal activity, see Figure 1.1, potential changes in crime should be part of the policy debate.

Many economists have tested how the decision to commit crimes changes with respect to the probability or severity of punishment.[1] However, it was not until Schmidt and Witte (1984) and Grogger (1998) that they began to test the effects of labor market changes on people's criminal actions. The conclusions from these studies are as economic theory suggests: people choose to commit more crimes when unemployment increases

Figure 1.1: Characteristics of Minimum Wage Workers and Criminals

Notes: Plotted in blue is the percent distribution of hourly workers working at or below the minimum wage by age in 2012. The data come from the Bureau of Labor Statistics Characteristics of Minimum Wage Workers Report. Plotted in green is the percent distribution of arrests for Type 1 Property Crimes as defined by the Federal Bureau of Investigation (FBI) by age in 2012. The data come from the FBI's Uniform Crime Reports.

[1]See for example: Becker (1968); Ehrlich (1973); Myers (1983); Grogger (1991); Owens (2009); Hansen (1993)

and less when they receive higher wages.[2] Therefore, economic theory alone can not determine how an increase in the minimum wage will affect the crime rate. Increasing the minimum wage can raise wages for workers, thus deterring them from crime. However, there exists empirical evidence that the minimum wage will displace some workers from jobs,[3] thus enticing them to commit more crimes. The employment effects from the minimum wage on specifically teen employment (the focus of this paper) is mixed; Allegretto et al. (2010) finding no significant employment effects and Neumark et al. (2014) finding significant employment effects on teens with estimated elasticities around -0.3. Although the literature is mixed, I show that the model presented below exhibits small employment effects, similar to those estimated in the empirical literature.

To find the direction of the effect, I use a search-theoretic framework to describe a world in which people make crime and labor market decisions jointly. I calibrate the model to match aggregate statistics of crime and the labor market to analyze the quantitative implications of changing the minimum wage. The existing literature trying to identify and quantify the effect of the minimum wage on crime rates is sparse. Hashimoto (1987) finds evidence of a positive relationship using national time-series data of the minimum wage and teenage arrest rates relative to adults.[4] In a recent micro-level study, Beauchamp and Chan (2014) find a positive effect of minimum wage increases on crime for people employed at a binding wage. I focus on a general equilibrium analysis in which

[2] For a more recent literature reaffirming these results see Gould et al. (2002), Mocan and Unel (2011), Machin and Hansen (2003) and Schnepel (2014) for estimates of the elasticity of crime with respect to wages and Gould et al. (2002), Corman and Mocan (2005) and Lin (2008) for estimates of an elasticity of crime with respect to unemployment.

[3] See Neumark and Wascher (2007) for a review of how changes in the minimum wage affect labor market conditions. For new evidence from the Seattle minimum wage increases see Jardim et al. (2017).

[4] Hashimoto (1987) is limited by the use of national data which may lose much of its identifying variation through aggregation and is subject to spurious correlations.

the minimum wage can change all workers' crime decisions and examine the effect on the aggregate crime rate. Both increased schooling and work have been proposed as methods for reducing youth crime rates. Grogger (1998) finds the elasticity of crime with respect to wages for teens to be -0.18 while **?** find that an increase of one year of schooling decreases teen arrest rates by $0.1 - 0.3$ implying similar returns. Therefore, increasing the minimum wage could be a policy tool that is as effective as education for decreasing teen crime rates as long as the negative employment effects are outweighed by the wage effects. To effectively implement the minimum wage as a policy tool for deterring teens from crime it is crucial to know for what level of minimum wage each effect dominates – which is exactly the goal of this paper.

The basic structure of the model is as follows: in the labor market, workers receive job offers at an exogenous rate and wages are determined by strategic bargaining between workers and firms. Workers are heterogeneous in ability which influences their labor market outcomes; heterogeneity among workers is essential for analyzing the effects of a minimum wage policy on labor market outcomes, since not all workers are affected equally.[5] For the minimum wage to have positive welfare effects, firms must have some monopsony power; search frictions and match specific productivity create monopsony power for the firms which shifts the gains from trade toward the firm. In the model, the minimum wage will act as a policy tool that can be used to shift some of the gains from trade back to the worker.

The crime market is as in Burdett et al. (2003), workers receive random crime opportunities while employed and unemployed. I add two levels of heterogeneity to capture two important interactions between changes in the labor market and the crime market.

[5] Meyer and Wise (1983a) and Meyer and Wise (1983b) provide evidence of heterogeneities by showing that the effect of a minimum wage on employment and earnings differ across the group of workers for which it is binding.

First, in contrast to other models of crime and the labor market, workers are ex-ante heterogeneous in ability, making the stock of criminals endogenous and allowing changes in the labor market to have an extensive effect on crime. This extensive effect is also modeled in Huang et al. (2004), where workers specialize in criminal activities, however among those that commit crimes, their propensity for criminal behavior is identical. In contrast, in Burdett et al. (2003) all workers are criminals and have the same propensity for criminal behavior therefore changes in labor market conditions will not have an extensive effect on crime. In Engelhardt et al. (2008) all workers commit crimes with propensities differing across employment states, again changes in labor market conditions will not have an extensive effect on crime as everyone is a criminal. Second, matches are ex-post heterogeneous with respect to productivity, allowing the "quality" of a job to enter into the worker's crime decision, and creating a range of wages for which he commits crimes, in contrast to a single criminal wage as in Burdett et al. (2003) and Burdett et al. (2004). Therefore changes in labor market outcomes can have an intensive effect on crime, changing the propensity for criminal behavior differentially across individuals. Including this intensive effect on crime creates the wage effect: when the minimum wage increases, wages increase and the criminal propensity for those committing crimes while employed decreases. In the model, the minimum wage will also act as a policy tool used to deter workers from crime and decrease the prison population. Indeed, the minimum wage has multiple roles, lessening the effects of monopsony power, as well as deterring the worker from crime. To the best of my knowledge, this is the first study to investigate both roles in a general equilibrium model.

Using the benchmark model, I introduce a minimum wage by imposing a constraint on the bargaining problem faced by firms and workers. The model is calibrated to match the crime decisions and labor market outcomes of 16-19 year olds from the National Longitudinal Survey of Youth 1997 in 1998. I vet the model by simulating data and estimating the elasticity of crime with respect to wages and the elasticity of employment with respect to the minimum wage - finding that the model generated elasticities, although not targeted in the calibration, are similar to those found in the empirical literature. Increasing the minimum wage within the calibrated model reveals a non-monotomic, U-shape relationship between the minimum wage and the crime rate. The results from the calibrated model and empirical evidence from county level crime data and state level minimum wage changes from 1995 to 2014 suggest that the crime minimizing minimum to median wage ratio for 16-19 year olds is 0.91. However, welfare is not maximized when crime is minimized. The welfare maximizing minimum to median wage ratio is 0.87, which leaves crime at 0.02 crimes per person per month higher than the crime minimizing minimum to median wage ratio. If policy makers abstract from the effect of a minimum wage on crime, the welfare maximizing minimum to median wage ratio is 0.7, leaving crime 42% higher than when considering the effects of the wage floor on crime. In sum, the results from the calibrated model suggest that real changes in the wage floor as large as those passed in California and New York City may have the unintended consequence of boosting criminal activity among young and unskilled workers.

1.2 Model

To begin, I describe a world in which people in the labor market receive both exogenous job and crime opportunities and show how they jointly decide whether or not to take a job or act on a crime opportunity in the absence of a binding minimum wage. The question of interest is: how does a binding minimum wage change the behavior of a worker? How does it change his decision to accept jobs and act on crime opportunities, and in turn how do these changes translate into the aggregate crime rate? To answer these questions, I introduce a minimum wage into the model as a constraint that workers and firms must consider when bargaining over the wage. Using the theoretical framework, I analyze how the existence of such a constraint changes employment decisions and subsequently wages, as well as the crime decisions of employed and unemployed workers.

1.2.1 Workers

The model is in continuous time and composed of a unit measure of workers, who: are risk neutral, discount at rate r, and are ex-ante heterogeneous in their ability, a, given by the c.d.f. $F(a)$. There exists an exogenous distribution of jobs of productivity λ with c.d.f. $G(\lambda)$. While unemployed, a worker receives flow utility b and matches with a job at exogenous rate μ_j. When a worker of ability a matches with a job of productivity λ the total productivity of the match is $a\lambda$.[6] Wages for the match are determined by strategic bargaining à la Rubinstein's alternating offers, discussed in detail below, and workers separate from jobs at exogenous rate δ.

Workers also receive opportunities to commit crimes at rate μ_u while unemployed and μ_e while employed. If the worker receives a crime opportunity he has the chance to steal some fixed amount g. If a worker commits a crime, the probability he is caught and sent to jail is π. The decision to act on a crime opportunity is based on the expected cost and expected utility from committing the crime. Given the probability is zero that a worker receives both a crime and job opportunity, the expected utility from committing a crime while unemployed, $K_u(a)$, is equal to the instantaneous gain from committing the crime, g, and the weighted average of his continued state: his prison utility if he is caught or his unemployment utility if he is not. The expected utility from committing a crime while

[6] This assumption is similar to Postel-Vinay and Robin (2002) and Cahuc et al. (2006) who estimate the productivity of a match to have a firm and individual component.

employed, $K_e(a,\lambda)$, is calculated analogously. Therefore,

$$K_u(a) = g + \pi V_p(a) + (1-\pi)V_u(a) \tag{1.1}$$

$$K_e(a,\lambda) = g + \pi V_p(a) + (1-\pi)V_e(a,\lambda) \tag{1.2}$$

where, $V_p(a)$ is the value of prison, $V_u(a)$ is the value of unemployment, and $V_e(a,\lambda)$ is the value of being employed at a job with productivity λ, all defined below. Workers commit crimes rationally; if the expected gain $(K_u(a) - V_u(a))$ of committing the crime is greater than zero a worker will choose to act on the opportunity. Given a crime opportunity, let $\phi_u(a)$ and $\phi_e(a,\lambda)$ be the probability that a worker commits a crime while unemployed and employed at a job of productivity λ. The crime decisions for an unemployed and an employed worker are:

$$\phi_u(a) = \begin{cases} 1 & \text{if } g + \pi(V_p(a) - V_u(a)) > 0 \\ 0 & \text{if } g + \pi(V_p(a) - V_u(a)) \leq 0, \end{cases} \tag{1.3}$$

$$\phi_e(a,\lambda) = \begin{cases} 1 & \text{if } g + \pi(V_p(a) - V_e(a,\lambda)) > 0 \\ 0 & \text{if } g + \pi(V_p(a) - V_e(a,\lambda)) \leq 0. \end{cases} \tag{1.4}$$

Both employed and unemployed workers can be victims of crime at rate χ; victims of crime suffer a loss of L. The flow return to being unemployed for a worker of ability a, $rV_u(a)$, is equal to the flow utility of unemployment times the workers ability[7], net of being a victim of crime plus the expected value of receiving either a crime or job opportunity:

$$rV_u(a) = ab - \chi L + \mu_u\phi_u[K_u(a) - V_u(a)] + \mu_j \int_\lambda max\{V_e(a,\lambda) - V_u(a), 0\}\ dG(\lambda) \tag{1.5}$$

Similarly, the flow return of employment for a worker of ability a employed at a job with productivity λ is:

$$rV_e(\lambda,a) = w(a,\lambda) - \chi L + \mu_e\phi_e(a,\lambda)[K_e(a,\lambda) - V_e(a,\lambda)] + \delta[V_u(a) - V_e(a,\lambda)] \tag{1.6}$$

[7] This assumption is similar to those made in Postel-Vinay and Robin (2002) and Flinn and Mullins (2015).

where $w(a, \lambda)$ is the wage paid to the worker. Workers in prison receive flow value z and are exogenously released at rate γ. All workers released from prison are released into unemployment. The flow return of prison is:

$$rV_p(a) = z + \gamma(V_u(a) - V_p(a)). \tag{1.7}$$

Notice from equation (1.3) that the crime decision of an unemployed worker is only a function of his unemployment value. Therefore, there exits a unique value of unemployment that makes workers indifferent to committing crimes while unemployed:

$$V_u(a)^* = \frac{g(r+\gamma)}{r\pi} + \frac{z}{r}. \tag{1.8}$$

If $V_u(a) < V_u(a)^*$, the worker will commit crimes while unemployed and if $V_u(a) \geq V_u(a)^*$ he will not. Since $V_u(a)$ is strictly increasing in a, there exits a unique ability, a^*, such that $V_u(a^*) = V_u(a)^*$, and workers with ability $a < a^*$ commit crimes while unemployed, while workers with ability $a \geq a^*$ do not. Proposition 1 proves that workers who do not commit crimes while unemployed also forge crime opportunities while employed. Since workers with ability greater than a^* will never commit crimes, $F(a^*)$ can be thought of as the stock of criminals in the economy.

Proposition 1. *If $a \geq a^*$ then $\phi_e(a, \lambda) = 0$ for all $\lambda \geq \lambda^R(a)$. Where $\lambda^R(a)$ is the workers reservation job productivity defined as $V_e(a, \lambda^R(a)) = V_u(a)$.*

Proof. See proof in Appendix section A.1.1. □

1.2.2 Jobs

There exist a continuum of firms that randomly meet workers. After a firm meets a worker, the firm observes the productivity of the job, λ, and the ability of the worker, a.

The value of a successful match with a worker of ability a, a job productivity λ, and a wage w is:

$$J(w, a, \lambda) = \frac{a\lambda - w}{r + \delta + \mu_e \phi_e(a, \lambda)\pi}. \tag{1.9}$$

Notice that the expected duration of the job depends on the worker's decision to commit crimes while employed. If the worker chooses to commit crimes while employed the job can end with him getting caught and going to prison. If the match is not successful the worker and firm part ways, in which case the firm receives a payoff of zero.

For tractability of the model, I do not explicitly model the matching process. From the worker perspective, he only cares about the probability of a successful match, that is, the probability of meeting a firm, μ_j, times the probability that the total job productivity is above his reservation wage. With the implementation of a binding minimum wage, the meeting probability remains fixed, however the probability that the match is successful now hinges on whether the total job productivity is above the value of the minimum wage. Thus as the minimum wage increases, the job finding rate for the worker decreases. The elasticity of employment with respect to the minimum wage is important for answering the question at hand since it determines, in part, the unemployment effect on crime. The assumption that the meeting probability, μ_j, remains fixed with an increase in the minimum wage is consistent with Flinn (2006) who can not reject that the meeting probability changes with an increase in the minimum wage from \$4.75 to \$5.15 in 1997. Although the meeting probability is fixed with respect to the minimum wage, I show in subsection 1.5.1 that the model matches the empirically estimated employment elasticity with respect to the minimum wage well.

1.2.3 Wages

As noted by Engelhardt et al. (2008), when the worker can choose to commit crimes while employed, the feasible set of allocations that split the surplus of the match is non-convex, therefore the axiomatic approach to bargaining cannot be implemented.[8] I choose to split the surplus through strategic bargaining: the worker and the firm determine the wage in a two stage game à la Rubinstein's alternating offers.

In the first stage the firm offers the worker a wage. If he accepts the offer, bargaining ends and the job begins at the offered wage. If he rejects the wage the game moves to the second stage where he gets to set the final wage with probability β and the firm gets to set the final wage with probability $1 - \beta$. The probability that the match breaks up during negotiations is zero and neither the firm nor the worker discount the future during the bargaining process.

At this point it is simplest to rewrite the value of employment as a function of the workers ability and the wage instead of the workers ability and the productivity of the job; let $V_e(w(a, \lambda), a)$ denote the value of employment for a worker of ability a employed at a job or productivity λ which pays wage $w(a, \lambda)$. There are two wages that are of particular interest. First, the reservation wage, $w_R(a)$[9], defined as $V_u = V_e(w_R(a), a)$ such that if $w \geq w_R(a)$ the worker chooses to stop searching and accept the job. By the value of unemployment, (1.6), and the fact that a worker who chooses not to commit crimes while unemployed, will never commit a crime while employed, Proposition 1, the reservation wage is

$$w_R(a) = \begin{cases} \chi L + rV_u(a) - \mu_e \left[g + \pi \left(\frac{z - rV_u(a)}{r+\gamma} \right) \right] & \text{if } V_u(a) < V_u(a)^* \\ \chi L + rV_u(a) & \text{if } V_u(a) \geq V_u(a)^*. \end{cases} \tag{1.10}$$

[8]The problem is similar to that of on the job search, see Shimer (2006) for details.

[9]I have suppressed the job productivity value since workers only care about the wage they receive, not the productivity of the job.

The second wage of interest is the crime reservation wage, $w_C(a)$ defined as $g + \pi[V_p - V_e(w_C(a), a)] = 0$ such that if $w \geq w_C(a)$ the worker chooses to stop searching, accept the job, and does not commit crimes while employed.[10] Again using the value of unemployment, (1.6), one can solve for the crime reservation wage:

$$w_C(a) = \chi L + \frac{r(r+\delta)}{r+\gamma} V_u(a)^* + \frac{r(\gamma-\delta)}{r+\gamma} V_u(a) \tag{1.11}$$

for $V_u(a) < V_u(a)^*$. Workers that do not commit crimes while unemployed do not have a crime reservation wage since they forgo crime opportunities for all wages.

Equilibrium wages can be found by solving the two stage game through backwards induction, first solving the optimal wage offers in the second stage for the worker and the firm, then solving for the firm's optimal offer in the first stage given the second stage outcomes. In the first stage the firm offers the profit maximizing wage subject to the worker accepting the offer. Therefore, in equilibrium wages will be determined without delay.

In the second stage, if a worker of ability a gets to set the final wage he will choose to set the wage equal to the total productivity of the match, $w = a\lambda$, thus taking the entire surplus of the match. If the worker is a criminal, then he continues to commit crimes while employed if $a\lambda < w_C(a)$ and forges crime if $a\lambda \geq w_C(a)$. If the firm matches with a criminal and gets to set the final wage in the second stage, the firm must choose between setting the wage at the reservation wage or setting the wage at the crime reservation wage. So for $V_u(a) < V_u(a)^*$, the firm faces the following problem in the second stage:

$$w(a, \lambda) = \underset{\{w_R, w_C\}}{\text{argmax}} \left\{ \frac{a\lambda - w_R(a)}{r + \delta + \mu_e \pi} \, , \, \frac{a\lambda - w_C(a)}{r+\delta} \right\} \tag{1.12}$$

It is easy to show that $w_R(a) < w_C(a)$, therefore the firm faces a trade off between receiving a higher flow value for the job for a shorter expected duration, or a lower flow

[10] I will assumed that workers are moral, such that a worker that is indifferent to committing crimes will chose not to commit crimes.

value for the job for a longer expected duration. Problem (1.12) has a unique solution for the job productivity that equates the two choices, call it $\lambda^{D2}(a)$:

$$\lambda^{D2}(a) = \frac{(r+\delta+\mu_e\pi)w_C(a) - (r+\delta)w_R(a)}{a\mu_e\pi}. \tag{1.13}$$

If $\lambda < \lambda^{D2}(a)$ the firm sets the wage $w_R(a)$ and if $\lambda \geq \lambda^{D2}(a)$ then the firm sets the wage $w_C(a)$ in the second stage. If the firm matches with a non-criminal, $V_u(a) \geq V_u(a)^*$, then it has no choice to make and it sets the wage to the workers reservation wage, $w_R(a)$.

In the first stage the firm chooses to offer the wage that maximizes profits subject to the worker accepting the offer. The worker will accept the offer if it is at least as large as his expected value of the second stage. For non-criminals, the expected value of the second stage is:

$$\beta V_e(a\lambda, a) + (1-\beta)V_e(w_R(a), a) = V_e(\beta a\lambda + (1-\beta)w_R(a), a) \tag{1.14}$$

since the value of employment for non-criminals is linear in the wage. For non-criminals the firm must offer a wage at least as large as the expected wage in the second stage, so the firm faces the following problem in the first stage:

$$w(a,\lambda) = \underset{w}{\operatorname{argmax}} \frac{a\lambda - w}{r+\delta} \quad \text{s.t.} \quad w \geq \beta a\lambda + (1-\beta)w_R(a). \tag{1.15}$$

Therefore, the firm offers wage $w(a,\lambda) = \beta a\lambda + (1-\beta)w_R(a)$ whenever $V_u(a) \geq V_u(a)^*$ and the worker accepts the offer. Since matches are heterogeneous in their productivity, not all matches lead to a filled job. When a worker matches with a firm the productivity must be high enough for him to give up his value of continued search and enter employment. The worker will choose employment whenever $w(\lambda, a) \geq w_R(a)$, so his reservation match value is $\lambda^R(a) = w_R(a)/a$.

If the firm matches with a criminal, the problem it faces in the first stage depends on the productivity of the job. It is easy to show that $a\lambda^{D2}(a) > w_C(a)$ for all a^*, so if the match productivity is greater than $\lambda^{D2}(a)$ the wage in either outcome of the second stage will be high enough to deter the worker from crime. Again the firm must offer at least the expected wage of the second stage, so the firm's problem in the first stage is:

$$\beta V_e(a\lambda, a) + (1-\beta)V_e(w_C(a), a) = V_e(\beta a\lambda + (1-\beta)w_C(a), a) \tag{1.16}$$

since the value of employment is linear in the wage if the worker does not commit crimes in either state of the second stage. If $\beta > 0$ then the expected value of the second stage is greater than or equal to $w_C(a)$, implying that if the firm deters a worker from crime in the second stage it will also deter him in the first stage. Therefore the firm's first stage problem is:

$$w(a,\lambda) = \underset{w}{\operatorname{argmax}} \frac{a\lambda - w}{r+\delta} \quad \text{s.t.} \quad w \geq \beta a\lambda + (1-\beta)w_C(a). \tag{1.17}$$

Again the firm offers the worker the expected wage of the second stage $w(a,\lambda) = \beta a\lambda + (1-\beta)w_C(a)$, and the worker accepts the job and does not commit crimes while employed.

If the total match productivity is below the crime reservation wage, $a\lambda < w_C(a)$ then in either outcome of the second stage the wage is not high enough to deter the worker from committing crimes while employed. In this case the expected value of the second stage for the worker is:

$$\beta V_e(a\lambda, a) + (1-\beta)V_e(w_R(a), a) = V_e(\beta a\lambda + (1-\beta)w_R(a), a) \tag{1.18}$$

since the value of employment is linear in the wage if the worker commits crimes in either state in the second stage. Therefore the firm must offer at least the expected wage of the second stage for the worker to accept the offer. Since the total productivity of the match is less than the crime reservation wage in this case, the firm will never deter the worker from crime. Therefore the problem the firm faces for such match values is:

$$w(a,\lambda) = \underset{w}{\operatorname{argmax}} \frac{a\lambda - w}{r+\delta} \quad \text{s.t.} \quad w \geq \beta a\lambda + (1-\beta)w_R(a). \tag{1.19}$$

and the firm offers the worker the expected wage of the second stage, $w(a,\lambda) = \beta a\lambda + (1-\beta)w_R(a)$ and the worker accepts the job and commits crimes while employed.

If the total match productivity is above the crime reservation wage but below the productivity needed for the firm to deter the worker from crime in the second stage, $w_C(a) < a\lambda < a\lambda^{D2}(a)$, the expected value of the second stage for the worker is:

$$\beta V_e(a\lambda, a) + (1-\beta)V_e(w_R(a), a) \\ = \beta\left[\frac{a\lambda - \chi L + \delta V_u(a)}{r+\delta}\right] + (1-\beta)\left[\frac{w_R(a) - \chi L + \delta V_u(a) + \mu_e(g + \pi V_p(a))}{r+\delta+\mu_e\pi}\right] \tag{1.20}$$

Since the worker will commit crimes if the firm makes the offer in the second stage but forgo crime opportunities if he gets to set the wage in the second stage. The constraint the firm faces in the second stage is to offer a wage such that the value of employment is at least as large as the expected value of the second stage:

$$V_e(w,a) \geq \beta\left[\frac{a\lambda - \chi L + \delta V_u(a)}{r+\delta}\right] + (1-\beta)\left[\frac{w_R(a) - \chi L + \delta V_u(a) + \mu_e(g + \pi V_p(a))}{r+\delta+\mu_e\pi}\right] \tag{1.21}$$

First, one can show that if $(r+\delta)/\mu_e\pi \leq (1-\beta)/\beta$ then all match productivities for which $w_C(a) < a\lambda < a\lambda^{D2}(a)$, the wage which makes the worker indifferent between accepting the first round offer and moving to the second stage is not high enough to deter the worker from crime. Therefore Equation 1.21 simplifies to

$$w \geq \frac{\beta(r+\delta+\mu_e\pi)[a\lambda - (\chi L + rV_u(a))]}{r+\delta} + w_R(a) \tag{1.22}$$

In this case the firm has a choice to make in the first stage: offer a wage at least as large as the wage constraint in Equation 1.22 for which the worker will commit crimes on the job or raise the wage to the crime reservation wage, $w_C(a)$, to deter the worker from crime. The firm's first stage problem is:

$$w(a,\lambda) = \underset{w}{\text{argmax}}\left\{\underset{\substack{w \\ \text{s.t.} \quad w \geq w_C(a)}}{\text{argmax}} \frac{a\lambda - w}{r+\delta}, \quad \underset{\substack{w \\ \text{s.t.} \quad w_C(a) > w \ \&\ \text{Equation 1.22}}}{\text{argmax}} \frac{a\lambda - w}{r+\delta+\mu_e\pi}\right\}. \tag{1.23}$$

As before, the firm faces the trade off between a higher flow value for a shorter duration or a lower flow value for a longer duration. There exists a productivity, $\lambda^{D1}(a)$, such that if $\lambda < \lambda^{D1}(a)$ the firm will offer the wage which makes Equation 1.22 bind and the worker will accept the job, at which he continues to commit crimes. If $\lambda \geq \lambda^{D1}(a)$ the firm will offer the crime reservation wage and the worker will accept the offer, since the value of employment at the crime reservation wage is above the expected value of the second stage. While employed at $w_C(a)$, the worker will not commit crimes. The productivity above which firms deter workers from crime in the first stage is

$$\lambda^{D1}(a) = \frac{(r+\delta+\mu_e\pi)[w_C(a)+\beta(\chi L + rV_u(a))] - (r+\delta)w_R(a)}{a(\mu_e\pi + \beta(r+\delta+\mu_e\pi))}. \tag{1.24}$$

The full wage profile for criminals in this case is:

$$w(a,\lambda) = \begin{cases} \beta a\lambda + (1-\beta)w_R(a) & \text{if } \lambda^R(a) \leq \lambda < w_C(a)/a \\ \frac{\beta(r+\delta+\mu_e\pi)[a\lambda - (\chi L + rV_u(a))]}{r+\delta} + w_R(a) & \text{if } w_C(a)/a \leq \lambda < \lambda^{D1}(a) \\ w_C(a) & \text{if } \lambda^{D1}(a) \leq \lambda < \lambda^{D2}(a) \\ \beta a\lambda + (1-\beta)w_C(a) & \text{if } \lambda \geq \lambda^{D2}(a). \end{cases} \tag{1.25}$$

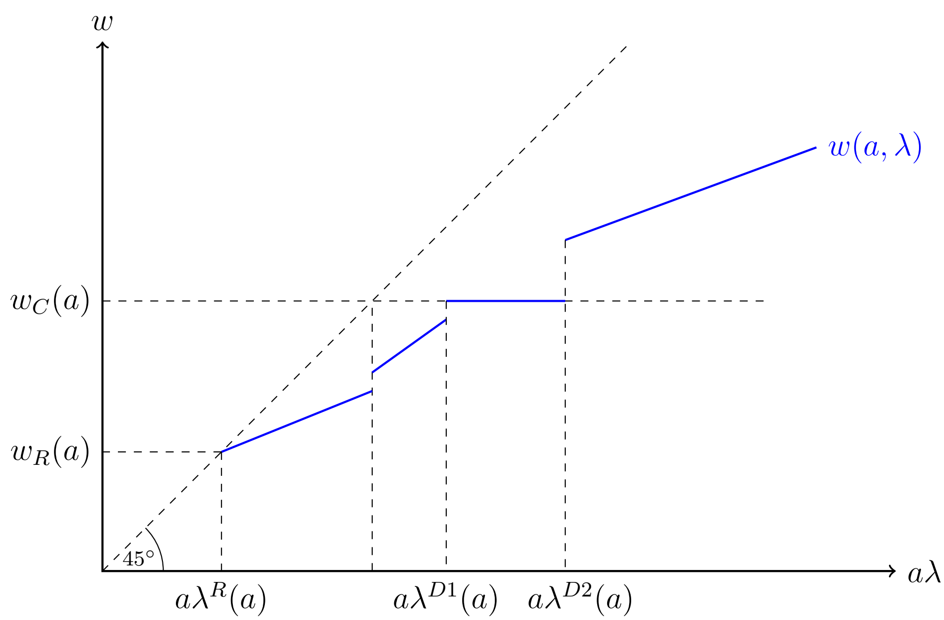
Figure 1.2 shows the wage profile for a worker of type $V_u(a) < V_u(a)^*$. The worker gets the expected wage of the second stage for all matches with productivity $\lambda^R(a) \leq \lambda < w_C(a)/a$, the wage that makes constraint Equation 1.22 bind for all match productivities $w_C(a)/a \leq \lambda < \lambda^{D1}(a)$, the crime reservation wage for matches with productivity $\lambda^{D1}(a) \leq \lambda < \lambda^{D2}(a)$ and the expected wage of the second stage for matches with productivity $\lambda \geq \lambda^{D2}(a)$. Proposition 2 gives a summary of the worker's employment and crime decisions for all match values.

Proposition 2. *If $(r+\delta)/\mu_e\pi \leq (1-\beta)/\beta$ then,*

a. *If $\phi_u(a) = 0$ then for all $\lambda \geq \lambda^R(a)$ the worker accepts the job and $\phi_e(a, w(a,\lambda)) = 0$.*

b. *If $\phi_u(a) = 1$ then for all $\lambda^R(a) \leq \lambda \leq \lambda^{D1}(a)$ the worker accepts the job and $\phi_e(a, w(a,\lambda)) = 1$.*

Figure 1.2: Wage Profile for Workers with $V_u(a) < V_u(a)^*$



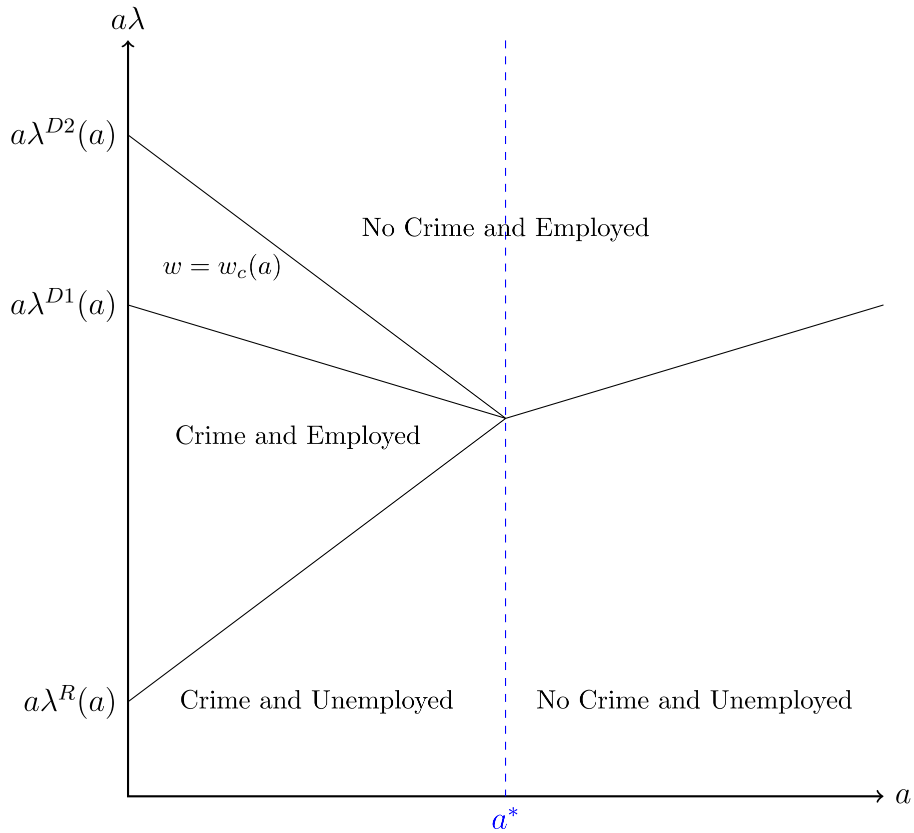
c. *If* $\phi_u(a) = 1$ *then for all* $\lambda \geq \lambda^{D1}(a)$ *the worker accepts the job and* $\phi_e(a, w(a, \lambda)) = 0$.

Proof. See proof in Appendix section A.1.1. □

Figure 1.3 gives a graphical representation of Proposition 2; note the figure plots total match productivity on the y-axis. The slopes of the deterrence match values, $\lambda^{D1}(a)$ and $\lambda^{D2}(a)$, depend on parameter values and can be either negative or positive, however since the worker's reservation wage is always less than his crime reservation wage one can show that $\lambda^{D1}(a) < \lambda^{D2}(a)$. The figure shows the case where both $\lambda^{D1}(a)$ and $\lambda^{D2}(a)$ are decreasing in ability.

Notice that both wage profiles are fully characterized by the match productivity and the workers values of unemployment $V_u(a)$ through the reservation wage and crime

Figure 1.3: Reservation match values and decision rules



reservation wage. For criminals, $V_u(a) < V_u(a)^*$, the value of unemployment is

$$\begin{aligned} rV_u(a) = ab - &\chi L + \mu_u \phi_u [K_u(a) - V_u(a)] \\ &+ \mu_j \Bigg[\int_{\lambda^R(a)}^{w_C(a)/a} V_e(\beta a\lambda + (1-\beta) w_R(a), a) - V_u(a)\ dG(\lambda) \\ &\quad + \int_{w_C(a)/a}^{\lambda^{D1}(a)} V_e\left(\frac{\beta(r+\delta+\mu_e\pi)[a\lambda - (\chi L + rV_u(a))]}{r+\delta} + w_R(a), a \right) - V_u(a)\ dG(\lambda) \\ &\quad + \int_{\lambda^{D1}(a)}^{\lambda^{D2}(a)} V_e(w_C(a), a) - V_u(a)\ dG(\lambda) \\ &\quad + \int_{\lambda^{D2}(a)} V_e(\beta a\lambda + (1-\beta) w_C(a), a)\ dG(\lambda) \Bigg]. \end{aligned} \tag{1.26}$$

Equation 1.26 recursively defines $V_u(a)$ for each a, given the equations for the reservation match values, $\lambda^R(a) = w_R(a)/a$, Equation 1.24 for $\lambda^{D1}(a)$, and Equation 1.13 for $\lambda^{D2}(a)$, as well as the equations for the reservation wage, Equation 1.10, the crime reservation wage, Equation 1.11, and the value of employment, Equation 1.6.

1.3 Steady State

To solve for the steady-state distribution of workers across states. First define for workers with ability a the measure $u(a)$, unemployed; $e_c(a)$, employed and committing crimes; $e_{nc}(a)$, employed and not committing crimes; and $p(a)$, in prison. A worker with $a < a^*$ is a potential criminal and can flow between all four states, and a worker with $a \geq a^*$ will never commit a crime and can only flow between $u(a)$ and $e_{nc}(a)$.

For a potential criminal the flow from unemployment to employment and crime is equal to the probability that he receives a job offer times the probability that the productivity of the job is above his reservation match value and below the productivity at which a firm will deter him from crime:

$$\mu_j \big[G\big(\lambda^{D1}(a)\big) - G\big(\lambda^{R}(a)\big) \big] \equiv \mu_j D(a). \tag{1.27}$$

The flow from unemployment to employment and not committing crimes is equal to the probability that the worker receives a job offer, times the probability that the productivity of the job is above the value at which a firm will deter him from crime:

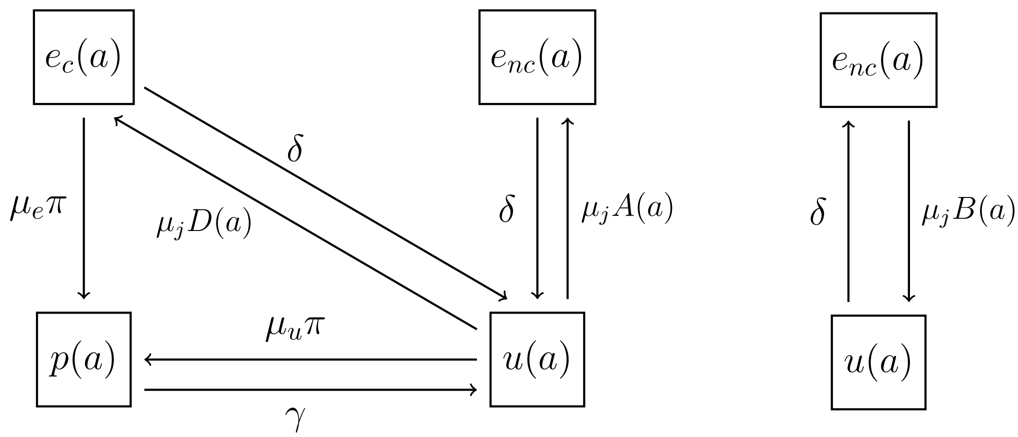
$$\mu_j \big[1 - G\big(\lambda^{D1}(a)\big) \big] \equiv \mu_j A(b). \tag{1.28}$$

For a non-criminal, the flow from unemployment to employment is equal to the probability that he receives a job offer, times the probability that the productivity of the job is above his reservation match value:

$$\mu_j \big[1 - G\big(\lambda^{R}(a)\big) \big] \equiv \mu_j B(a). \tag{1.29}$$

Figure 1.4 shows the labor market flows for both types of workers.

Figure 1.4: Labor Market Flows



(a) Flows for $a < a^*$ (b) Flows for $a > a^*$

A steady state is a set of measures $\{u(a), e_c(a), e_{nc}(a), p(a)\}$ for all a such that the flows between states are equal. The solution to the steady state measures can be found in appendix section A.1.2. The aggregate measure of unemployed criminals and aggregate measure of unemployed non-criminals are:

$$u_c = \int^{a^*} u(a)\ dF(a) \tag{1.30}$$

$$u_{nc} = \int_{a^*} u(a)\ dF(a). \tag{1.31}$$

The aggregate measure of workers employed and committing crimes and the aggregate measure of workers employed and not committing crimes are:

$$e_c = \int^{a^*} e_c(a)\ dF(a) \tag{1.32}$$

$$e_{nc} = \int e_{nc}(a)\ dF(a). \tag{1.33}$$

The aggregate measure of workers in prison is:

$$p = \int^{a^*} p(a)\ dF(a). \tag{1.34}$$

The steady state unemployment rate is:

$$U = \int \frac{u(a)}{1 - p(a)}\ dF(a) \tag{1.35}$$

and the crime rate is:

$$C = \int^{a^*} \frac{\mu_u u(a) + \mu_e e_c(a)}{1 - p(a)}\ dF(a). \tag{1.36}$$

Here I have use the non-institutionalized population as the denominator for the aggregate unemployment rate and the aggregate crime rate.

1.4 A Binding Minimum Wage

The minimum wage will change the interactions between the firm and the worker by acting as a constraint that each must consider when making a wage offer. I will assume the minimum wage, m, is set exogenously by the government and that all matches are subject to this constraint. Since wages are the only transfer from the firm to the worker, the firm cannot alter any other forms of compensation to undo the effect of the minimum wage. A minimum wage is binding if it alters the outcome of the bargaining problem for at least one type of worker and at least one job productivity. The question of interest is then: how does the minimum wage change wages and in turn a worker's decision to commit crimes?

1.4.1 Wages

The minimum wage enters the bargaining problem as a constraint; firms and workers can never offer a wage below m in the first stage or the second stage of the bargaining process. Under the constrained game, there exists a new value of unemployment for the worker that will depend on the minimum wage, I denote this value as $V_u(a, m)$. First, the lowest wage payed to a worker of ability a is $a\lambda^R(a, m)$, thus any minimum wage for which there exists an a such that $m > a\lambda^R(a, m) = w_R(a)$ is binding. An immediate implication of a binding minimum wage is that matches with total productivity less than m are no longer feasible.

Starting with the simplest case, if the minimum wage is binding for a non-criminal the firm must offer at least m in the second stage. The expected wage of the second stage for the worker becomes $\beta a\lambda + (1 - \beta)m$. In the first stage the firm offers a wage that maximizes profits subject to the worker accepting the offer. As before, it offers the expected wage of the second stage and since $m > a\lambda^R(a, m)$, wages increase for all productivities.

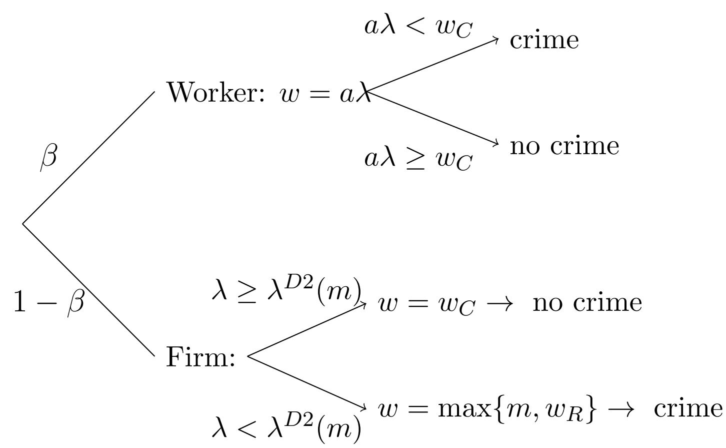
For a potential criminal, the solution to the constrained bargaining problem depends on whether or not the minimum wage is larger than the crime reservation wage. If $m < w_C(a)$ then only jobs with productivities at which the firm does not deter the worker in the second stage are constrained. Figure 1.5a shows the constrained second stage. Since the minimum wage is less than the worker's crime reservation wage the firm must choose whether or not to deter the worker from crime in the second stage. The firm faces the following problem in the second stage:

$$w(a, \lambda) = \underset{\{m, w_C\}}{\text{argmax}} \left\{ \frac{a\lambda - m}{r + \delta + \mu_e \pi} \ , \ \frac{a\lambda - w_C(a)}{r + \delta} \right\}. \tag{1.37}$$

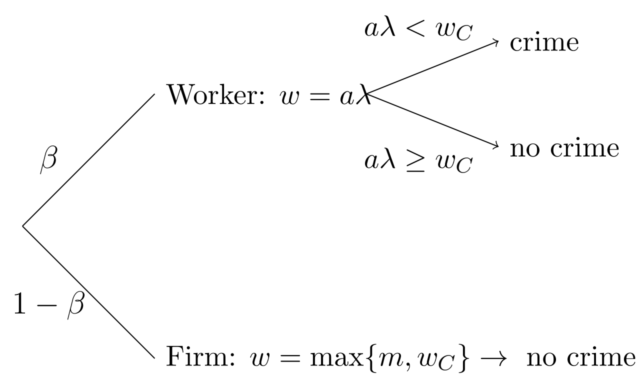
As with the unconstrained problem, for low productivity jobs, the firm will choose to pay the minimum wage and have a shorter job duration. The match value that makes the firm indifferent between deterring and not deterring the worker in the second stage is now,

$$\lambda^{D2}(a, m) = \frac{(r + \delta + \mu_e \pi)w_C(a) - (r + \delta)m}{a\mu_e \pi} \tag{1.38}$$

Figure 1.5: Constrained Second Stage



(a) For a worker of ability a with $m < w_C(a)$



(b) For a worker of ability a with $m \geq w_C(a)$

above which the firm will choose to offer the crime reservation wage and receive a lower flow value for a longer duration. In the case that the total match productivity less than the crime reservation wage, $w_C(a)$, a binding minimum wage implies that the expected value of the second stage is now,

$$\beta V_e(a\lambda, a) + (1-\beta)V_e(m, a) = V_e(\beta a\lambda + (1-\beta)m, a) \tag{1.39}$$

since the worker will commit crimes in both possible outcomes of the second stage, the value of employment is linear in the wage. If the total match productivity of the job is less than the crime reservation wage, the firm will not deter the worker from crime in the first stage, so it offers the worker the expected wage of the second stage, $w(\lambda, a) = \beta a\lambda + (1-\beta)m$.

If the total match productivity is greater than the crime reservation wage but not high enough for the firm to deter in the second stage, $w_C(a) < a\lambda < a\lambda^{D2}(a)$, then the workers expected value of the second stage is:

$$V_e(w,a) \geq \beta\left[\frac{a\lambda - \chi L + \delta V_u(a)}{r+\delta}\right] + (1-\beta)\left[\frac{m - \chi L + \delta V_u(a) + \mu_e(g + \pi V_p(a))}{r + \delta + \mu_e\pi}\right] \quad (1.40)$$

which simplifies to the follow constraint on the wage:

$$w \geq \frac{\beta(r+\delta+\mu_e\pi)[a\lambda - (\chi L + rV_u(a))]}{(r+\delta)} + w_R(a) + (1-\beta)(m - w_R(a)). \quad (1.41)$$

Again the firm can choose to deter the worker from crime in the first stage by offering at lease the crime reservation wage or it can offer the worker the expected value of the second stage, in which case it receives a higher flow value for a shorter duration. The firms problem in the first stage is:

$$w(a,\lambda) = \underset{w}{\text{argmax}}\left\{\underset{\substack{w \\ \text{s.t.} \quad w \geq w_C(a)}}{\text{argmax}} \frac{a\lambda - w}{r+\delta}\ , \quad \underset{\substack{w \\ \text{s.t.} \quad w_C(a) > w \ \& \ \textit{Equation 1.41}}}{\text{argmax}} \frac{a\lambda - w}{r+\delta+\mu_e\pi}\right\}. \quad (1.42)$$

The solution is similar to the unconstrained problem: the firm gives the worker the expected value of the second stage by paying the wage that makes Equation 1.41 bind, for low productivities and there exits some productivity, $\lambda^{D1}(a,m)$, above which the firm deters the worker from crime by offering the crime reservation wage.

$$\lambda^{D1}(a,m) = \frac{(r+\delta+\mu_e\pi)[w_C(a) + \beta(\chi L + rV_u(a))] - (r+\delta)[w_R(a) + (1-\beta)(m - w_R(a))]}{a(\mu_e\pi + \beta(r+\delta+\mu_e\pi))} \quad (1.43)$$

Figure 1.6 shows the wage profile with the minimum wage imposed. The new wage offered by the firm is

$$\tilde{w}(a,\lambda;m) = \begin{cases} \beta a\lambda + (1-\beta)m & \text{if } m \leq \lambda < w_C(a) \\ \frac{\beta(r+\delta+\mu_e\pi)[a\lambda-(\chi L + rV_u(a))]}{(r+\delta)} + w_R(a) + (1-\beta)(m - w_R(a)) & \text{if } w_C(a) \leq \lambda < \lambda^{D1}(a,m) \\ w_C(a) & \text{if } \lambda^{D1}(a,m) \leq \lambda < \lambda^{D2}(a,m) \\ \beta a\lambda + (1-\beta)w_C(a) & \text{if } \lambda \geq \lambda^{D2}(a,m). \end{cases} \tag{1.44}$$

Figure 1.6 shows that a binding minimum wage compresses the wage distribution for a worker up to $\lambda^{D2}(a)$. Proposition 3 summarizes the effects on the wage distribution. Part a.i. implies that a firm will deter the worker from crime for a larger range of productivities. With the minimum wage, the flow value of a filled job decreases since the expected value of the second stage increases. A reduction in the flow value of the job reduces the benefit to the firm from offering a wage lower than the worker's crime reservation wage, and therefore the firm will choose to deter the worker from crime for more job productivities.

Proposition 3.

a. If $(r+\delta)/\mu_e\pi \leq (1-\beta)/\beta$ *and* $m < w_C(a)$ *then*

  i. $\frac{\partial\lambda^{D1}(a,m)}{\partial m} < 0$

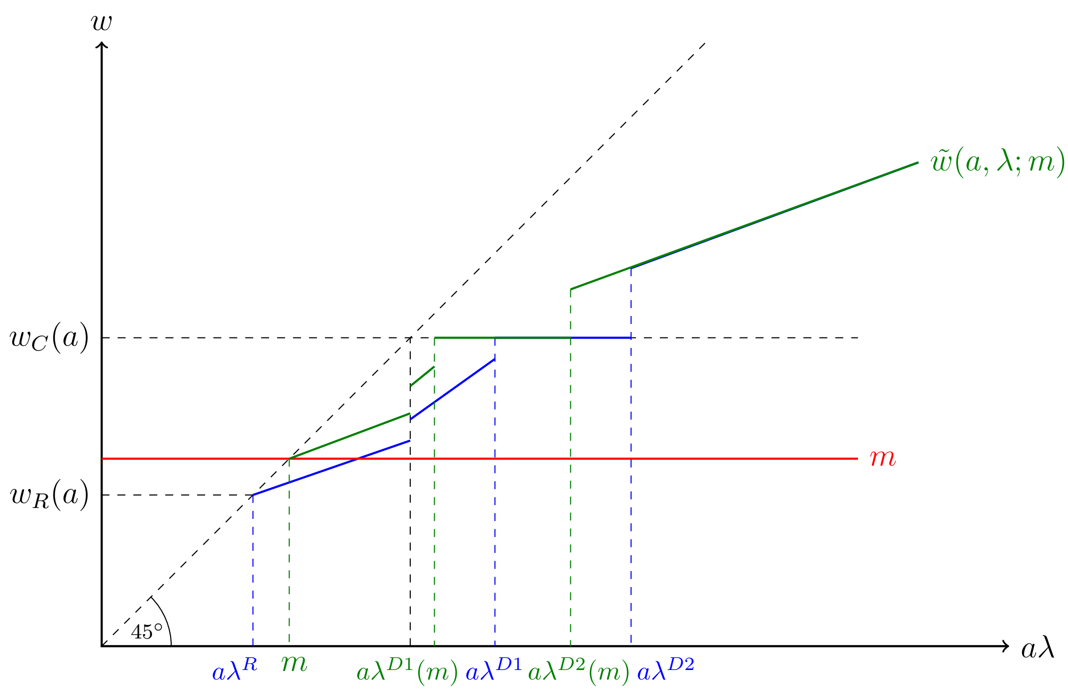
  i. $\frac{\partial\lambda^{D2}(a,m)}{\partial m} < 0$

  iii. $\tilde{w}(a,\lambda;m) \geq w(a,\lambda)$ *for all* $m \leq \lambda < \lambda^{D2}(a,m)$

b. If $m \geq w_C(a)$ *then* $\tilde{w}(a,\lambda;m) > w(a,\lambda)$ *for all matches values that lead to a filled job.*

If the minimum wage is above the crime reservation wage the firm has no decision to make in the second stage since all wages it can offer will deter the worker from crime while employed. Figure 1.5b shows the constrained second stage for which the expected wage is now $\beta a\lambda + (1-\beta)m$ for all feasible matches. Since the worker will forge crime

Figure 1.6: Wage Profile for Constrained Workers with $V_u(a) < V_u(a)^*$

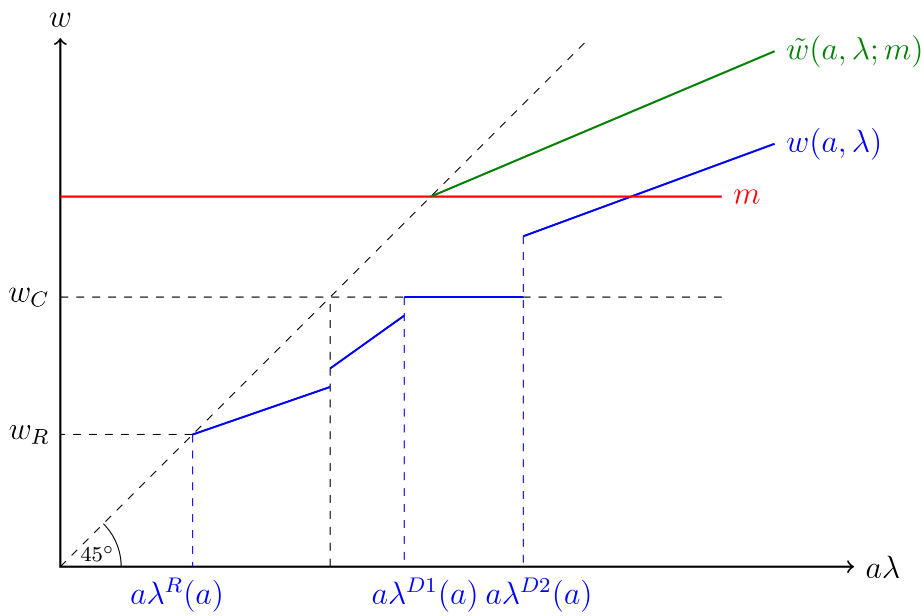


opportunities in either state, the expected value for the worker of the second stage is liner and so the firm must offer at least the expected wage of the second stage. If there is some positive probability that the worker gets to set the wage in the second stage, then the expected wage of the second stage is strictly greater than the crime reservation wage. Therefore, the firm does not need to decide whether or not to deter the worker from crime in the first stage and faces the following problem in the first stage:

$$w(a,\lambda) = \underset{w}{\text{argmax}} \frac{\lambda - w}{r + \delta} \text{ s.t. } \; w \geq \beta\lambda + (1-\beta)m. \tag{1.45}$$

The firm maximizes profits by offering the expected wage of the second stage which the worker will accept and forgo crimes while employed. The wage is simply $\tilde{w}(a,\lambda;m) = \beta a\lambda + (1-\beta)m$ for all $\lambda \geq m$. Part b. of Proposition 3 summarizes the effect of a minimum wage in this case and Figure 1.7 shows the effect on the worker's wage profile, which increases for all feasible matches.

Figure 1.7: Constrained Wage Profile for workers with $V_u(a) < V_u(a)^*$ when $m \geq w_C(a)$



1.4.2 Workers

Since meeting rates are exogenous the minimum wage will have no effect on the rate at which a worker meets with a firm. However, the minimum wage will change the range of productivities at which a worker will choose to commit crimes and therefore the rate at which he flows into and out of a criminal state. A potential criminal will commit crimes for all matches with productivity less than $\lambda^{D1}(a, m)$; if the productivity is less than $\max\{m/a, \lambda^R(a, m)\}$ he will commit crimes at rate μ_u because he is unemployed and if the productivity is greater than $\max\{m/a, \lambda^R(a, m)\}$ but less than $\lambda^{D1}(a, m)$ he will commit crimes at rate μ_e because the wage offered by such a job is not high enough to deter him from crime.

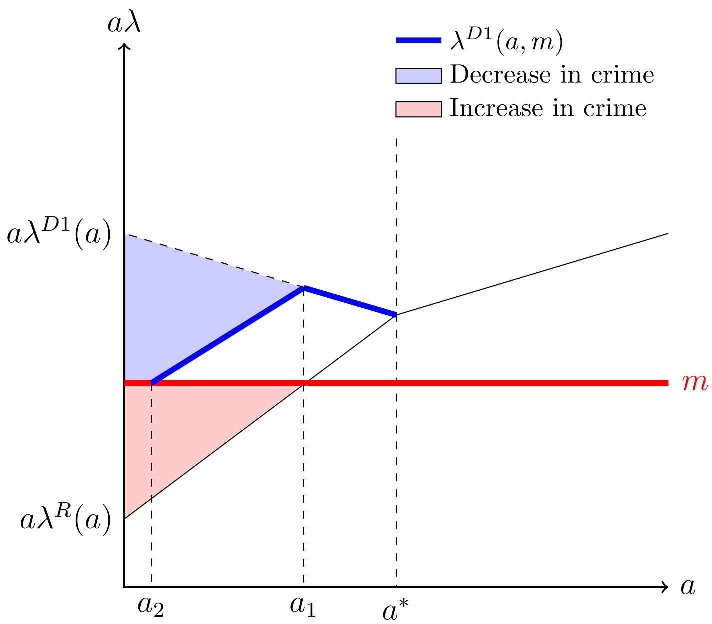
A binding minimum wage will have three effects on a worker's propensity to commit crimes: a wage effect, an unemployment effect, and an indirect effect. The wage effect occurs when workers are deterred from committing crimes due to receiving a higher wage. The unemployment effect occurs when either: (1) a worker is displaced from jobs at which he would not have committed crimes or (2) the rate at which he receives crime opportunities differs across states and he is displaced from any job. The indirect effect is driven by changes in the unemployment value, $V_u(a, m)$. A change in the minimum wage will affect a worker's value of unemployment and therefore indirectly affect the flows between criminal and non-criminal states.

Wage Effect

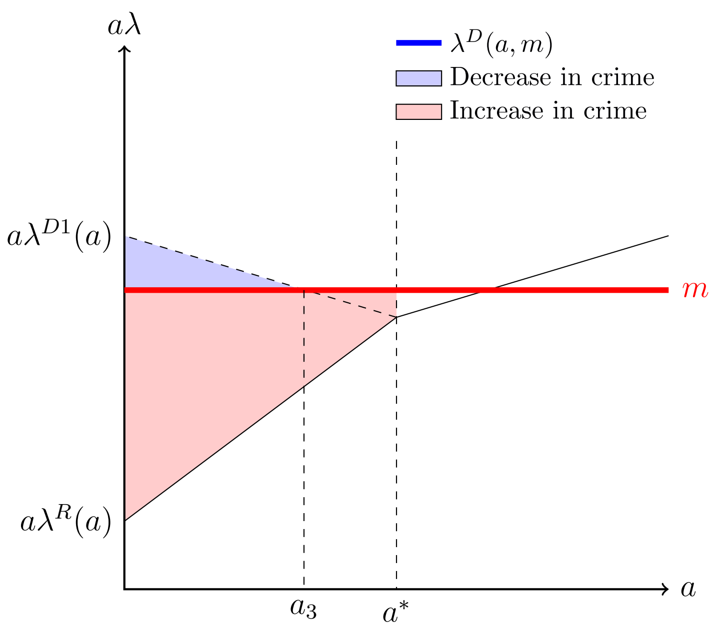
Since all workers affected by the minimum wage experience an increase in wages for a range of productivities, the wage effect exists for all workers with a reservation wage less than the minimum wage. In Figure 1.8a this is all workers with ability less than a_1. For a worker with ability less than a_2 in Figure 1.8a, the minimum wage is higher than his crime reservation wage, and he will never commit crimes while employed. Therefore, he flows out of a criminal state if he receive a job offer with productivity greater than or equal to m/a.

For a worker with ability greater than a_2 but less than a_1 in Figure 1.8a, the crime reservation wage is above the minimum wage and he will continue to commit crimes while employed at some jobs. However, the range of productivities for which he commits crimes has decreased (part a.i. of Proposition 3.) as shown by the fact that $\lambda^{D1}(a)$ is greater than $\lambda^{D1}(a, m)$ in Figure 1.8a. All together, the blue shaded region of Figure 1.8a shows the matches that no longer lead to crime while employed due to an increase in wages. In Figure 1.8b the minimum wage is above all workers' crime reservation wage and therefore all workers forgo crime while employed. Again, the wage effect corresponds to the blue shaded region; these are matches at which a worker would have committed crimes before the minimum wage.

Figure 1.8: Minimum Wage Effects on Matches



(a) Low Minimum Wage



(b) High Minimum Wage

Unemployment Effect

There are two channels through which a worker will change the amount of crimes he commits due to unemployment. First, if the rate at which he receive crime opportunities differs across states. Specifically, if he receives more crime opportunities while unemployed, $\mu_e < \mu_u$, then when he is displaced from a job, he will commit more crimes. In Figure 1.8a, this corresponds to the red shaded region; these are productivities at which workers would have accepted a job and committed less crime in the absence of the minimum wage.

Second, if a worker is displaced from a job at which he would not have committed a crime, then the minimum wage will increase the amount of crimes he commits. This occurs when the minimum wage is above the productivity at which the firm would have chosen to deterred the worker from crime. This corresponds to matches with a total productivity greater than $a\lambda^{D1}(a)$ and less than m in Figure 1.8a. Only workers with ability greater than a_3 and less than a^* are displaced from jobs at which they would not have committed crimes. The red shaded region of Figures 1.8a and 1.8b show the matches that lead to an increase in crime through both channels.

Indirect Effect

The indirect effect of the minimum wage on a worker's crime decisions is driven by changes in his value of unemployment. Take, for example, a worker with ability greater than a_2 and less than a_1. From Figure 1.8a it is clear that his value of unemployment has changed for two reasons: (1) some matches are no longer feasible and (2) some matches experience a wage increase. The fact that some matches no longer lead to filled jobs decreases his value of unemployment. On the other hand, the wage increase for some matches increases his value of unemployment. Therefore, the overall effect of a minimum wage on the worker's value of unemployment is ambiguous, depends on the size of the minimum wage, and varies across workers.

1.4.3 Equilibrium Crime Rate

The equilibrium crime rate given in equation (1.36) depends on the steady state measures, $u(a)$, $e_c(a)$, and $p(a)$, and the rates at which workers receive crime opportunities while employed, μ_e, and unemployed, μ_u. When the minimum wage changes, the aggregate crime rate is affected by changes in workers' decisions to commit crimes and accept jobs. From Figure 1.8a it is clear that workers are affected differentially by the minimum wage; some workers are deterred from crime for more job productivities and are displaced from more jobs. Therefore, analytical results for a change in the crime rate depend on the distribution of ability, the distribution of job productivities and the size of the minimum wage.

1.5 Calibration

The unit of time is one month and the rate of time preference is $r = 0.0101$. The model is calibrated to match the crime and labor market in 1998. The model is normalized by setting the flow utility of prison, z, equal to zero.[11] The probability a worker gets to set the wage in the second stage, β, acts as the worker's bargaining power, which is set to $\beta = 0.4$ as estimated by Flinn (2006).

The crimes considered are Type 1 property crimes defined by the Federal Bureau of Investigation (FBI) as larceny, burglary and motor vehicle theft. The probability of being caught is derived from the clearance rate and the incarceration rate of these crimes

[11] Since individuals can not choose how long to say in prison, these does not exist an empirical moment that could pin down the flow utility of prison.

as reported by the FBI's Uniform Crime Reports (UCR). The UCR defines the clearance rate as the ratio of arrests to crimes reported and the incarceration rate as the ratio of convictions to arrests. In 1998 the clearance rate for property crimes was 17.5% and the incarceration rate for property crimes was 65%, implying the probability a worker goes to prison is $\pi = 0.175 * 0.65 = 0.114$. The prison release rate is calibrated to target the average time in prison for property crimes as reported by the National Corrections Reporting Program. In 1998, the average time in prison for property crimes was 20 months implying $\gamma = 1/20 = 0.05$. The UCR reports that the average loss per property crime in 1998 was $\$1,407$ implying the gain from crime is $g = \$1,407$. The expected loss, χL, is set such that the crime market is in equilibrium, that is, the expected loss is the gain from crime times the crime rate, which is calculated below.

The remaining set of parameters (b, $\mu_e, \mu_u, \mu_j, \mu_\lambda, \sigma_\lambda, \mu_a, \sigma_a$, δ), where μ_λ and σ_λ are the mean and standard deviation of the job productivity distribution and μ_a and σ_a are the mean and standard deviation of the ability distribution, are calibrated to match a set of empirical moments derived from the National Longitudinal Survey of Youth 1997 (NLSY97). The data are collected from 8,984 respondents who were ages 12-17 when first interviewed in 1997. Respondents were asked questions about their labor market status including employment status, wages, and hours worked. The survey also asks individuals to report the crimes they committed during the year, specifically useful for the question posed here are individuals' responses to the number of times they stole more than $50 worth and the number of times they committed other property crimes such as fencing, receiving, possessing or selling stolen property. In the first round of the survey, respondents were administered the computer-adaptive form of the Armed Services Vocational Aptitude Battery (CAT-ASVAB).[12]

[12]The CAT-ASVAB measures an individual's knowledge in the following areas:Arithmetic Reasoning, Electronics Information, Numerical Operations, Assembling Objects, General Science, Paragraph Com-

Nine empirical moments are constructed using the NLSY97 data for 1998, to target the remaining parameters. The moments constructed are: the monthly crime rate, the ratio of the crime rate among the unemployed to employed, the monthly unemployment rate, the monthly job finding probability, the monthly separation rate, the 10th percentile to median and median to 90th percentile ratios of the CAT-ASVAB scores, the minimum wage to median wage ratio, and the median to 75th percentile wage ratio. Details of how these moments are constructed can be found appendix section A.1.4. Table 1.1 gives a summary of the empirical moments.

Table 1.1: Summary of Empirical Moments

Moment	Value
Unemployment rate	0.124
Crime rate	0.042
Crime rate of Unemp. / Crime rate of Emp.	1.159
Job finding rate	0.160
Seperation rate	0.011
10th Percentile / 50th Percentile exp(CAT-ASVAB)	0.312
50th Percentile / 90th Percentile exp(CAT-ASVAB)	0.454
Minimum Wage / 50th Percentile Wage	0.880
50th Percentile / 75th Percentile Wage	0.900

Since jobs separate at an exogenous rate in the model, $\delta = 0.011$ to match the monthly separation rate in the NLSY97. The two moments derived from the CAT-ASVAB scores are used to calibrate a distribution of abilities. The CAT-ASVAB scores have a normal distribution in the data; however, since ability multiplicatively enters into the total productivity of a job, a negative ability level would imply never finding a productive job. Therefore, the CAT-ASVAB scores are exponentiated, giving ability a log-normal distribution. Further, since the lower bound of a log-normal distribution is

prehension, Auto Information, Mathematics Knowledge, Shop Information, Coding Speed, Mechanical Comprehension, Word Knowledge.

zero, one is added to the exponentiated test scores, again insuring that all individuals have a non-zero probability of finding a productive match. These assumptions lead to a distribution of abilities, $a - 1 \sim \ln N(\mu_a, \sigma_a)$, where μ_a and σ_a are chosen to match the ratio of the 10th/50th percentile and the 50th/90th percentile of the exponentiated CAT-ASVAB scores. Matching the ratios of test scores assumes test scores ordinally identify ability.

The remaining six parameters, $(b,\ \mu_e,\ \mu_u,\mu_j,\mu_\lambda,\ \sigma_\lambda)$, are calibrated to match the remaining six moments jointly using simulated method of moments. Although all six parameters influence all six moments, intuitively the job productivity parameters, μ_λ and σ_λ, are chosen to target the ratios of the wage distribution. The distribution for job productivities is log normal, $\lambda \sim \ln N(\mu_\lambda, \sigma_\lambda)$. The crime arrival rates μ_u and μ_e are chosen to target the aggregate crime rate and relative crime rate of the unemployed to employed. The job contact rate, μ_j, is chosen to target the job finding rate and the flow value of unemployment b is chosen to target the unemployment rate.

The average weekly hours worked in the NLSY97 for 1998 was 21.7 and the minimum wage in 1998 wage \$5.15 implying a monthly minimum wage of $m = 5.15 \times 21.7 \times 4 = 446.06$. The monthly crime rate in 1998 measured from the NLSY97 was 0.042 and the gain from crime was \$1,407 so the expected loss from crime is $\chi L = \$58.47$. Table 1.2 and Table 1.3 summarize all parameters and Table 1.4 gives the empirical and model generated moments.

The estimated crime arrival rates are 0.24 while employed and 0.05 while unemployed, implying a monthly probability of finding a crime opportunity of 0.21 while employed and 0.05 while unemployed. The job offer rate is 4.2, implying a monthly probability of receiving a job offer of 0.98. The calibrated mean and variance of the job productivity distribution and the ability distribution imply a mean total job productivity, $a\lambda$, of \$341.31 and a standard deviation of \$346.14.

Table 1.2: Parameter Values

Parameter	Value	Description
r	0.0101	real interest rate
β	0.4	bargaining power of workers
χL	\$58.47	expected loss from crime
z	0	prison utility
γ	0.05	prison release rate
π	0.114	probability of getting caught
m	\$446.06	minimum wage job
g	$\$1,407$	gain from crime

Table 1.3: Simulated Method of Moments Estimates

Parameter	Estimate	p5	p95	Description
δ	0.011	0.001	0.013	separation rate
b	−26.70	−31.6930	−25.0907	flow utility of unemployment
μ_e	0.2391	0.1835	0.3074	arrival rate of crime opp. while emp.
μ_u	0.0468	0.0213	0.0581	arrival rate of crime opp. while unemp.
μ_j	4.1692	3.5595	5.0588	arrival rate of jobs opportunities
μ_λ	0.8623	0.6947	0.9578	mean of productivity distribution
σ_λ	0.5291	0.4939	0.5809	s.d. of productivity distribution
μ_a	4.6256	4.5545	4.7296	mean ability
σ_a	0.6293	0.5945	0.6738	s.d. of ability

Note: The columns labeled p5 and p95 give the 5th and 95th percentile of estimates from 500 bootstrapped samples.

1.5.1 Model Generated Elasticities

Since the effect of the minimum wage on the crime rate is driven through changes in the labor market, I test the model in two dimensions: the response of workers' crime decisions with respect to changes in the labor market and changes in the labor market with respect to changes in the minimum wage. Specifically, two data sets are generated through simulation of the model, similar to those used by empirical researchers, and

Table 1.4: Moments Matched

Moment	Empirical	Model
Unemployment rate	0.124	0.124
Crime rate	0.042	0.041
Crime rate of Unemp. / Crime rate of Emp.	1.159	1.159
Job finding rate	0.160	0.159
10th Percentile / 50th Percentile exp(CAT-ASVAB)	0.312	0.312
50th Percentile / 90th Percentile exp(CAT-ASVAB)	0.454	0.454
Minimum Wage / 50th Percentile Wage	0.880	0.883
50th Percentile / 75th Percentile Wage	0.900	0.899

used to estimate the elasticity of crime with respect to unemployment and wages and the elasticity of employment and earnings with respect to the minimum wage. I compare the estimated elasticities that the calibrated model delivers to those found in the empirical literature to validate the relationship between the labor market and criminal propensity and the minimum wage and the labor market. Both data sets are generated based on variation in the real minimum wage observed across states from 1990 to 2011. Table 1.5 summaries the variation in the minimum wage across the sample; the real binding minimum wage is the maximum of the state and federal minimum wage in 1998 dollars.

Table 1.5: Minimum Wage Summary Statistics

	Mean	St. dev.	Min	Max
Federal Min. Wage	5.24	0.99	3.80	7.25
State Min. Wage	5.30	1.31	1.6	8.67
Binding Min. Wage	5.46	1.15	3.80	8.67
Real Binding Min. Wage	5.09	0.55	4.34	6.83

The first data generated is a panel of 1,000 individuals for every realization of the real binding minimum wage; this gives a total sample size of 204,000. For each individual the probability of unemployment and employment, probability of committing a crime, and expected wage are simulated using the calibrated parameters. Full details of the simulations can be found in appendix section A.1.5. Using the simulated unemployment probability and simulated expected wage, expected monthly earnings are calculated as the employment probability times the expected wage. Panel A of Table 1.6 gives the summary statistics for the generated sample.

The generated sample is used to estimate the elasticity of workers' crime decisions with respect to unemployment and wages and the model generated elasticities are compared to those found in the empirical literature. The model generated elasticities are estimated by the following regressions:

$$(1) \quad \ln crime_{i,m} = \alpha_0 + \alpha_1 U_m + \varepsilon_{i,m}$$

$$(2) \quad \ln crime_{i,m} = \beta_0 + \beta_1 \ln Earnings_{i,m} + \varepsilon_{i,m}$$

where $\ln crime_{i,m}$ is the natural log of the simulated probability of committing a crime for worker i for minimum wage m, U_m is the unemployment probability for minimum wage m, $\ln Earnings_{i,m}$ is the natural log of earnings for worker i at minimum wage m and $\varepsilon_{i,m}$ is statistical noise generated in the simulation through the random draw of a crime opportunity and job productivity. Panel B of Table 1.6 gives the regression results.

Several empirical studies have estimated the elasticity of crime with respect to unemployment and wages and find a semi-elasticity of crime with respect to unemployment, $\hat{\alpha}_1$, of 1.2 to 2, and an elasticity of crime with respect to earnings, $\hat{\beta}_1$, of -0.5 to -2 (Gould et al., 2002; Mocan and Unel, 2011; Schnepel, 2014). The model generated elasticity of crime with respect to earnings, -0.29, is on the low side of the empirically estimated range. The model generates an elasticity of crime with respect to unemployment, 2.15, that is slightly higher than the empirically estimated elasticities.

To estimate the response of the labor market to changes in the minimum wage within the model, a cross section of aggregate employment probabilities, and expected wages

Table 1.6: Simulated Individual Analysis

Panel A: Simulated Data Summary Statistics				
	Mean	St. dev.	Min	Max
Crime	0.036	0.034	0	0.154
Wage	609.51	213.95	394.71	2424.40
Earnings	532.31	267.01	0	2385.61
Unemployment	0.143	0.240	0	1

Panel B: Regression Results		
	ln Crime (1)	ln Crime (2)
Unemployment	2.15	
ln (Earnings)		−0.29
N	*204,000*	*204,000*

Note: Observations for which crime or earnings equal 0 were replace with 0.0001 before taking logs.

for every unique realization of the real binding minimum wage within the sample is generated. The generated data has a sample size of 1,122. Full details of the simulations can be found in appendix section A.1.5. Aggregate monthly earnings are constructed by multiplying the unemployment rate by wages. Using the aggregate sample, the model's generated elasticities are estimated by the following regressions:

$$(1) \quad \ln Emp_m = \xi_0 + \xi_1 \ln MinWage_m + \varepsilon_m$$

$$(2) \quad \ln Earnings_m = \psi_0 + \psi_1 \ln MinWage_m + \varepsilon_m$$

where $\ln Emp_m$ is the natural log of the average employment probability for minimum wage m, $\ln Earnings_m$ is the natural log of average earnings for minimum wage m, and ε_m is statistical noise generated from the random draws from the productivity distribution. Panel A of Table 1.7 gives summary statistics for the aggregate data and Panel B of Table 1.7 gives the regression results.

Table 1.7: Simulated Aggregates Analysis

Panel A: Simulated Data Summary Statistics				
	Mean	St. dev.	Min	Max
Unemployment	0.127	0.026	0.072	0.221
Employment	0.873	0.026	0.779	0.927
Wage	598.57	36.78	534.19	722.86
Earnings	524.35	19.71	469.12	594.73

Panel B: Regression Results		
	Dependent Variable	
	$\ln Emp$	$\ln Wage$
ln MinWage	−0.264	0.299
N	*1,122*	*1,122*

The literature on employment effects of the minimum wage is lengthy and mixed, see Neumark and Wascher (2007) for a review. Dube et al. (2010) study employment effects on restaurant workers and find no significant effect. The employment effects from the minimum wage on teen employment is mixed as well; Allegretto et al. (2010) finding no significant employment effects and Neumark et al. (2014) finding significant employment effects on teens with estimated elasticities around −0.3. The estimated elasticity of employment with respect to the minimum wage within the calibrated model −0.264, lower than the upper bound of the empirical literature. However, recent work from Jardim et al. (2017) suggests that the elasticity of employment with respect to the minimum wage may be much higher than previously estimated. The empirically estimated elasticity of wages with respect to the minimum wage is between 0.15 and 0.22 (Dube et al., 2010; Allegretto et al., 2010). The model delivers an estimated elasticity of 0.3, slightly higher than the empirical literature.

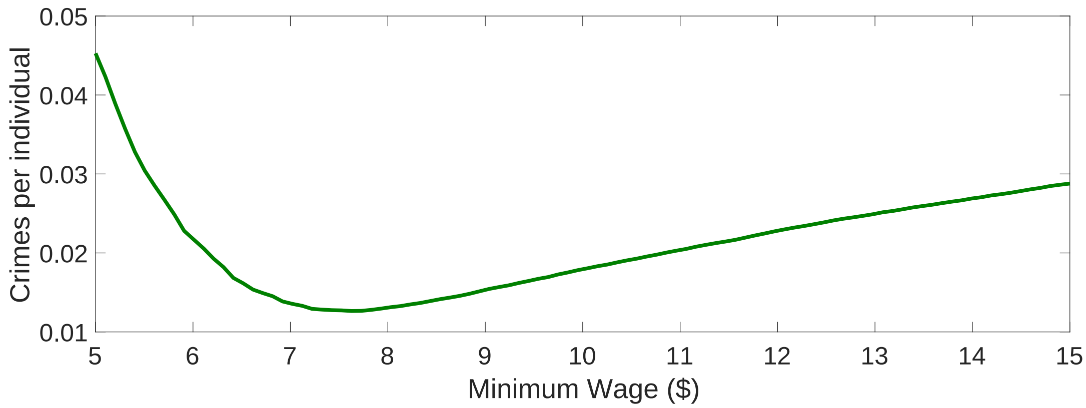
Overall, the calibrated model generates elasticities similar to those estimated in the empirical literature; changes in labor market conditions within the calibrated model affect individual's crime decisions similarly to what can be observed in data. Furthermore, the effect of minimum wages on aggregate labor market conditions within the calibrated model are comparable to those estimated in the empirical literature. Since the calibrated model does not match these elasticities I argue that these results establish a degree of external validity for the calibrated model.

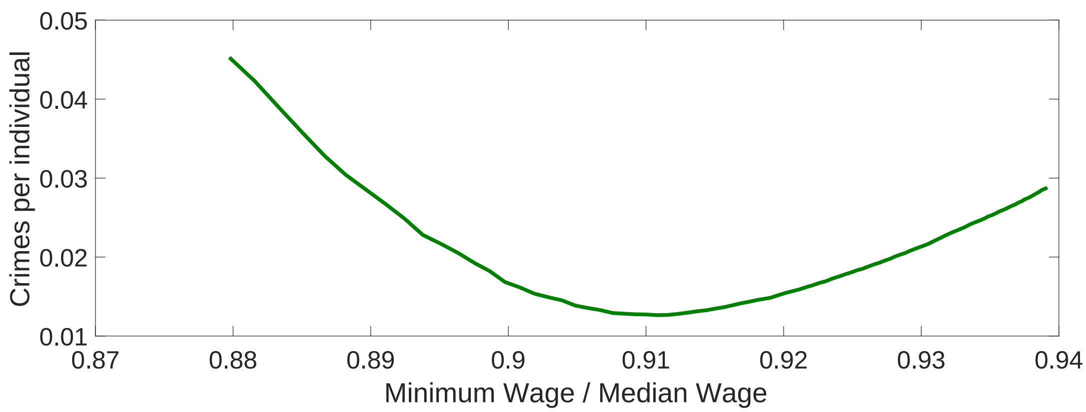
1.6 Increasing the Minimum Wage

Using the calibrated parameters, I solve the model for minimum wages between \$5 and \$15. For this exercise, the probability of being victimized, χ, is endogenized such that it is equal to the crime rate in steady state. Figure 1.9 shows the change in the aggregate crime rate, equation (1.36), over the range of minimum wages. The figure shows that the aggregate crime rate decreases with minimum wages between \$5 and \$7.50, implying that the wage effect outweighs the unemployment effect over this range. With minimum wages above \$7.50, the crime rate begins to increase as the unemployment effect begins to dominate. Figure 1.9 also plots the crime rate with respect to the minimum to median wage ratio. Since increases in the minimum wage affect the entire wage distribution, observing how the crime rate changes with respect to the minimum to median wage ratio is more informative for optimal policy. The model reveals that the crime rate is minimized when the minimum wage is 0.91 of the median wage of 16 to 19 year olds.

The fact that the aggregate crime rate responds more to changes in wages than to changes in unemployment for relatively small increases in the minimum wage stems from the fact that employment decreases only marginally. This finding is similar to Imrohoroglu et al. (2004) who find that rising average incomes from 1980 to 1996 alone could account for 20% of the decrease in crime observed over the period, whereas the small

Figure 1.9: Crime Rate





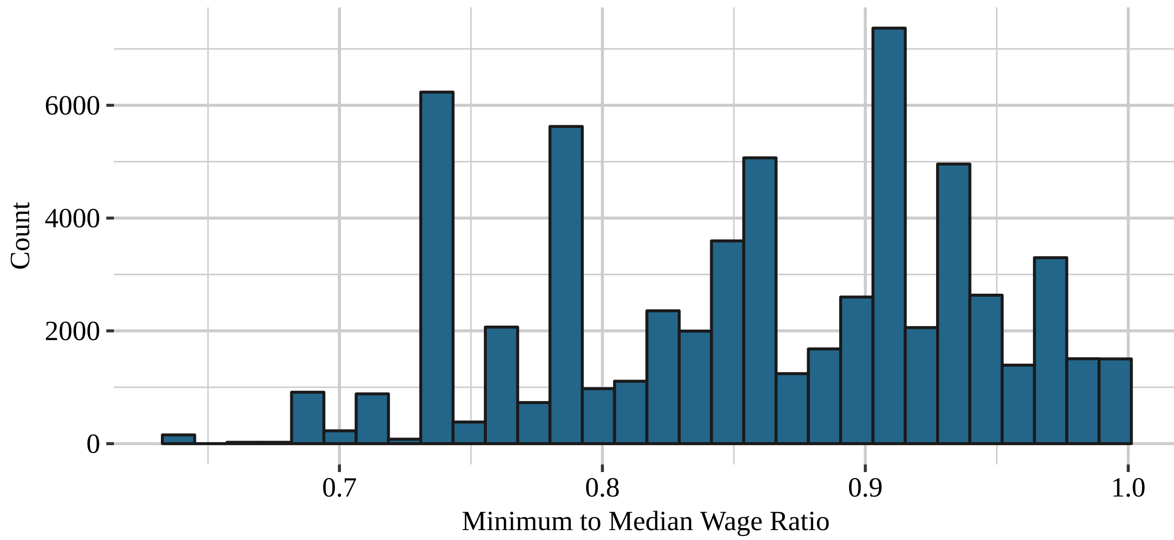
increases in youth unemployment over the same period had no effect on the aggregate crime rate. The non-monotonicity of the crime rate is driven by a similar mechanism as in Engelhardt et al. (2008), who show that the crime rate is non-monotonic in the worker's bargaining power. For low minimum wages, as for low bargaining powers, the worker has a larger incentive to commit crimes because his labor market outcomes are low in terms of wages. As the minimum wage increases, or bargaining power increases, the worker's incentive to commit crimes decreases because his labor market outcomes in terms of wages increase. However, once the minimum wage increase above a certain point, the probability he finds a feasible match is too low and his labor market outcomes decease because of high unemployment, which increases his incentive to commit crime. Similarly in Engelhardt et al. (2008) a high bargaining power for the worker decreases the firms incentive to open vacancies, decreasing the workers labor market outcomes through high unemployment, increasing his incentive to commit crimes. As Flinn (2006) points out, one can think of the minimum wage as a policy tool that increases the worker's bargaining power.

1.6.1 Empirical Evidence

Figure 1.9 shows that the model predicts the minimum wage to have a U-shaped effect on the crime rate. In this section I use county level crime data from 1995 to 2014 to test this prediction. The county level crime data come from the FBI's UCR; the data include the number of Type 1 property primes (burglary, larceny, and motor vehicle theft) and the number of robberies, classified as a Type 1 violent crime, reported to the police. The variable of interest is the minimum to median wage ratio, which is constructed at the state level for 16 to 19 year olds using the Current Population Survey's Outgoing Rotation Groups. Since crimes reported to the police can not be broken up by age, I test the U-shape prediction on the aggregate crime rate in the county. Figure 1.10 shows the variation of the minimum to median wage ratio over the full sample. The average minimum to median wage ratio is 0.86 with a standard deviation of 0.08. A full description of the data can be found in appendix section A.1.4.

I test the prediction of the model using a non-parametric regression of county level crime rates on state level variation of the minimum to median wage ratio. The minimum to median wage ratio is binned into quintiles; Table 1.8 gives the mean and median value

Figure 1.10: Minimum to Median Wage Ratio Histogram



in each quintile. The model that is estimated is as follows:

$$\text{crime}_{ct} = \beta_1 + \sum_{j=2}^{5} \beta_j^1 \mathbb{1}\{MM_{st} \in (q(j-1), q(j)]\} + \beta_6 X_{ct} + \beta_7 \text{crime}_{ct-1} + \gamma_c + \varepsilon_{ct} \tag{1.46}$$

where $q(j)$ is the j^{th} quintile of the minimum to median wage ratio (MM) in state s at time t, and $\mathbb{1}$ is the indicator function. γ_c are county fixed effects and X_{ct} are demographic controls, the poverty rate, and the log of average household income in county c in year t. The specification includes a lag dependent variable to capture county level trends in the crime rate. The specification is estimated for five dependent variables: burglary, larceny, motor vehicle theft, total Type 1 property crimes (the sum of burglary, larceny and motor vehicle theft) and robbery. Since ordinary least squares (OLS) delivers inconsistent estimates with fixed effects and lagged dependent variables,[13] I use the second

[13] See **?** for reference.

Table 1.8: Mean Real Binding Minimum Wage by Quantile

Quintile	Min-to-Median Ratio	
	Mean	Median
1	0.738	0.736
2	0.816	0.817
3	0.871	0.863
4	0.915	0.906
5	0.962	0.964

lag, crime_{ct-2}, to instrument for the first lag, as suggested by **?**.

Table 1.9 gives the estimated coefficients on the quintiles of the minimum to median wage ratio for each dependent variable under OLS. Column (1) of Table 1.9 shows that moving from the first quintile to the third quintile of the minimum to median wage ratio has a negative and significant effect on property crimes within the county, decreasing property crimes by 82 crimes per 100,000 people. Moving from the first to the fourth quintile decreases property crimes by 120 crimes per 100,000 people. Moving from the first to the fifth quintile has a negative and significant effect on crime, however, the effect is less than when moving to the fourth quintile. A move from the first quintile to the fifth quintile decreases crime by 98 crimes per 100,000 people. Panel (a) of Figure 1.11 plots the estimated coefficients at the mean minimum to median wage ratio of each quintile, along with the 95% confidence intervals. The figure reveals a clear U-shape in the relationship between the minimum to median wage ratio and the property crime rate. Comparing panel (a) of Figure 1.11 to Figure 1.9 shows that the model and empirical exercise predict that the crime minimizing minimum to median wage ratio for 16 to 19 year olds is 0.91. Columns (2) – (5) of Table 1.9 and panels (b) – (e) reveal similar U-shaped relationships for the disaggregated categories of Type 1 property crimes and

Table 1.9: Regression Results: OLS

	(1) Property Crimes	(2) Burglary	(3) Larceny	(4) Motor Vehicle Theft	(5) Robbery
Quintile of Min-to-Median Ratio					
2nd.	-8.785	0.999	5.733	-5.829***	-0.569
	(7.762)	(2.386)	(5.199)	(0.950)	(0.318)
3rd.	-81.74***	-6.178*	-15.13*	-9.961***	-1.491***
	(8.996)	(2.739)	(6.093)	(1.131)	(0.399)
4th.	-120.4***	8.876**	-8.960	-15.53***	-1.883***
	(8.988)	(2.878)	(5.835)	(1.134)	(0.414)
5th.	-97.76***	19.94***	2.854	-13.90***	-0.515
	(9.572)	(3.073)	(6.450)	(1.123)	(0.399)
Mean Dep. Variable	2370.83	564.94	1566.92	152.30	40.61
N	51,418	51,418	51,418	51,418	51,418

Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income, poverty levels and a lag dependent variable. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

robbery.

Table 1.10 gives the estimated coefficients on the quintiles of the minimum to median wage ratio for each dependent variable for the instrumental variable (IV) regression. The magnitudes of the effect of a move from the first quintile to subsequent quintiles differ from the IV estimates to the OLS estimates but the U-shaped relationship continues to hold. A move from the first quintile to all higher quintiles is negative for property crimes. However, a move from the first quintile to the fifth quintile is smaller in absolute magnatude than a move from the first to the fourth quintile, suggesting a U-shaped

Table 1.10: Regression Results: IV

	(1) Property Crimes	(2) Burglary	(3) Larceny	(4) Motor Vehicle Theft	(5) Robbery
Quintile of Min-to-Median Ratio					
2nd.	-6.064	-0.288	6.580	-4.511***	-0.681*
	(7.727)	(2.375)	(5.173)	(0.904)	(0.332)
3rd.	-87.48***	-10.28***	-23.52***	-9.196***	-1.929***
	(8.492)	(2.540)	(5.641)	(1.042)	(0.400)
4th.	-115.4***	3.903	-12.12*	-12.33***	-2.432***
	(8.235)	(2.646)	(5.209)	(0.982)	(0.378)
5th.	-104.4***	13.65***	-4.954	-11.96***	-1.553***
	(8.959)	(2.941)	(5.917)	(1.017)	(0.351)
First Stage F-Stat	2,334.8	1,068.3	2,540.2	2,494.4	1,189.0
N	50,619	50,619	50,619	50,619	50,619

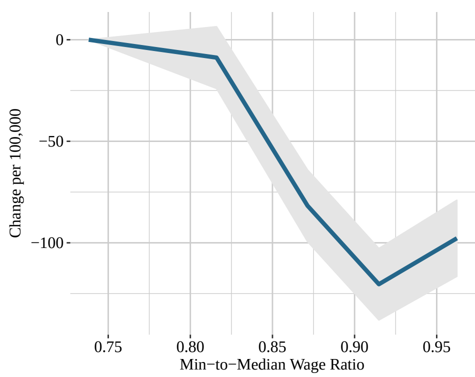
Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income, poverty levels. The lagged dependent variable is instrumented with the second lag. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

relationship between the minimum to median wage ratio and the property crime rate. Similar relationship between the minimum to median wage ratio and the burglary, larceny, motor vehicle theft, and robbery rates can be seen in columns (2) – (5) of Table 1.10.

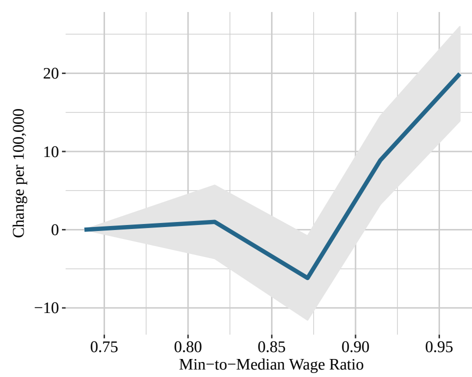
To test the strength of the U-shape relationships revealed in the non-parametric regression, I test for equality among the estimated coefficients on the quintiles of the minimum to median wage ratio. Table 1.11 gives the F statistic and corresponding p-values for each test for both the OLS and IV results. Column (4) tests if all coefficients are simultaneously equal; the test shows a constant effect of the minimum to median

Figure 1.11: Regression Coefficients

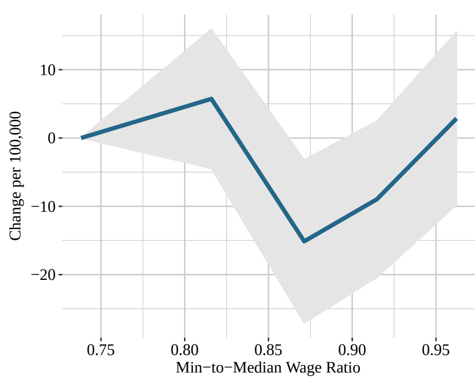
(a) Property Crimes



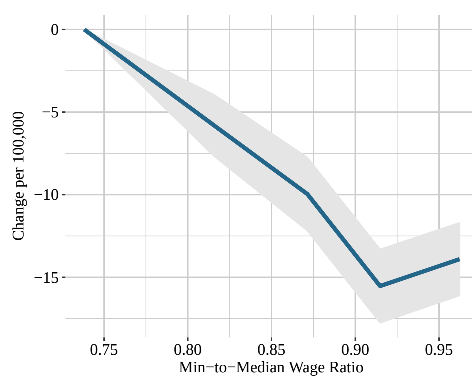
(b) Burglary



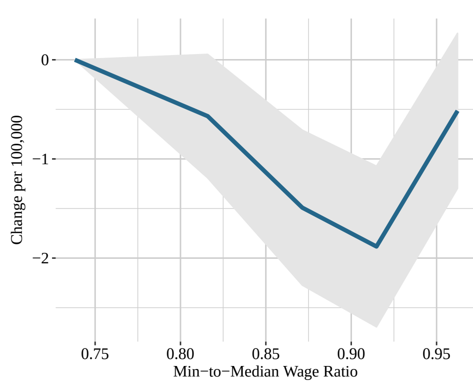
(c) Larceny



(d) Motor Vehicle Theft



(e) Robbery



wage ratio on all crimes can be ruled out for estimates from both specifications. Since the estimated coefficient on the fifth quintile is less than the fourth quintile for property crimes, column (3) tests for the U-shape relationship. Column (3) rules out that the decrease in property crimes from moving from the first quintile to the fourth quintile is equal to a move from the first quintile to the fifth quintile of the minimum to median wage ratio with a p-value of 0.003 for the estimates from the OLS specifications. For the estimates from the IV specifications, the test shows that the decrease in the property crime rate from moving from the first quintile to the fourth quintile is equal to a move from the first quintile to the fifth quintile can be ruled out at 13% significance level with a p-value of 0.12. Similarly, linearity can be ruled out for the other crime categories under the OLS specifications, and for burglary and robbery for the IV specification.

Appendix section A.1.6 shows the U-shaped relationship is robust to different specifications. Table A.1 shows that the U-shaped pattern is robust to excluding the lagged dependent variable for all crime categories, and dispalys a much stronger U-shape for the effect of the minimum to median wage ratio on the property crime rate. Table A.2 shows that the U-shape is preserved with the inclusion of both linear and quadratic time trends at the national and state level. Finally, Table A.3 and Table A.4 show that the U-shape is also revealed when the effect of the minimum to median wage ratio on the crime rate is parameterized using a quadratic function.

1.7 Welfare

Since the model is stationary, the welfare analysis in this section will consider the long term outcomes of a minimum wage. The workers in the model can be in one of five states at any given point in time: unemployed and committing crimes (uc), unemployed and not committing crimes (unc), employed and committing crimes (ec), employed and

Table 1.11: Significance of Coefficients

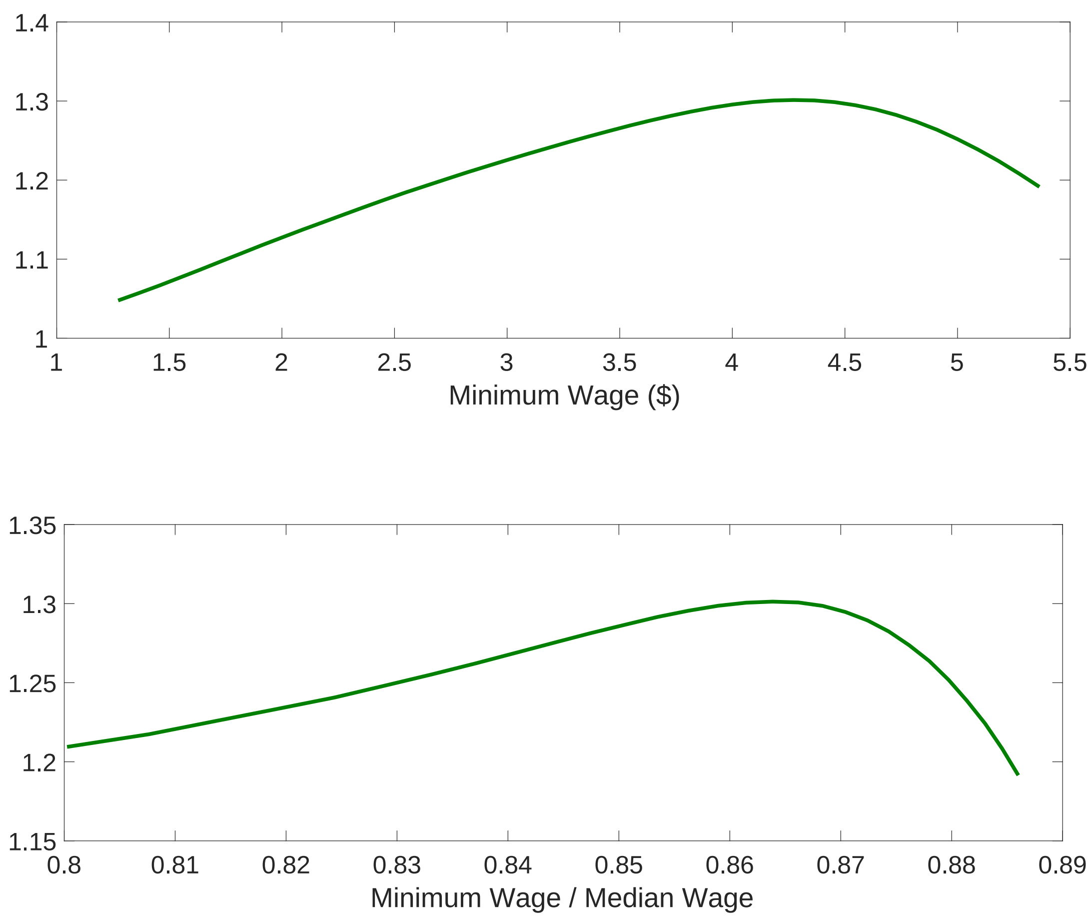
	Test of Coefficient on Quintile			
	(1) $2 = 3$	(2) $3 = 4$	(3) $4 = 5$	(4) $2 = 3 = 4 = 5$
Property Crimes				
F-stat: OLS	66.39	27.17	9.13	50.16
p-value: OLS	0.000	0.000	0.003	0.000
F-stat: IV	94.81	14.77	2.38	60.73
p-value: IV	0.000	0.000	0.122	0.000
Burglary				
F-stat: OLS	6.56	33.30	16.77	30.21
p-value: OLS	0.011	0.000	0.000	0.000
F-stat: IV	13.59	30.04	13.31	24.84
p-value: IV	0.000	0.000	0.000	0.000
Larceny				
F-stat: OLS	11.46	1.47	5.57	5.97
p-value: OLS	0.001	0.225	0.018	0.001
F-stat: IV	25.11	5.28	2.19	9.34
p-value: IV	0.000	0.022	0.140	0.000
Motor Vehicle Theft				
F-stat: OLS	17.75	32.73	3.87	34.92
p-value: OLS	0.000	0.000	0.049	0.000
F-stat: IV	23.91	12.64	0.23	26.26
p-value: IV	0.000	0.000	0.6319	0.000
Robbery				
F-stat: OLS	5.51	1.39	21.58	9.12
p-value: OLS	0.019	0.238	0.000	0.000
F-stat: IV	9.92	1.98	9.15	8.73
p-value: IV	0.002	0.159	0.003	0.000

not committing crimes (enc), or in prison (p). Assuming the minimum wage is the only policy instrument available to the social planner, the planner wishes to maximize the following objective function:

$$W(m) = unc(m)\bar{V}_{unc}(m) + uc(m)\bar{V}_{uc}(m) + enc(m)\bar{V}_{enc}(m) + ec(m)\bar{V}_{ec}(m) + p(m)\bar{V}_{p}(m)$$

where $i(m)$ is the size of the set of workers in state $i \in \{uc, unc, ec, enc, p\}$ and $\bar{V}_i$ is the average welfare level in state i, expressions for $\bar{V}_i(m)$ can be found in appendix section A.1.3.

Figure 1.12: Welfare



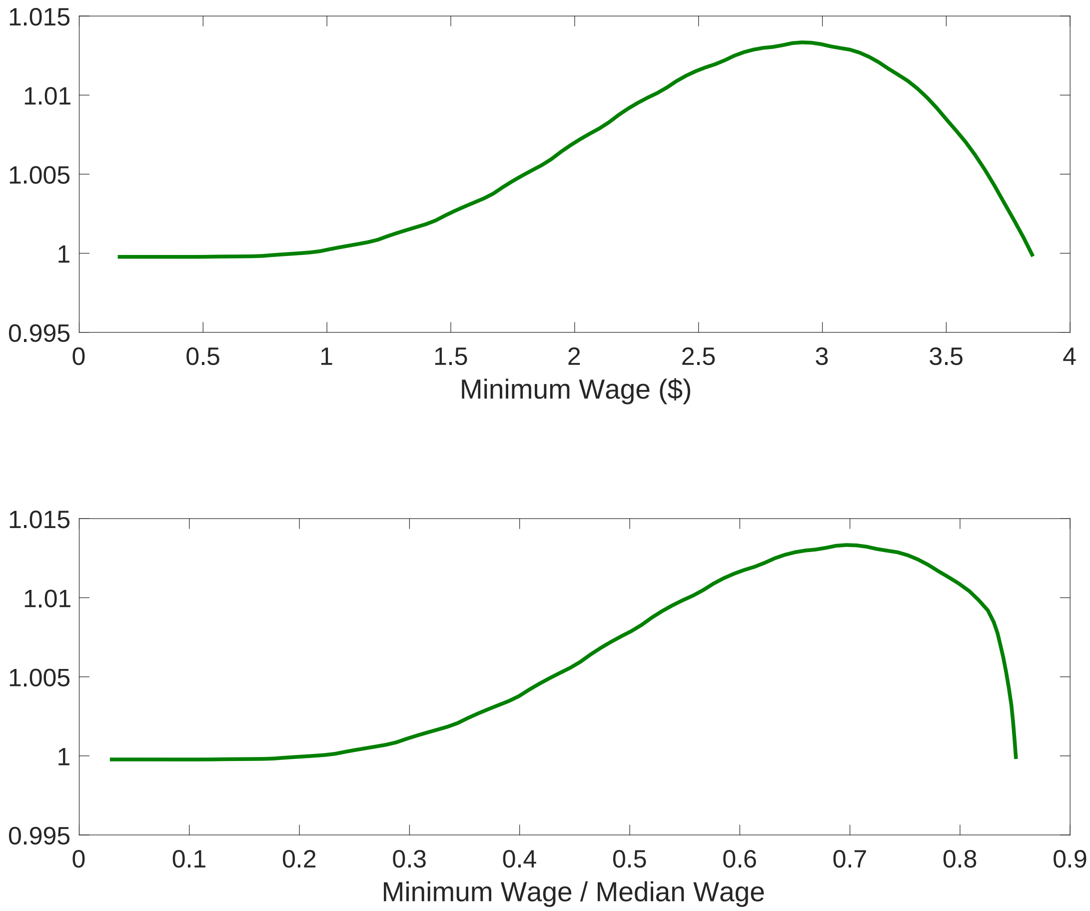
The top panel of Figure 1.12 plots welfare for different levels of the minimum wage.

The figure reveals that welfare is maximized at a \$4.30 minimum wage, which corresponds to a minimum to median wage ratio of 0.865, see the bottom panel of Figure 1.12. The welfare maximizing minimum wage is different than the crime minimizing minimum wage because the minimum wage affects aggregate welfare through changes in the unemployment rate, expected wages and crime. Over the range of minimum wages for which crime is decreasing in the minimum wage, an increase in the minimum wage increases welfare through increases in expected wages and decreases in crime and decreases welfare only through increases in the unemployment probability. For larger minimum wages, in the range over which crime is increasing, an increase in the minimum wage increases welfare only through increases in expected wages and decreases welfare by increasing the crime rate and increasing the unemployment probability. The welfare maximizing minimum wage, \$4.30, implies a monthly crime rate of 0.07 crimes per person.

Figure 1.13 plots the same welfare function for the model without crime ($\mu_e = 0, \mu_u = 0, \chi = 0$)[14]. The welfare maximizing minimum wage in this case is \$3, which corresponds to a minimum to median wage ratio of 0.7. The model does not consider the effect of a minimum wage on crime; therefore, welfare is maximized at a lower minimum wage. In this case, the welfare increases from a decreasing crime rate are ignored. If policy makers ignore the effects of changes in the minimum wage on crime, choosing the welfare maximizing minimum wage, \$3, implies a monthly crime rate of 0.11 crimes per person, 57% higher than when considering the effects of the minimum wage on crime.

[14]The model without crime was recalibrated to match the unemployment rate, job finding rate, minimum wage to median wage ratio and the median wage to 75th percentile wage ratio. All parameters in Table 1.2 remain the same. The job destruction rate and parameters of the ability distribution in Table 1.3 remain the same. The estimated mean and variance of the job productivity distribution, the offer arrival rate, and flow unemployment utility are: $\hat{\mu}_\lambda = 0.8111$, $\hat{\sigma}_\lambda = 0.535$, $\hat{\mu}_j = 3.958$, and $\hat{b} = -28.723$.

Figure 1.13: Welfare Without Crime



1.8 Conclusion

The minimum wage has been discussed extensively around the country, leading many states and cities to increases minimum wages by real amounts that we have not seen in the past. The increases are targeted to improve labor market condition primarily for young and unskilled workers; however, increasing the minimum wage may have unforeseen effects on these workers' decisions to commit crimes. I have shown that the relationship between the aggregate crime rate and the minimum wage is U-shaped due to two opposing effects: the wage effect and the unemployment effect. Which effect dominates, and ultimately how the aggregate crime rate will change depends on how much the minimum wage increases. The calibrated model, as well as the empirical evidence from county level crime rates shows that the crime rate is minimized when the minimum wage is 0.91 of the median wage of 16 to 19 year olds. However, the crime minimizing minimum wage is not the welfare maximizing minimum wage, since not only crime effects welfare but all labor market outcomes. The welfare maximizing minimum to median wage ratio is 0.87. If policy makers abstract from the effect of a minimum wage on crime, the welfare maximizing minimum to median wage ratio is 0.7, leaving crime 42% higher than when considering the effects of the wage floor on crime.

The goal of this paper is to establish the relationship between the minimum wage and the crime rate, and quantify the effects. Many cities across the country have recently passed or proposed legislation that moves to increase the minimum wage well above any threshold found in this paper, notably Seattle, New York City and California have moved to push the floor to $15 per hour. These increases would surely lead to minimum to median wage ratios for young and uneducated workers well above not only the welfare maximizing levels, but also the crime minimizing levels. As the discussion about the minimum wage and its effects on the labor market continues, it is my hope that policy makers use the ideas presented in this paper and consider the consequences on crime.

Chapter 2

Testing the Independence of Job Arrival Rates and Wage Offers in Models of Job Search

Joint with Ben Griffy, Bryan Engelhardt, and Peter Rupert

2.1 Introduction

Is the arrival rate of a job independent of the wage that it pays? The random search model of Pissarides (2000) assumes a worker's search intensity determines the number of job offers they receive, but productivity of the job is drawn randomly, and therefore wages are independent of arrival rates. Alternatively, the competitive search model of Moen (1997) assumes the existence of submarkets characterized by job arrival rates and wages. In this paper, we test the defining feature between these types of models. Specifically, we test the assumption that job finding rates and the wages offered are independent, conditional on a set of worker characteristics.

We show that a testable implication of the independence of job arrival rates and wages is that the semi-elasticity of the hazard rate with respect to unemployment insurance (UI) is constant across the wage distribution. We test this using a mixed proportional hazards competing risks (MPHCR) model with data from the National Longitudinal Survey of Youth 1997 (NLSY97). We find that the semi-elasticity of the hazard with respect to UI and other worker characteristics is not constant across the wage distribution. Therefore, we reject the null hypothesis that the arrival rate of a job is independent of the wage that it pays.

We find that an increase in UI decreases the hazard rate more for low wages than for high wages. Specifically, if UI is collected in the first nine weeks of unemployment, the hazard rate decreases by 32% for wages above the 75th percentile and by 63% for wages between the 25th and 75th percentiles. The differences are robust to specifications of the baseline hazard rate and is particularly prominent for those with only a high school degree.

Beyond testing for independence, we analyze three prominent job-search models and show how they map into our testable implication. We show that in search models of random matching and bargaining with match-specific productivity, and on-the-job search, as described in Rogerson et al. (2005), job arrival rates and wage offers are independent while in competitive search they are not. Our results are in line with a competitive search environment but inconsistent with many models of random search and matching. Given how our results are applicable in differentiating types of job-search models, our work is similar to other work comparing random and competitive search such as Engelhardt and Rupert (2017) and Moen and Godøy (2011). Distinguishing between random and competitive search has implications for labor market policies. In models of random search, workers may inefficiently reject jobs in equilibrium. For this reason, labor market policies that reduce this inefficiency may be welfare improving in this class of models.

Under competitive search, workers do not reject jobs in equilibrium. Absent additional frictions, labor market policies are not welfare improving in models of competitive search.

Aside from how our results map into prominent job-search models, we help shed some light onto the matching process. We show that conditional on observable characteristics and unobservable heterogeneity, the job arrival rate is correlated with the wage of a job. The presence of this correlation may have ramifications for empirical studies of frictional wage dispersion, as these studies rely on the independence of job offers and wages to quantify the degree to which wage dispersion is caused by search frictions, see for example Burdett et al. (2016) and Hornstein et al. (2011). Similarly, such a correlation has implications for modeling the way in which workers match to jobs and the degree of mismatch within the labor market. Recent studies of sorting and mismatch again fail to incorporate such a correlation by specifying a matching function that is independent of job productivity, see for example Gautier et al. (2010), Gautier and Teulings (2015), and Lise et al. (2016).

2.2 Independence of Wages and Job Arrival Rates

In this section, we present a theoretical framework in which the arrival rate of jobs is or is not independent of the wage offered conditional on worker characteristics. All of the tests will be conditional on worker characteristics and we will refer to this simply as independence. Assume that there exists J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J} = \{w_1, w_2, \ldots, w_J\}$, and the probability of drawing each wage w_j is $P(X_i(t), w = w_j, t)$ where t is time, and $X_i(t)$ is worker i's characteristics at time t. The job arrival rate at time t for wage $w_j > w_R^i$, where w_R^i is the reservation wage of worker i, is composed of the probability the worker receives a job arrival, $\mu(X_i(t), t)$, times the probability of drawing wage w_j. The hazard rate for transitioning to a particular wage, when job arrival rates are independent of the wages offered is

$$h(X_i(t), w_j, t) = \mu(X_i(t), t)P(X_i(t), w = w_j, t), \tag{2.1}$$

a common assumption in many standard job-search models. The total hazard rate of transitioning to employment at time t is

$$\begin{aligned} h(X_i(t), t) &= \sum_{w_j \geq w_R^i}^{J} \mu(X_i(t), t)P(X_i(t), w = w_j, t) \\ &= \mu(X_i(t), t)P(X_i(t), w \geq w_R, t). \end{aligned} \tag{2.2}$$

Alternatively, if job arrival rates are dependent on the wage offered the hazard rate is

$$h(X_i(t), w_j, t) = \mu_j(X_i(t), t)P(X_i(t), w = w_j, t) \tag{2.3}$$

$$= \mu_j(X_i(t), t). \tag{2.4}$$

where the job arrival rate, $\mu_j(X_i(t), t)$, is specific to the wage w_j and therefore $P(X_i(t), w = w_j, t) = 1$. If the job arrival rate is wage specific, the total hazard of leaving unemployment to any wage above the reservation wage is

$$h(X_i(t), t) = \sum_{w_j \geq w_R^i}^{J} h(X_i(t), w_j, t).$$

Assume there exists a factor $\bar{X}$ that has no effect on the distribution of wages offered, i.e., $\partial P(X_i, w_j)/\partial \bar{X} = 0$, but has an effect on the job arrival rate, $\partial \mu_j(X_i, t)/\partial \bar{X} \neq 0$. Then if job arrival rates are independent of the wage offered, the semi-elasticity of the hazard with respect to $\bar{X}$ is

$$\frac{\frac{\partial h(X_i, w_i, t)}{\partial X}}{h(X_i, w_i, t)} = \frac{\frac{\partial \mu(X_i, t)}{\partial X} P(X_i, w_j)}{\mu(X_i, t)P(X_i, w_j)} = \frac{\frac{\partial \mu(X_i, t)}{\partial X}}{\mu(X_i, t)} \; for\ all\ w_j > w_R^i. \tag{2.5}$$

Factors that do not affect the wage offered should affect the hazard rate uniformly across the distribution of wages; the semi-elasticity with respect to $\bar{X}$ does not differ across wages.

We test for independence by examining how changes in unemployment insurance (UI) affects the hazard rate across the wage distribution. In the case of independence, if UI rises, the hazard rate changes uniformly across the wage distribution. Alternatively, if the job arrival rate and the wage offered are dependent, then the semi-elasticity of the hazard rate with respect to UI differs across the wage distribution.

2.3 Data

To test the independence assumption, we use data from the National Longitudinal Survey of Youth (1997), conducted by the U.S. Bureau of Labor Statistics, for the years 1997 through 2009. The survey tracks men and women in the United States over time who were between 12 and 16 in 1997. We use the individual-level panel data set information on gender, education, race, age, urban status, hourly wage, unemployment insurance collection status, searching for a job, and labor force status over time. With the information on labor force status, we are able to determine whether an individual is employed, not employed and searching for work, or not employed and not searching for work.

We use a flow sampling approach to construct the data set that we use in our analysis. This means that we record the beginning of each duration when an individual transitions into a new labor force state as defined by employed or not employed. We limit the number of observations per individual starting each state to ten and begin tracking an individual's weekly labor force status after an individual has completed his or her most recently obtained level of education. Our starting point follows Bowlus et al. (1995), Eckstein and Wolpin (1995) and Engelhardt (2010) among others. When a respondent transitions into a new labor force state, the duration is recorded as well as why the state ended. We cut the data in two ways and refer to each as the standard and inclusive data sets. In what we define as the "standard," we record the time the unemployed is in the unemployed state and capture whether he or she became employed. If an individual transitions out of the labor force during a spell, then the spell is excluded from the standard data set following van den Berg and Ridder (1998), Bontemps et al. (2000), among many others. We analyze this less inclusive cut of the data because it is effectively the standard as it aligns with most theoretical search models focused on those strictly in the labor force. Alternatively, the second "inclusive" data set estimates the model where unemployment is redefined as not employed. As a result, the number of spells greatly increases. To account for whether an individual is searching, we include a time varying covariate that records whether an individual is searching for a job. We do not estimate two states, unemployed and outside the labor force, because many individuals transition from outside the labor force to employment in our data (a standard empirical fact). To keep the notation and terminology of the empirical model simple, we will define the unemployed and those outside the labor force as not employed for both data sets. Estimation using the standard and inclusive data sets is effectively identical with this rewording.

In terms of notation, we account for how an individual spell ends. Our notation for individuals who are hired while not employed (or unemployed) is $d = 1$ and zero otherwise. The duration of time spent not employed is represented by t. Some of the durations are censored as seen by the fact that the mean number of individuals transition to employment is not one. The model we estimate assumes censoring occurs randomly and the estimation is adjusted accordingly. In these cases, $d = 0$. We cut the data into three submarkets at the 25th and 75th percentiles, as required by our empirical specification; therefore if a duration ends with a low, medium, or high wage draw, then we represent the event as $d_L = 1$, $d_M = 1$, and $d_H = 1$, respectively. If a duration ends and the wage offer is missing, then $d_i = 0$ for $i \in \{L, M, H\}$ and the missing observations are assumed to occur randomly and the probability is excluded. The covariates used in the analysis are the respondent's gender, years of schooling completed, race, urban status, age, wage at the time of transition to employment, and a dummy for whether the individual is collecting unemployment insurance. When using the inclusive data set, a dummy for whether an individual is searching for employment is incorporated into the covariates. We define $X(t)$ as the baseline covariates for the not employed, which includes unemployment insurance, and in the case of the inclusive data set, job searching. Due to the non-parametric baseline, computational weight of the model, and known measurement issues, the unemployment insurance (UI) collection status is a dummy variable equal to one if the individual collected UI in any particular 10 week interval. Similarly, whether a worker is searching for employment is averaged over 10 week intervals. Intervals are collected for the first 50 weeks and one final variable for all the time after 50 weeks.

The descriptive statistics of the not employed for each data set are in Table 2.1.

2.4 Empirical Specification

We build our test on the duration literature and specifically the MPHCR model. If there exist J different wages, where $J = |\mathcal{J}|$ and $\mathcal{J}$ is the set of all wages, then the observed failure time T is the minimum of the failure time at each wage, that is, $T = min_{i\in\mathcal{J}}(T_i)$ and the cause of failure, I, is the argument minimum. In terms of a competitive search model, the cause of failure is observed by the wage, that is, if an individual leaves unemployment to a wage $j \in \mathcal{J}$, then failure is caused by matching at w_j. Thus, we observed the joint distribution (T, W) where W identifies the argument minimum I.

It is well known that without further assumptions the latent distribution of failure times is not identified from the observed distribution (T, W) (Cox (1959)). We impose a mixed proportional hazard structure so that latent failure times depend multiplicatively on the observed regressors, duration length and unobserved heterogeneity. Heckman and Honoré (1989) show identification of such models relies on variation in latent failure times with the regressors. Abbring and van den Berg (2003) relax this assumption and show that less variation is needed with multiple independent draws from an individual's observed distribution, that is, multiple spells.

We rely on the MPHCR model to identify a baseline hazard across time for each wage, $\lambda_{w_j}(t)$, that is constant for all individuals, an unobservable component, $V^n_{w_j}$, that is individual specific that varies across wages, and an individualized observable component $e^{\sum_{k=1}^{K} \beta_j^k X_i^k(t)} = e^{\beta_j X_i(t)}$, for wage j, individual i, and covariates $k = 1, ..., K$. The functional form is described in detail in Abbring and van den Berg (2003) including the notation we are using such as the matrix notation $X_i(t)$ and β_i. This results in three types of heterogeneity: matching rates across wages are heterogeneous in terms of matching time, and individuals are heterogeneous with respect unobservable and observable factors (e.g., value of leisure and age, respectively). We assume three wage categories, a low wage (w_L), a medium wage (w_M), and a high wage (w_H), in which individuals can find jobs; and three unobservable components, or $n = \{0, 1, 2\}$. For example, $V^0_{w_L}$ can imply low search intensity of an individual of type "0" in finding a low wage job and $V^1_{w_M}$ can imply high search intensity of an individual of type "1" in finding a medium wage job. Since we only use two continuous covariates, we are restricted to estimating three different wages due to identification restrictions. Furthermore, we do not include more than three individual unobservable factors because the fit does not improve significantly after three.

Given the unobservable components, number of markets, and non-parametric approach, we are left to identify a discrete distribution of agents with 3^3 points of support.

For example, individual of type $X_i(t)$ with an unobservable type $n = 0$ across all wages will match at rate $\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}$ for w_L, at rate $\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}$ for w_M and at rate $\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}$ for w_H making the worker's total hazard rate:

$$\lambda(t) = \lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L} + \lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M} + \lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}. \tag{2.6}$$

The probability of observing an unemployment spell of length t ending with a wage w for the individual described above is:

$$f(t, w, X_i(t)) = \lambda(t)e^{-\lambda(t)}\left(\frac{\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L}}{\lambda(t)}\right)^{d_L}\left(\frac{\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M}}{\lambda(t)}\right)^{d_M}\left(\frac{\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H}}{\lambda(t)}\right)^{d_H} \tag{2.7}$$

$$= e^{-\lambda(t)}(\lambda_{w_L}(t)e^{\beta_L X_i(t)}V^0_{w_L})^{d_L}(\lambda_{w_M}(t)e^{\beta_M X_i(t)}V^0_{w_M})^{d_M}(\lambda_{w_H}(t)e^{\beta_H X_i(t)}V^0_{w_H})^{d_H} \tag{2.8}$$

where d_j is a dummy that takes on the value 1 if $w = w_j$ is observed for $j \in \{L, M, H\}$ and 0 otherwise.

2.4.1 Likelihood Function

Since we allow for three types of unobserved heterogeneity in each wage hazard the support for the mixing distribution has 27 points. Denote p_k, $k = 1, \ldots, 27$ as the probability associated with each point in the support and

$$V = \{(V^0_{w_L}, V^0_{w_M}, V^0_{w_H}), (V^1_{w_L}, V^0_{w_M}, V^0_{w_H}), \ldots, (V^2_{w_L}, V^2_{w_M}, V^2_{w_H})\}$$

as the set of points in the support. Following the identification restrictions in Heckman and Honoré (1989) and Abbring and van den Berg (2003), we normalize the mixing distribution in each market such that $V^0_{w_L} = V^0_{w_M} = V^0_{w_H} = 1$.

An individual's contribution to the likelihood function is:

$$l_i = \sum_{k=1}^{27} p_k \prod_{s=1}^{10} f(t_s, w_s | X_i(t), V) \tag{2.9}$$

where t_s is the length of unemployment spell, and $s = 1, 2, \ldots 10$ is the maximum number of possible spells per individual. Note the multiple spells for each individual, or *stratum*, provides both power and dependence between the covariates and unobservables. The total log likelihood function is:

$$L(\{p_k\}_{k=1}^{27}, \{\lambda_{w_j}(t), \beta_j\}_{j\in\{L,M,H\}}, \{V_{w_j}^n\}_{(j\in\{L,M,H\},n=1,2)}|X, t, w) = \sum_{i=1}^{N} \log(l_i) \tag{2.10}$$

We estimate the likelihood function for two specifications for the baseline hazard: Weibull, $\lambda_{w_j}(t) = \frac{k_j}{a_j}\left(\frac{t}{a_j}\right)^{k_j-1}$ where a_j is the scale parameter and k_j is the shape parameter in market j and piecewise exponential, $\lambda_{w_j}(t) = \lambda_{w_j}^q$, where $q = 1\ldots, 6$ is allowed to vary at 10 week intervals and is constant after the first 50 weeks.

2.4.2 Likelihood Ratio Tests

We construct and estimate the MPHCR model to test for the independence between wage offers and job arrival rates, i.e., (2.2). We test for independence using (2.5), i.e., semi-elasticities are constant across wages. We test for a constant semi-elasticity by restricting the coefficients on individual characteristics and the mixing distribution. Since changes in individual characteristics such as age or education can change the reservation wage, we focus on changes across the medium and high wage hazards.

The semi-elasticities, such as those described in (2.5), for the MPHCR model with respect to unobserved heterogeneity at the medium and high wages are

$$\begin{aligned}
\frac{\frac{\partial h(X_i(t),w_M,t)}{\partial V_{w_M}^n}}{h(X_i(t), w_M, t)} &= \frac{\lambda_{w_M}(t)e^{\beta_M X_i(t)}}{\lambda_{w_M}(t)e^{\beta_M X_i(t)}V_{w_M}^n} \\
&= \frac{1}{V_{w_M}^n}, \textit{ and similarly} \\
\frac{\frac{\partial h(X_i(t),w_H,t)}{\partial V_{w_H}^n}}{h(X_i(t), w_H, t)} &= \frac{1}{V_{w_H}^n}.
\end{aligned} \tag{2.11}$$

The semi-elasticitiies of the MPHCR model with respect to a specific individual characteristic k in the medium and high wage markets are

$$\begin{aligned} \frac{\frac{\partial h(X_i(t),w_M,t)}{\partial X_i^k(t)}}{h(X_i(t),w_M,t)} &= \frac{\lambda_{w_M}(t)\beta_M^k e^{\beta_M X_i(t)} V_{w_M}^n}{\lambda_{w_M}(t) e^{\beta_M X_i(t)} V_{w_M}^n} \\ &= \beta_M^k, \ \textit{and similarly} \\ \frac{\frac{\partial h(X_i(t),w_H,t)}{\partial X_i(t)}}{h(X_i(t),w_H,t)} &= \beta_H^k. \end{aligned} \tag{2.12}$$

Therefore, if the independence assumption holds, or (2.2) and (2.5), then

$$V_{w_M}^n = V_{w_H}^n, \ \textit{and} \tag{2.13}$$

$$\beta_M^k = \beta_H^k \tag{2.14}$$

for βs of factors that do not effect the distribution of wages, i.e. $\partial P(X_i(t), w = w_j, t)/\partial X_i(t)^k = 0$. In other words, the the independence assumption implies a series of linear restrictions in the MPHCR model.

We test the linear restrictions using a likelihood ratio test. To explore the series of restrictions, we group them in several different ways to get an understanding of what might be the specific factor rejecting the null hypothesis of independence. Furthermore, the test requires $\partial P(X_i(t), w = w_j, t)/\partial X_i(t)^k = 0$. Therefore, we articulate a variety of restrictions in case the assumption does not hold for certain group of factors.

In what we call group 1, or restriction 1, we test all the restrictions we'll examine. Specifically, we test whether unobserved heterogeneity, unemployment insurance, search, and urban status affects the hazard rate differently for the high and medium wage market. If we fail to reject these restrictions, then we cannot reject that semi-elasticities for these variables are constant across the medium and high wage hazards. In other words, we will fail to reject the independence assumption under the assumption these variables do not affect the wage distribution. In terms of the parameters, we are testing

Restriction 1:

$$\begin{aligned} H_0^{(1)} : V^1_{w_M} &= V^1_{w_H} \\ V^2_{w_M} &= V^2_{w_H} \\ \beta^{UI}_{w_M} &= \beta^{UI}_{w_H} \\ \beta^{Urban}_{w_M} &= \beta^{Urban}_{w_H} \\ \beta^{Search}_{w_M} &= \beta^{Search}_{w_H} \end{aligned}$$

As some of the variables might not satisfy the assumption that they do not affect wage offers, we introduce several other groupings/restrictions. In restriction 2, we test for whether we can reject the null using only unobserved heterogeneity, or

Restriction 2:

$$\begin{aligned} H_0^{(2)} : V^1_{w_M} &= V^1_{w_H} \\ V^2_{w_M} &= V^2_{w_H} \end{aligned}$$

In restriction 3, we test whether the semi-elasticities of the hazard rate with respect to UI, urban status, and job search varies across the wage distribution:

Restriction 3:

$$\begin{aligned} H_0^{(3)} : \beta^{UI}_{w_M} &= \beta^{UI}_{w_H} \\ \beta^{Urban}_{w_M} &= \beta^{Urban}_{w_H} \\ \beta^{Search}_{w_M} &= \beta^{Search}_{w_H} \end{aligned}$$

Finally, we estimate our least strict restriction in which we assume only UI does not affect the underlying wage distribution and thus restrict its semi-elasticity across wage hazards to

Restriction 4:

$$H_0^{(4)} : \beta^{UI}_{w_M} = \beta^{UI}_{w_H}$$

To reiterate, Restriction 4 allows all other factors to affect the wage offer except UI. Also, the results related to this restriction is a key application to testing for the independence assumption. In particular, as discussed in Acemoglu and Shimer (2000) among others, UI could allow for workers to search for more productive jobs. If we fail to reject the independence assumption, then we will be putting such an analysis in doubt.

Given the restricted groupings, we refer to the unrestricted estimation of the model, as found in (2.10), as the baseline and use the unrestricted version to evaluate the restricted versions using likelihood ratio tests.

2.5 Estimation Results

The estimation results regarding the effect of demographic variables on the arrival rates of jobs, as well as the baseline time dependent hazard, line up with past studies. For references, Devine and Kiefer (1991) and Eckstein and Van den Berg (2007) provide in depth surveys on the empirical search literature with the former more closely related to our work given its focus on reduced form approaches. Tables 2.2, 2.4, 2.6, and 2.9 provide a summary of our results including the results from Restrictions 1-4 for the Weibull hazard with standard data, Weibull hazard with the inclusive data, the piecewise exponential hazard with the standard data, and the piecewise exponential with the inclusive data, respectively. Tables 2.3, 2.5, 2.8, and 2.11 provide the estimates from the demographic effects including UI for the Weibull hazard with standard data, Weibull hazard with the inclusive data, the piecewise exponential hazard with the standard data, and the piecewise exponential with the inclusive data, respectively. Finally, Tables 2.7 and 2.10 provide estimates for the piecewise exponential baseline using the standard and inclusive data sets, respectively. The estimated probabilities p_k for $k = 1, .., 27$ have been suppressed for brevity, but can be provided upon request.

In terms of race and gender, our estimates are in line with the broader wage literature as surveyed in Darity and Mason (1998) and many other places. Specifically, we estimate males are more likely to transition to high wage jobs and less likely to transition to low wage jobs across all the specifications and restrictions. Hispanics are relatively equally less likely to transition to any wage job while blacks are less likely to transition to high wage jobs with little or no effect for low wage jobs. Bowlus (1997) and Bowlus and Eckstein (2002) are two similar examples to ours that empirically analyze gender and racial discrimination, respectively.

In terms of education and experience, our results are in line with the classic Mincerian earning equations as pioneered in Mincer (1974) and more generally surveyed in Card (1999). Specifically, we find the level of schooling as well as a high school diploma increases the rate of transition to employment and more so for high wage jobs. Individuals with a college diploma are less likely to transition to low and medium wage jobs while more likely to transition to high wage jobs. Similarly, experience, as proxied by age, generally increases transition to high wage jobs and reduces transitions to low wage jobs although note the low dispersion in our data's age distribution.

In terms of the baseline hazard, the Weibull and piecewise exponential estimates show duration dependence to be effectively constant in the standard data set. The estimates for the inclusive data set provide evidence for the theoretically intuitive result of negative duration dependence. Given the nature of each data set, the difference in the results under each data set suggests the ability to transition from outside the labor force decreases over time. Intuitively, job offers are less likely to arrive the longer you've been unemployed when you aren't searching. However, if searching, duration dependence is less of a factor, if at all. These estimates are in line with other empirical studies as surveyed in Devine and Kiefer (1991).

A critical insight of our work is to expand the literature regarding the effects of UI on job finding rates, such as in Meyer (1990) and others. Our findings are consistent with those studies in that UI reduces job finding rates. However, we extend the work by showing the negative impact of UI on job finding rates falls for higher wage jobs.

Specifically, individuals are much less likely to transition to low wage jobs when collecting UI. However, this effect is less pronounced at higher wages. Put differently, UI reduces the transition rate for medium wage jobs more than for higher wage jobs. Restriction 1, 3 and 4, or where the coefficients on UI are equal across the wage types, is rejected at the 1% level in both types of baseline specifications and data sets. As UI discourages search, the results strongly suggest UI discourages search at the low end of the wage distribution more and less so at the upper end. We note this was predicted by Moen (1997) and others assuming UI affects the value of leisure when unemployed. Put differently, the competitive search assumption is critical in the analysis of UI as shown in Acemoglu and Shimer (2000) and others. Given our empirical results, the assumption of changing job finding rates across the wage offer distribution should be used when considering the efficacy of UI.

In terms of Restrictions 1 & 3, urban status was also considered and constrained with the assumption it is affecting job search specifically. The estimates are relatively consistent and show those in urban areas are more likely to transition to high wage jobs and less likely to transition to low wage jobs. However, the estimates are small relative to the effect of UI as well as its standard errors. The estimates are in line with the empirical work such as that surveyed in Holzer (1991). Refer to Wasmer and Zenou (2002) for modeling the dynamics in a search environment.

Under the inclusive data set, we estimate the effect of job search on the arrival rate of jobs. Furthermore, we include it in the Restriction 1 & 3 tests. We find it increases the transition rate for the low and medium wage hazards as the search literature suggests and more so for the low wages. Its impact on high wage jobs appears ambiguous and is an interesting fact for further study. Note, the standard errors are relatively large.

Finally, we test for variation in the unobservable factors. Historically, the literature has suggested search costs, which are unobservable, can explain the fact that individuals with low wages spend more time unemployed (Eckstein and Wolpin (1995)). As a result, these factors can be interpreted as search intensity. Given this view, we reject that search intensity is constant across wages at the 1% level in Restrictions 1 and 2 in all our results: the Weibull and piecewise exponential baseline and the standard and inclusive data sets. In effect, unobservable search intensity is variable after controlling for the reservation wage. Our results along this line, as well as those testing urban status's semi-elasticity, should be interpreted with caution as these unobservable factors could be affecting the likelihood of accepting an offer and not simply finding an opportunity.

2.6 Test Results

As noted above in Section 2.5, we nearly uniformly reject at the 5% level the restrictions imposed by (2.2), or more specifically, (2.5) for either of the different specifications of the data or baseline hazard. In particular, the effects of all the variables considered affect the medium and high wage differently! In other words, we reject the idea that the wage offer and job arrival rate are independent even after controlling for worker characteristics.

We run two different types of robustness checks of our results. In particular, what happens when the low, medium, and high wage thresholds are dependent upon an individuals education. Furthermore, how does the functional form of the MPHCR model compare to a standard search model.

2.6.1 Test Results with Education Based Wage Thresholds

In terms of controlling for years of schooling and graduation status, we vary the duration of unemployment by these factors. However, education is not being used to determine the definition of low, medium, and high wage thresholds. As a check of our results given this restrictive assumption required by the MPHCR model, we re-estimate the model by education group, that is, we assume there are separate markets by level of education, and given the separate markets, we redefine low, medium, and high wages by education type.

The descriptive statics of wages by education and accompanying thresholds are provided in Table 2.12. The results from the likelihood ratio tests are provided in Tables 2.13 and 2.14 for the Weibull and piecewise exponential specifications, respectively. In the separated case, we continue to reject all the restrictions at roughly the 5% significance level when looking at those with a High School education or less. We fail to reject the restrictions in the case of the College educated. However, the difference may be arising from the fact that we observe very few unemployment spells for the college educated relative to the number of parameters being estimated. However, it would be interesting to analyze the education component further if the identification strategy allowed it.

2.6.2 Applicability of Reduced-Form Estimates

We take a flexible reduced form approach to test the assumptions used in labor market search models. Therefore, our results can arguably be applied to the literature as a whole. However, the reduced form approach we take still contains some structure. In particular, we use a proportional hazard function. As a result, the identification strategy we employ may not be flexible enough to fit the entire class of search models. To investigate the issue, we simulate data using the model and parameter estimates from Eckstein and Wolpin (1995) and estimate our reduced from model using the simulated data. We then estimate the Kullback-Leibler (KL) divergence of our model to the true data generating model of Eckstein and Wolpin (1995). Define q as the probability distribution of duration times produced from our reduced from estimates, and p as the probability distribution of duration times from the true model. The KL distance is defined as

$$D_{KL}(p||q) = \int_0^\infty p(t) \ln \left(\frac{p(t)}{q(t)} \right) dt$$

where t represents time. As we note below, in our interpretation, D_{KL} is relative to the entropy of the true distribution, given by

$$H(p) = \int_0^\infty p(t) \ln[p(t)] dt,$$

and measures the additional data required to capture the true model using the incorrect one. The entropy of the true distribution, $H(p)$, measures the uncertainty of duration times, which can be interpreted as how informative a draw from the distribution is for understanding the underlying random variable, unemployment duration. The KL distance is the relative entropy between the true distribution of duration times and the distribution of duration times estimated by our reduced form approach. The entropy of our reduced form model is $H(p) + D_{KL}(p||q)$. If $D_{KL} = 0$ then a draw from our reduced form model is exactly as informative about the duration of unemployment as a draw from the true distribution; therefore, we use the KL distance as a measure of how informative our reduced form model it about the true distribution of unemployment duration times.

The Kullback-Leibler divergence values are in Table 2.15 where we give the KL values for the different sub-markets estimated in Eckstein and Wolpin (1995). Although the Eckstein and Wolpin (1995) estimates have enormous flexibility by re-estimating the parameters for each sub-market, we estimate all the markets simultaneously. Therefore, our unobservable heterogeneity in particular is not as flexible as that found in what we assume to be the true model.

Given the interpretation of KL, we require between 1.65% and 5.37% additional bits of information to describe the distribution of unemployment duration using our reduced form version depending upon the sub-market one's considering. Given the limited amount of information required to describe the Eckstein and Wolpin (1995) versus our reduced form estimates, we argue the reduced form estimation can adequately capture more specific search models.

2.7 Application to Common Models

In this section, we discuss two sets of models our results reject. Due to the large and varied literature on labor market search models, we discuss two classic examples in which the hazard rate of unemployment does and does not respond as we have shown. Let $\lambda(w, X)$ equal the rate at which an individual transitions from not employed to employed with a wage w where X is observable and unobservable factors affecting an individual's transition rate. Finally, let w_R represent an individual's reservation wage. Specifically, if $w_i < w_R$, then $\lambda(w_i, X) = 0$. To reiterate, for a model's hazard rate to be consistent with the data it must satisfy the following criterion:

$$\frac{\frac{\partial h(X_i,w_i,t)}{\partial X}}{h(X_i, w_i, t)} \neq \frac{\frac{\partial h(X_i,w_j,t)}{\partial X}}{h(X_i, w_j, t)} \tag{2.15}$$

for any $w_i \neq w_j$, the semi-elasticity of the hazard rate with respect to some observable or unobservable factor that affects the offer rate cannot be constant across wages. To show how this applies to common search models of the labor market, we discuss the hazard rate of two well cited search models.

Example 1: Random Matching and Bargaining with Match-Specific Productivity

We are defining this example using the terminology described in Rogerson et al. (2005), which surveys a large group of search models found in Section 4.4 of their paper. The model describes a wide variety of models in the literature. Following the notation and description in Rogerson et al. (2005), one can determine the model's equilibrium with two conditions,

$$y_R = b + \frac{\alpha_\omega \theta k}{\alpha_e(1-\theta)}, \text{ and} \tag{2.16}$$

$$(r+\lambda)k = \alpha_e(1-\theta)\int_{y_R}^{\infty}(y-y_R)dF(y), \tag{2.17}$$

where y is productivity, y_R the reservation wage, b is unemployment utility, θ is a bargaining parameter, k is the vacancy cost for a firm to hold a job open until filled, r is the discount rate, α_e is the rate a firm matches with a worker and α_ω is the rate a worker matches with a firm, and λ the job destruction rate.

Given the standard equilibrium conditions,

$$\lambda(w,b) = \alpha_\omega f\left(\frac{w-(1-\theta)y_R(b)}{\theta}\right) \tag{2.18}$$

because $w = y_R + \theta(y - y_R)$. Notice that the underlying unobservable characteristic that determines the reservation wage is the unemployment utility b. Therefore, the only observable or unobservable factor X that could change the hazard rate is b. Below we suppress the reservation wage's dependence on b, i.e. $y_R = y_R(b)$, for ease of notation. If one assumed that b is a function of unobservables and an observable unemployment insurance (UI) component, then the result would be

$$\frac{\frac{\partial\lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial\alpha_\omega}{\partial b} f\left(\frac{w-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}{\partial y_R}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w-(1-\theta)y_R}{\theta}\right)}, \tag{2.19}$$

and the criterion $\frac{\frac{\partial\lambda(w_i,b)}{\partial b}}{\lambda(w_i,b)} \neq \frac{\frac{\partial\lambda(w_j,b)}{\partial b}}{\lambda(w_j,b)}$ in this model would simplify from

$$\frac{\frac{\partial\alpha_\omega}{\partial b} f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial\alpha_\omega}{\partial b} f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right) + \alpha_\omega \frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y}\frac{\partial y_R}{\partial b}}{\alpha_\omega f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0 \tag{2.20}$$

to

$$\frac{\frac{\partial f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)}{\partial y}}{f\left(\frac{w_i-(1-\theta)y_R}{\theta}\right)} - \frac{\frac{\partial f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)}{\partial y}}{f\left(\frac{w_j-(1-\theta)y_R}{\theta}\right)} \neq 0. \tag{2.21}$$

Given the simplified model and interpretation of b and UI, the criterion is satisfied and our results do not reject this model. Our criterion does not reject this model because the distribution $f(y)$ is not discrete or flat and bargaining exists. To put it differently, if the surplus was split evenly irrespective of the reservation wage, or drawing a particular wage is uniformly distributed, then the model would fail our criterion test.

However, the naive interpretation of b as being a function of UI is not correct. In particular, UI is only collected when an individual is laid off due to lack of work. Therefore, the workers outside option used during the bargaining does not include UI. As a result, the standard model must be rewritten. Following the notation of Rogerson et al. (2005), the flow utility for unemployed workers is either

$$rU = b + \alpha_\omega \int_{y_R}^{\infty} (W_y[w(y)] - U)dF(y), \text{ or} \tag{2.22}$$

$$rU_{UI} = b + b_{UI} + \alpha_\omega \int_{y_R}^{\infty} (W_y[w(y)] - U)dF(y) \tag{2.23}$$

where the latter is the asset value of unemployment for those laid off collecting UI, i.e., those who lose their jobs, and the former equation determines the asset value used as the threat point in the Nash bargaining process. As a result, the wage equation becomes

$$w = rU + \theta(y - rU), \tag{2.24}$$

and the hazard rate becomes

$$\lambda(w,b) = \alpha_\omega f\left(\frac{w-(1-\theta)rU(b)}{\theta}\right). \tag{2.25}$$

As U is not a function of whether an individual is collecting UI, our empirical results reject this more accurate representation of the model. Specifically,

$$\frac{\partial \lambda(w,b)}{\partial b_{UI}} = 0, \tag{2.26}$$

for all $w > y_R$ and as a result the elasticity is constant across w.

To summarize, our criterion for this class of models rejects them when UI does not change the bargaining position of the workers. However, in the naive case, we fail to reject these models due to bargaining.

Although we will not prove it here, it may be of interest that one could extend the model to include search intensity. In such a case, $\frac{\partial \alpha_\omega}{\partial b} \neq 0$. As it is equal across wage draws, we reject these predictions using our empirical estimates.

Example 2: On-the-Job Search via Burdett and Mortensen (1998)

Again following the notation in Rogerson et al. (2005), for the simplest case where the arrival rates of job offers while unemployed (α_0) and employed (α_1) are equal, $\alpha_0 = \alpha_1 = \alpha$ and the interest rate is approximately zero, $r \approx 0$, the wage offer distribution is

$$F(w) = \frac{\lambda^* + \alpha}{\alpha}\left(1 - \sqrt{\frac{y-w}{y-b}}\right) \tag{2.27}$$

where λ^* is the separation rate, y is the productivity of the job, and b is the worker's flow value of unemployment. The support of F is $[b, \bar{w}]$ for some $\bar{w} < y$ where the upper bound can be found using $F(\bar{w}) = 1$. It can be shown that (2.27) is continuous on its support; therefore, the derivative exists and the p.d.f. is:

$$f(w) = \frac{\lambda^* + \alpha}{2\alpha}\sqrt{\frac{y-b}{y-w}}. \tag{2.28}$$

Given the p.d.f of the wage distribution, the hazard rate of matching at wage w is,

$$\lambda(w,b) = \alpha f(w) \tag{2.29}$$

$$= \frac{\alpha(\lambda^* + \alpha)}{2}\sqrt{\frac{1}{(y-w)(y-b)}} \tag{2.30}$$

and the elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{1}{2(y-b)} \tag{2.31}$$

Since the elasticity of the matching function with respect to the workers unemployment insurance as defined by b is independent of the wage at which they match, the model fails to satisfy our empirical results.

Example 3: Competitive Search via Moen (1997)

Following notation from Moen (1997)[1], the probability a worker receives a job offer from sub market i is

$$p(\theta_i) = \frac{rU - b}{w_i - rU}(r+s). \tag{2.32}$$

The hazard rate to matching to wage w_i is given by

$$\lambda(w_i, b) = p(\theta_i) prob(w = w_i) \tag{2.33}$$

$$= \frac{rU - b}{w_i - rU}(r+s) \tag{2.34}$$

since $prob(w = w_i) = 1$ if matching in submarket i.

The semi-elasticity of the hazard rate with respect to b is,

$$\frac{\frac{\partial \lambda(w,b)}{\partial b}}{\lambda(w,b)} = \frac{\frac{\partial rU}{\partial b}}{w - rU} + \frac{\frac{\partial rU}{\partial b} - 1}{rU - b}. \tag{2.35}$$

Since the value of search U must be the same across submarkets it is clear that the semi-elasticity of the hazard rate with respect to b is not constant across wages.

To summarize, our rejection of the independence assumption has the implication of rejecting two canonical job-search models: Random matching and Bargaining with Match-Specific Productivity, and On-the-Job Search. However, in a model of competitive search in which workers are identical, job arrival rates and wage offers are not independent.

[1] We have changed the flow value of unemployment from z to b for consistency across examples.

2.8 Conclusion

Using a multi-spell mixed proportional hazards competing risks model with National Longitudinal Survey of Youth (1997) data, we reject the assumption that the semi-elasticity of the hazard rate is constant for factors which do not change the wage distribution. We show that this assumption can be rejected if these factors include unemployment insurance, urban status, and unobservable characteristics. In other words, after controlling for worker characteristics, we reject an assumption that the wage and job arrival rates are independent.

The implications are important in interpreting the effect of UI as well as job-search models in general. In particular, we have shown our results reject two well used models in the job-search literature. Furthermore, we provide empirical support for the hypothesis that UI affects job hiring rates differently across the wage offer distribution.

Given the importance of unemployment insurance and the use of search in modeling the duration of unemployment, our results are an important step in defining the future trajectory of the search literature. In particular, our results point heavily toward a world where workers search in a market where wage offers and the rate of job arrivals are not independent.

2.9 Tables

Table 2.1: Descriptive Statistics of Unemployed

	Standard Data Set		Inclusive Data Set	
	Mean	Std. Dev.	Mean	Std. Dev.
Hired ($d = 1$)	0.92	0.27	0.9	0.31
Duration unemployed (t)	11.15	14.2	24.34	44.06
Wage	12.81	24.24	16.56	131.04
Low wage ($d_L = 1$)	0.22	0.41	0.21	0.41
Medium wage ($d_M = 1$)	0.42	0.49	0.41	0.49
High wage ($d_H = 1$)	0.21	0.41	0.21	0.41
Male	0.61	0.49	0.52	0.5
Black	0.31	0.46	0.29	0.45
Hispanic	0.19	0.4	0.21	0.41
Education, years completed	11.75	2.25	11.79	2.31
High School, completed	0.82	0.38	0.81	0.39
College, completed	0.09	0.28	0.09	0.29
Urban	0.89	0.31	0.89	0.31
Age	22.99	3.04	22.89	2.99
UI Collected, weeks 1-9	0.12	0.32	0.05	0.22
Searched for Employment, weeks 1-9	1	0	0.39	0.45
Observations	5308		17593	

Note: Observations are based on each spell not employed and not on each individual who could be not employed one or more times. Durations are weekly. Transitions do not sum to one due to right censoring. Wage bins do not sum to one due to missing values. Missing data on wages, education, and urban status is assumed to occur randomly and observations are excluded from the estimation.

Table 2.2: Summary of Results: Weibull Hazard with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.2139	0.2119	4.0578	0.2478	4.0918
$V^2_{w_L}$	4.7575	0.0472	18.3742	4.5099	18.5591
$V^1_{w_M}$	0.1954	0.1900	0.2360	0.0990	0.2338
$V^2_{w_M}$	3.6357	3.5354	2.4196	0.4169	2.4549
$V^1_{w_H}$	0.1954	0.1900	0.0215	0.1905	0.0262
$V^2_{w_H}$	3.6357	3.5354	0.1914	0.0213	0.2036
UI-low	-1.4427	-1.4670	-1.4382	-1.4384	-1.4656
	(-1.82,-1.09)	(-1.86,-1.11)	(-1.82,-1.08)	(-1.82,-1.09)	(-1.87,-1.11)
UI-medium	-0.8398	-1.0468	-0.8542	-0.8551	-1.0393
	(-1.01,-0.68)	(-1.25,-0.83)	(-1.03,-0.69)	(-1.03,-0.69)	(-1.23,-0.83)
UI-high	-0.8398	-0.4607	-0.8542	-0.8551	-0.5169
	(-1.01,-0.68)	(-0.76,-0.24)	(-1.03,-0.69)	(-1.03,-0.69)	(-0.80,-0.27)
Urban-low	-0.0873	-0.0910	-0.0968	-0.1017	-0.1017
	(-0.31,0.18)	(-0.31,0.18)	(-0.32,0.16)	(-0.32,0.17)	(-0.32,0.15)
Urban-medium	0.2249	-0.0487	0.2159	-0.0511	0.1872
	(0.03,0.41)	(-0.07,-0.03)	(0.04,0.40)	(-0.07,-0.03)	(-0.01,0.38)
Urban-high	0.2249	0.2557	0.2159	0.3122	0.3099
	(0.03,0.41)	(-0.06,0.63)	(0.04,0.40)	(-0.06,0.72)	(-0.05,0.69)
a_L	0.0657	0.0143	0.2356	0.0597	0.2441
	(0.03,0.15)	(0.01,0.04)	(0.11,0.66)	(0.03,0.15)	(0.11,0.65)
a_M	9.2550	10.0264	9.6728	4.1466	10.4067
	(5.09,26.69)	(5.82,29.89)	(5.78,24.71)	(2.08,8.66)	(6.24,25.88)
a_H	1313.2464	1006.1187	182.1945	186.3248	175.2755
	(570.04,3745.22)	(440.75,3068.80)	(61.38,635.00)	(62.66,710.94)	(60.57,631.72)
k_L	1.0219	1.0217	1.0209	1.0211	1.0217
	(0.98,1.08)	(0.98,1.08)	(0.97,1.08)	(0.98,1.09)	(0.97,1.08)
k_M	1.0537	1.0643	1.0415	1.0413	1.0502
	(1.00,1.10)	(1.02,1.12)	(1.01,1.09)	(1.01,1.09)	(1.01,1.10)
k_H	1.0745	1.0555	1.1076	1.1084	1.0861
	(1.02,1.15)	(1.01,1.13)	(1.05,1.20)	(1.05,1.20)	(1.03,1.17)
$\ln L$	-19347.7622	-19339.3965	-19340.2380	-19340.0085	-19333.1813
LR test	29.1618	12.4303	14.1133	13.6544	
p-value	0.0000	0.0020	0.0009	0.0002	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2,3, and 4 are 4,2,2, and 1, respectively. 95% bootstrap intervals in parenthesis.

Table 2.3: Coefficient Estimates: Weibull Hazard with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.6463	-0.6447	-0.6410	-0.6411	-0.6423
	(-0.81,-0.47)	(-0.81,-0.47)	(-0.80,-0.48)	(-0.80,-0.47)	(-0.80,-0.48)
Black	-0.0394	-0.0364	-0.0195	-0.0188	-0.0229
	(-0.24,0.18)	(-0.24,0.17)	(-0.21,0.18)	(-0.23,0.18)	(-0.21,0.17)
Hispanic	-0.2974	-0.3010	-0.2985	-0.2972	-0.2984
	(-0.53,-0.04)	(-0.53,-0.06)	(-0.54,-0.07)	(-0.53,-0.06)	(-0.54,-0.08)
Education	-0.0553	-0.0552	-0.0559	-0.0560	-0.0559
	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)	(-0.10,0.00)
High School	0.0580	0.0596	0.0730	0.0735	0.0731
	(-0.18,0.30)	(-0.19,0.29)	(-0.15,0.29)	(-0.19,0.30)	(-0.15,0.30)
College	-0.4867	-0.4812	-0.4722	-0.4709	-0.4723
	(-1.02,-0.03)	(-1.03,-0.02)	(-1.01,-0.02)	(-1.02,-0.03)	(-1.03,-0.01)
Urban	-0.0873	-0.0910	-0.0968	-0.1017	-0.1017
	(-0.31,0.18)	(-0.31,0.18)	(-0.32,0.16)	(-0.32,0.17)	(-0.32,0.15)
Age	-0.2530	-0.2523	-0.2539	-0.2538	-0.2527
	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)	(-0.29,-0.22)
UI	-1.4427	-1.4670	-1.4382	-1.4384	-1.4656
	(-1.82,-1.09)	(-1.86,-1.11)	(-1.82,-1.08)	(-1.82,-1.09)	(-1.87,-1.11)
w_M market					
Male	0.0304	0.0316	0.0136	0.0130	0.0135
	(-0.13,0.15)	(-0.13,0.15)	(-0.11,0.14)	(-0.11,0.14)	(-0.12,0.14)
Black	-0.4741	-0.4899	-0.4549	-0.4537	-0.4668
	(-0.60,-0.32)	(-0.62,-0.34)	(-0.59,-0.31)	(-0.59,-0.31)	(-0.60,-0.33)
Hispanic	-0.1905	-0.1959	-0.1787	-0.1759	-0.1779
	(-0.34,-0.02)	(-0.35,-0.03)	(-0.33,-0.01)	(-0.33,-0.01)	(-0.33,-0.02)
Education	0.0429	0.0432	0.0386	0.0386	0.0398
	(-0.00,0.09)	(-0.00,0.10)	(-0.00,0.09)	(-0.00,0.09)	(0.00,0.09)
High School	0.2407	0.2431	0.2693	0.2708	0.2706
	(0.05,0.48)	(0.05,0.51)	(0.07,0.49)	(0.08,0.49)	(0.07,0.49)
College	-0.4962	-0.5014	-0.4656	-0.4636	-0.4751
	(-0.84,-0.20)	(-0.85,-0.20)	(-0.80,-0.17)	(-0.80,-0.17)	(-0.80,-0.20)
Urban	0.2249	0.2194	0.2159	0.1883	0.1872
	(0.03,0.41)	(0.00,0.42)	(0.04,0.40)	(0.01,0.39)	(-0.01,0.38)
Age	-0.0534	-0.0487	-0.0517	-0.0511	-0.0472
	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)	(-0.07,-0.03)
UI	-0.8398	-1.0468	-0.8542	-0.8551	-1.0393
	(-1.01,-0.68)	(-1.25,-0.83)	(-1.03,-0.69)	(-1.03,-0.69)	(-1.23,-0.83)
w_H market					
Male	0.3740	0.3735	0.3691	0.3693	0.3758
	(0.19,0.59)	(0.18,0.58)	(0.15,0.61)	(0.14,0.61)	(0.13,0.60)
Black	-1.0700	-1.0383	-1.1103	-1.1127	-1.0666
	(-1.33,-0.83)	(-1.30,-0.81)	(-1.38,-0.86)	(-1.39,-0.86)	(-1.34,-0.81)
Hispanic	-0.1253	-0.1461	-0.1778	-0.1867	-0.1693
	(-0.39,0.14)	(-0.40,0.13)	(-0.41,0.13)	(-0.42,0.11)	(-0.42,0.13)
Education	0.1994	0.1958	0.1955	0.1943	0.1941
	(0.14,0.28)	(0.14,0.27)	(0.13,0.27)	(0.12,0.28)	(0.13,0.27)
High School	0.4156	0.3850	0.4685	0.4734	0.4335
	(0.05,0.80)	(0.06,0.76)	(0.10,0.82)	(0.09,0.83)	(0.08,0.75)
College	0.1770	0.2103	0.2636	0.2624	0.2671
	(-0.18,0.54)	(-0.15,0.54)	(-0.19,0.63)	(-0.20,0.63)	(-0.14,0.59)
Urban	0.2249	0.2557	0.2159	0.3122	0.3099
	(0.03,0.41)	(-0.06,0.63)	(0.04,0.40)	(-0.06,0.72)	(-0.05,0.69)
Age	0.0553	0.0440	0.0619	0.0601	0.0461
	(0.02,0.09)	(0.01,0.08)	(0.02,0.10)	(0.02,0.10)	(0.01,0.08)
UI	-0.8398	-0.4607	-0.8542	-0.8551	-0.5169
	(-1.01,-0.68)	(-0.76,-0.24)	(-1.03,-0.69)	(-1.03,-0.69)	(-0.80,-0.27)

Note: 95% bootstrap intervals in parenthesis.

Table 2.4: Summary of Results: Weibull Hazard with Inclusive Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.0299	0.0301	3.5387	0.0307	0.0308
$V^2_{w_L}$	0.2829	0.2836	0.1053	0.2845	0.2846
$V^1_{w_M}$	0.1036	0.0942	0.0545	0.0588	0.0590
$V^2_{w_M}$	3.6067	3.6119	0.3203	0.3262	0.3253
$V^1_{w_H}$	0.1036	0.0942	0.0956	0.0851	0.0857
$V^2_{w_H}$	3.6067	3.6119	5.1366	4.8292	4.7895
UI-low	-1.0486	-1.0498	-1.0491	-1.0467	-1.0499
	(-1.31,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.31,-0.82)
UI-medium	-0.7563	-0.7945	-0.7647	-0.7201	-0.7901
	(-0.86,-0.65)	(-0.94,-0.67)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.93,-0.66)
UI-high	-0.7563	-0.5763	-0.7647	-0.7201	-0.5914
	(-0.86,-0.65)	(-0.76,-0.38)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.78,-0.38)
Search-low	0.6342	0.6464	0.6350	0.6468	0.6474
	(0.54,0.73)	(0.55,0.75)	(0.54,0.74)	(0.55,0.75)	(0.55,0.75)
Search-medium	0.2651	0.4617	0.2727	0.4574	0.4657
	(0.20,0.32)	(0.39,0.54)	(0.20,0.33)	(0.38,0.54)	(0.39,0.54)
Search-high	0.2651	-0.2322	0.2727	-0.2075	-0.2343
	(0.20,0.32)	(-0.35,-0.12)	(0.20,0.33)	(-0.32,-0.07)	(-0.35,-0.09)
Urban-low	-0.1189	-0.1203	-0.1164	-0.1190	-0.1192
	(-0.24,0.02)	(-0.25,0.02)	(-0.24,0.02)	(-0.25,0.02)	(-0.25,0.02)
Urban-medium	0.1202	0.1062	0.1177	0.1008	0.0998
	(0.01,0.22)	(-0.00,0.21)	(0.01,0.21)	(-0.01,0.20)	(-0.01,0.20)
Urban-high	0.1202	0.1790	0.1177	0.1932	0.1955
	(0.01,0.22)	(-0.08,0.38)	(0.01,0.21)	(-0.06,0.41)	(-0.06,0.42)
a_L	0.1318	0.1316	0.6396	0.1326	0.1326
	(0.05,0.31)	(0.05,0.22)	(0.20,1.14)	(0.04,0.29)	(0.04,0.22)
a_M	542.9676	565.4240	102.8465	102.5173	104.3179
	(330.95,881.33)	(356.80,888.65)	(56.65,157.13)	(52.30,327.17)	(54.08,163.32)
a_H	49855.9353	49854.7140	49853.9882	49854.3001	49854.1379
	(49854.80,49875.31)	(49853.49,49859.27)	(49853.92,59498.28)	(49854.28,56203.36)	(49854.09,83603.59)
k_L	0.8039	0.8036	0.8041	0.8038	0.8038
	(0.79,0.82)	(0.78,0.82)	(0.78,0.83)	(0.78,0.82)	(0.78,0.82)
k_M	0.7956	0.7999	0.7934	0.7971	0.7981
	(0.78,0.81)	(0.78,0.82)	(0.78,0.81)	(0.78,0.81)	(0.78,0.81)
k_H	0.8337	0.8316	0.8468	0.8485	0.8459
	(0.81,0.86)	(0.81,0.86)	(0.82,0.87)	(0.82,0.87)	(0.82,0.87)
$\ln L$	-70434.2613	-70370.9237	-70420.6155	-70360.0084	-70358.2940
LR test	151.9346	25.2594	1013.3394	3.4290	
p-value	0.0000	0.0000	0.0000	0.0641	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction

1,2,3, and 4 are 5,2,3, and 1 respectively. 95% bootstrap intervals in parenthesis.

Table 2.5: Coefficient Estimates: Weibull Hazard with Inclusive Data

	Restriction (1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.2933	-0.2927	-0.2932	-0.2929	-0.2929
	(-0.40,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)	(-0.42,-0.20)
Black	-0.0255	-0.0254	-0.0204	-0.0217	-0.0222
	(-0.18,0.07)	(-0.16,0.07)	(-0.16,0.07)	(-0.16,0.07)	(-0.16,0.07)
Hispanic	-0.1854	-0.1865	-0.1833	-0.1861	-0.1868
	(-0.35,-0.07)	(-0.35,-0.06)	(-0.35,-0.06)	(-0.36,-0.07)	(-0.34,-0.07)
Education	0.0140	0.0138	0.0143	0.0142	0.0141
	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)	(-0.03,0.05)
High School	0.1115	0.1114	0.1081	0.1093	0.1091
	(-0.03,0.26)	(-0.02,0.26)	(-0.04,0.25)	(-0.03,0.25)	(-0.03,0.25)
College	-0.1578	-0.1441	-0.1564	-0.1462	-0.1467
	(-0.43,0.17)	(-0.47,0.18)	(-0.48,0.18)	(-0.45,0.18)	(-0.46,0.19)
Urban	-0.1189	-0.1203	-0.1164	-0.1190	-0.1192
	(-0.24,0.02)	(-0.25,0.02)	(-0.24,0.02)	(-0.25,0.02)	(-0.25,0.02)
Age	-0.2174	-0.2173	-0.2174	-0.2173	-0.2173
	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)	(-0.24,-0.20)
UI	-1.0486	-1.0498	-1.0491	-1.0467	-1.0499
	(-1.31,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.30,-0.82)	(-1.31,-0.82)
Searching	0.6342	0.6464	0.6350	0.6468	0.6474
	(0.54,0.73)	(0.55,0.75)	(0.54,0.74)	(0.55,0.75)	(0.55,0.75)
w_M market					
Male	0.2055	0.1704	0.2090	0.1746	0.1752
	(0.13,0.29)	(0.10,0.25)	(0.14,0.29)	(0.10,0.26)	(0.11,0.26)
Black	-0.3691	-0.3766	-0.3671	-0.3727	-0.3748
	(-0.46,-0.27)	(-0.46,-0.28)	(-0.46,-0.28)	(-0.46,-0.28)	(-0.47,-0.28)
Hispanic	-0.1568	-0.1508	-0.1625	-0.1558	-0.1562
	(-0.26,-0.06)	(-0.25,-0.05)	(-0.26,-0.06)	(-0.25,-0.06)	(-0.26,-0.06)
Education	0.1009	0.1012	0.1004	0.1003	0.1007
	(0.07,0.13)	(0.07,0.13)	(0.08,0.13)	(0.07,0.13)	(0.07,0.13)
High School	0.3064	0.3003	0.3073	0.3021	0.3029
	(0.17,0.42)	(0.18,0.43)	(0.18,0.44)	(0.18,0.43)	(0.18,0.43)
College	-0.4377	-0.4504	-0.4342	-0.4459	-0.4490
	(-0.64,-0.26)	(-0.63,-0.27)	(-0.61,-0.25)	(-0.63,-0.26)	(-0.63,-0.26)
Urban	0.1202	0.1062	0.1177	0.1008	0.0998
	(0.01,0.22)	(-0.00,0.21)	(0.01,0.21)	(-0.01,0.20)	(-0.01,0.20)
Age	-0.0013	-0.0016	-0.0019	-0.0034	-0.0027
	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)
UI	-0.7563	-0.7945	-0.7647	-0.7201	-0.7901
	(-0.86,-0.65)	(-0.94,-0.67)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.93,-0.66)
Searching	0.2651	0.4617	0.2727	0.4574	0.4657
	(0.20,0.32)	(0.39,0.54)	(0.20,0.33)	(0.38,0.54)	(0.39,0.54)
w_H market					
Male	0.6730	0.6928	0.6901	0.7110	0.7097
	(0.51,0.83)	(0.56,0.87)	(0.52,0.86)	(0.58,0.89)	(0.57,0.89)
Black	-1.0501	-1.0267	-1.1085	-1.0789	-1.0677
	(-1.22,-0.87)	(-1.20,-0.85)	(-1.27,-0.86)	(-1.25,-0.84)	(-1.25,-0.84)
Hispanic	-0.1828	-0.1653	-0.2375	-0.2047	-0.1946
	(-0.35,0.02)	(-0.34,-0.00)	(-0.40,0.01)	(-0.38,0.03)	(-0.39,0.03)
Education	0.1947	0.1943	0.1929	0.1942	0.1942
	(0.16,0.23)	(0.16,0.23)	(0.15,0.24)	(0.15,0.23)	(0.15,0.24)
High School	0.4333	0.4265	0.5088	0.4707	0.4666
	(0.19,0.71)	(0.18,0.73)	(0.21,0.79)	(0.21,0.78)	(0.21,0.79)
College	0.3867	0.3067	0.3811	0.3198	0.3284
	(0.07,0.69)	(0.09,0.65)	(0.06,0.77)	(0.07,0.67)	(0.05,0.67)
Urban	0.1202	0.1790	0.1177	0.1932	0.1955
	(0.01,0.22)	(-0.08,0.38)	(0.01,0.21)	(-0.06,0.41)	(-0.06,0.42)
Age	0.1222	0.1208	0.1245	0.1228	0.1211
	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)	(0.10,0.14)
UI	-0.7563	-0.5763	-0.7647	-0.7201	-0.5914
	(-0.86,-0.65)	(-0.76,-0.38)	(-0.87,-0.65)	(-0.83,-0.62)	(-0.78,-0.38)
Searching	0.2651	-0.2322	0.2727	-0.2075	-0.2343
	(0.20,0.32)	(-0.35,-0.12)	(0.20,0.33)	(-0.32,-0.07)	(-0.35,-0.09)

Note: 95% bootstrap intervals in parenthesis.

Table 2.6: Summary of Results: Piecewise Exponential with Standard Data

	Restriction (1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.2396	0.2388	0.2402	0.2411	0.2414
$V^2_{w_L}$	0.0729	0.0714	0.0748	0.0756	0.0751
$V^1_{w_M}$	0.2597	0.2689	0.5213	0.5293	0.5364
$V^2_{w_M}$	0.0684	0.0632	0.1461	0.1488	0.1493
$V^1_{w_H}$	0.2597	0.2689	0.1590	0.1585	0.1796
$V^2_{w_H}$	0.0684	0.0632	3.9545	3.9680	3.8295
UI-low	-1.3166	-1.3446	-1.3189	-1.3188	-1.3454
	(-1.71,-0.98)	(-1.72,-1.01)	(-1.70,-0.98)	(-1.70,-0.98)	(-1.71,-1.01)
UI-medium	-0.7534	-0.9995	-0.7609	-0.7613	-0.9957
	(-0.88,-0.63)	(-1.17,-0.81)	(-0.89,-0.63)	(-0.89,-0.63)	(-1.17,-0.81)
UI-high	-0.7534	-0.3487	-0.7609	-0.7613	-0.3841
	(-0.88,-0.63)	(-0.59,-0.17)	(-0.89,-0.63)	(-0.89,-0.63)	(-0.59,-0.18)
Urban-low	-0.1057	-0.1024	-0.1023	-0.1062	-0.1058
	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)
Urban-medium	0.2027	0.1940	0.2009	0.1817	0.1788
	(0.06,0.36)	(0.03,0.37)	(0.07,0.36)	(0.02,0.35)	(0.02,0.36)
Urban-high	0.2027	0.2574	0.2009	0.2636	-0.9957
	(0.06,0.36)	(-0.02,0.60)	(0.07,0.36)	(-0.04,0.61)	(-1.17,-0.81)
$\ln L$	-19290.6370	-19279.2253	-19286.6209	-19286.5107	-19276.1730
LR test	28.9280	6.1047	20.8959	20.6754	
p-value	0.0000	0.0472	0.0001	0.0000	

Note: The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2, and 3 are 28,26, and 2, respectively. 95% bootstrap intervals in parenthesis.

Table 2.7: Baseline Hazard Rate Estimates: Piecewise Exponential with Standard Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
λ_L^1	66.9170	65.3203	68.1360	67.9360	66.3688
	(33.23,70.00)	(31.76,70.00)	(32.99,70.00)	(33.27,70.00)	(32.22,70.00)
λ_L^2	49.0532	47.9645	50.0648	49.9075	48.8300
	(24.92,59.91)	(24.00,59.66)	(24.49,59.92)	(24.56,59.92)	(23.94,60.12)
λ_L^3	46.8569	45.8900	47.8259	47.6626	46.6878
	(22.18,60.32)	(21.86,60.54)	(21.62,60.02)	(22.72,60.17)	(21.23,60.26)
λ_L^4	51.8568	50.9190	52.9481	52.7805	51.6902
	(26.19,70.00)	(24.95,70.00)	(24.65,70.00)	(25.71,70.00)	(24.87,70.00)
λ_L^5	42.8708	41.9775	43.4805	43.3459	42.4506
	(18.68,65.68)	(18.05,65.64)	(18.45,66.61)	(18.45,66.45)	(17.88,66.68)
λ_L^6	38.1520	37.5770	38.4766	38.3071	37.5366
	(14.78,70.00)	(14.56,69.71)	(15.00,69.96)	(16.00,69.30)	(14.70,70.00)
λ_M^1	0.4893	0.4150	0.2231	0.2206	0.1930
	(0.20,1.05)	(0.18,0.97)	(0.10,0.55)	(0.10,0.55)	(0.09,0.48)
λ_M^2	0.3255	0.2820	0.1493	0.1477	0.1318
	(0.14,0.67)	(0.12,0.63)	(0.07,0.37)	(0.07,0.36)	(0.06,0.33)
λ_M^3	0.3214	0.2820	0.1472	0.1455	0.1310
	(0.12,0.74)	(0.12,0.67)	(0.07,0.37)	(0.07,0.36)	(0.06,0.33)
λ_M^4	0.3919	0.3500	0.1783	0.1762	0.1596
	(0.15,0.90)	(0.13,0.89)	(0.08,0.45)	(0.08,0.44)	(0.07,0.41)
λ_M^5	0.3741	0.3381	0.1686	0.1667	0.1512
	(0.13,0.85)	(0.11,0.89)	(0.07,0.47)	(0.07,0.43)	(0.07,0.40)
λ_M^6	0.2148	0.1990	0.0956	0.0945	0.0856
	(0.08,0.55)	(0.07,0.57)	(0.04,0.27)	(0.04,0.27)	(0.03,0.23)
λ_H^1	0.0020	0.0042	0.0010	0.0010	0.0013
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^2	0.0015	0.0030	0.0008	0.0008	0.0010
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^3	0.0011	0.0022	0.0006	0.0006	0.0007
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^4	0.0014	0.0027	0.0007	0.0007	0.0009
	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^5	0.0010	0.0019	0.0005	0.0005	0.0006
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^6	0.0010	0.0021	0.0006	0.0006	0.0007
	(0.00,0.00)	(0.00,0.01)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)

Note: 95% bootstrap intervals in parenthesis.

Table 2.8: Coefficient Estimates: Piecewise Exponential with Standard Data

			Restriction		
	(1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.5981	-0.5936	-0.5897	-0.5893	-0.5909
	(-0.74,-0.43)	(-0.74,-0.44)	(-0.74,-0.44)	(-0.74,-0.43)	(-0.75,-0.44)
Black	0.0352	0.0291	0.0296	0.0298	0.0276
	(-0.15,0.21)	(-0.15,0.21)	(-0.15,0.20)	(-0.15,0.20)	(-0.15,0.20)
Hispanic	-0.2638	-0.2623	-0.2617	-0.2611	-0.2610
	(-0.49,-0.04)	(-0.48,-0.04)	(-0.49,-0.04)	(-0.49,-0.04)	(-0.48,-0.04)
Education	-0.0496	-0.0498	-0.0496	-0.0495	-0.0493
	(-0.09,0.00)	(-0.09,0.00)	(-0.08,0.00)	(-0.08,0.00)	(-0.08,0.00)
High School	0.0219	0.0255	0.0249	0.0246	0.0252
	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)	(-0.19,0.22)
College	-0.5022	-0.5101	-0.5140	-0.5142	-0.5156
	(-1.05,-0.07)	(-1.08,-0.08)	(-1.14,-0.08)	(-1.14,-0.08)	(-1.11,-0.08)
Urban	-0.1057	-0.1024	-0.1023	-0.1062	-0.1058
	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)	(-0.31,0.14)
Age	-0.2387	-0.2377	-0.2391	-0.2390	-0.2380
	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)	(-0.27,-0.21)
UI	-1.3166	-1.3446	-1.3189	-1.3188	-1.3454
	(-1.71,-0.98)	(-1.72,-1.01)	(-1.70,-0.98)	(-1.70,-0.98)	(-1.71,-1.01)
w_M market					
Male	0.0270	0.0298	0.0277	0.0277	0.0258
	(-0.08,0.14)	(-0.09,0.14)	(-0.09,0.14)	(-0.09,0.14)	(-0.09,0.13)
Black	-0.3919	-0.4127	-0.3912	-0.3903	-0.4042
	(-0.51,-0.27)	(-0.53,-0.28)	(-0.51,-0.27)	(-0.50,-0.27)	(-0.52,-0.28)
Hispanic	-0.1699	-0.1743	-0.1675	-0.1655	-0.1680
	(-0.31,-0.03)	(-0.32,-0.03)	(-0.31,-0.02)	(-0.31,-0.02)	(-0.31,-0.02)
Education	0.0366	0.0394	0.0398	0.0399	0.0415
	(-0.00,0.08)	(-0.00,0.08)	(0.00,0.08)	(0.00,0.08)	(0.00,0.08)
High School	0.2215	0.2111	0.2150	0.2153	0.2167
	(0.04,0.41)	(0.04,0.41)	(0.04,0.40)	(0.04,0.40)	(0.04,0.41)
College	-0.4773	-0.4932	-0.4842	-0.4834	-0.4963
	(-0.79,-0.21)	(-0.80,-0.22)	(-0.79,-0.23)	(-0.79,-0.23)	(-0.79,-0.24)
Urban	0.2027	0.1940	0.2009	0.1817	0.1788
	(0.06,0.36)	(0.03,0.37)	(0.07,0.36)	(0.02,0.35)	(0.02,0.36)
Age	-0.0456	-0.0405	-0.0452	-0.0448	-0.0394
	(-0.06,-0.03)	(-0.06,-0.02)	(-0.06,-0.03)	(-0.06,-0.03)	(-0.06,-0.02)
UI	-0.7534	-0.9995	-0.7609	-0.7613	-0.9957
	(-0.88,-0.63)	(-1.17,-0.81)	(-0.89,-0.63)	(-0.89,-0.63)	(-1.17,-0.81)
w_H market					
Male	0.3913	0.3781	0.3724	0.3725	0.3660
	(0.21,0.57)	(0.19,0.56)	(0.18,0.58)	(0.18,0.58)	(0.17,0.58)
Black	-0.9528	-0.9379	-0.9809	-0.9828	-0.9348
	(-1.20,-0.74)	(-1.17,-0.69)	(-1.24,-0.74)	(-1.24,-0.74)	(-1.18,-0.70)
Hispanic	-0.1105	-0.1449	-0.1595	-0.1658	-0.1470
	(-0.37,0.13)	(-0.37,0.10)	(-0.38,0.10)	(-0.40,0.10)	(-0.39,0.11)
Education	0.1948	0.1854	0.1870	0.1862	0.1833
	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)	(0.13,0.25)
High School	0.3282	0.3313	0.3894	0.3919	0.3659
	(0.01,0.68)	(-0.00,0.65)	(0.05,0.72)	(0.04,0.72)	(0.05,0.67)
College	0.2121	0.2531	0.2579	0.2571	0.2808
	(-0.10,0.55)	(-0.07,0.56)	(-0.10,0.58)	(-0.11,0.58)	(-0.09,0.61)
Urban	0.2027	0.2574	0.2009	0.2636	0.2608
	(0.06,0.36)	(-0.02,0.60)	(0.07,0.36)	(-0.04,0.61)	(-0.02,0.60)
Age	0.0604	0.0431	0.0626	0.0615	0.0463
	(0.03,0.09)	(0.01,0.08)	(0.03,0.09)	(0.03,0.09)	(0.01,0.08)
UI	-0.7534	-0.3487	-0.7609	-0.7613	-0.3841
	(-0.88,-0.63)	(-0.59,-0.17)	(-0.89,-0.63)	(-0.89,-0.63)	(-0.59,-0.18)

Note: 95% bootstrap intervals in parenthesis.

Table 2.9: Summary of Results: Piecewise Exponential with Inclusive Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
$V^1_{w_L}$	0.0168	0.0173	0.0171	0.0180	0.0180
$V^2_{w_L}$	0.2924	0.2939	0.2938	0.2950	0.2950
$V^1_{w_M}$	0.1245	0.1236	0.1549	0.1614	6.4302
$V^2_{w_M}$	3.3067	3.2538	2.9993	2.9250	19.0479
$V^1_{w_H}$	0.1245	0.1236	46.3672	46.2589	43.9762
$V^2_{w_H}$	3.3067	3.2538	8.6475	8.9545	8.7443
UI-low	-1.0611	-1.0619	-1.0614	-1.0600	-1.0620
	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.81)	(-1.32,-0.82)
UI-medium	-0.7301	-0.8037	-0.7312	-0.7042	-0.7945
	(-0.83,-0.64)	(-0.93,-0.68)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.92,-0.68)
UI-high	-0.7301	-0.5135	-0.7312	-0.7042	-0.5288
	(-0.83,-0.64)	(-0.70,-0.33)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.74,-0.33)
Search-low	0.4115	0.4203	0.4118	0.4199	0.4201
	(0.31,0.51)	(0.32,0.52)	(0.31,0.51)	(0.32,0.52)	(0.32,0.52)
Search-medium	0.0189	0.2053	0.0266	0.1989	0.2080
	(-0.04,0.08)	(0.13,0.27)	(-0.03,0.08)	(0.13,0.27)	(0.14,0.28)
Search-high	0.0189	-0.4354	0.0266	-0.3902	-0.4224
	(-0.04,0.08)	(-0.55,-0.32)	(-0.03,0.08)	(-0.51,-0.28)	(-0.54,-0.31)
Urban-low	-0.1303	-0.1311	-0.1277	-0.1287	-0.1294
	(-0.25,0.01)	(-0.25,0.00)	(-0.24,0.01)	(-0.24,0.01)	(-0.24,0.01)
Urban-medium	0.1255	0.1115	0.1295	0.1034	0.1039
	(0.04,0.22)	(-0.00,0.21)	(0.04,0.22)	(-0.01,0.20)	(-0.01,0.20)
Urban-high	0.1255	0.1581	0.1295	0.1834	0.1798
	(0.04,0.22)	(-0.05,0.41)	(0.04,0.22)	(-0.01,0.45)	(-0.01,0.44)
$\ln L$	-70061.1868	-70005.3872	-70048.1990	-69997.4836	-69993.9136
LR test	134.5463	22.9473	108.5708	7.1401	
p-value	0.0000	0.0000	0.0000	0.0075	

Note:The number of degrees of freedom used in the likelihood ratio test for Restriction 1,2,3, and 4 are 5,2,3 and 1, respectively. 95% bootstrap intervals in parenthesis.

Table 2.10: Baseline Hazard Rate Estimates: Piecewise Exponential with Inclusive Data

	Restriction				
	(1)	(2)	(3)	(4)	unrestricted
λ_L^1	3.7085	3.7136	3.5854	3.6268	3.7308
	(2.58,6.24)	(2.56,6.33)	(2.57,6.50)	(2.56,6.67)	(2.55,6.67)
λ_L^2	2.1442	2.1454	2.0712	2.0952	2.1552
	(1.43,3.72)	(1.44,3.72)	(1.46,3.74)	(1.45,3.82)	(1.46,3.88)
λ_L^3	1.7842	1.7840	1.7232	1.7419	1.7917
	(1.22,3.10)	(1.22,3.14)	(1.21,3.28)	(1.22,3.16)	(1.23,3.25)
λ_L^4	1.7721	1.7713	1.7071	1.7287	1.7787
	(1.23,3.22)	(1.22,3.19)	(1.24,3.19)	(1.20,3.23)	(1.21,3.21)
λ_L^5	1.7042	1.7029	1.6421	1.6618	1.7099
	(1.16,3.16)	(1.14,3.12)	(1.15,3.07)	(1.16,3.22)	(1.14,3.24)
λ_L^6	1.1105	1.1073	1.0723	1.0812	1.1120
	(0.77,2.01)	(0.76,2.00)	(0.76,2.03)	(0.77,2.03)	(0.76,2.03)
λ_M^1	0.0065	0.0063	0.0072	0.0073	0.0011
	(0.00,0.01)	(0.00,0.01)	(0.01,0.01)	(0.01,0.01)	(0.00,0.00)
λ_M^2	0.0034	0.0033	0.0037	0.0038	0.0006
	(0.00,0.01)	(0.00,0.01)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^3	0.0029	0.0028	0.0031	0.0032	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^4	0.0030	0.0029	0.0033	0.0034	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^5	0.0027	0.0027	0.0030	0.0030	0.0005
	(0.00,0.00)	(0.00,0.00)	(0.00,0.01)	(0.00,0.01)	(0.00,0.00)
λ_M^6	0.0017	0.0016	0.0018	0.0019	0.0003
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^1	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^2	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^3	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^4	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^5	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)
λ_H^6	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)	(0.00,0.00)

Note: 95% bootstrap intervals in parenthesis.

Table 2.11: Coefficient Estimates: Piecewise Exponential with Inclusive Data

	Restriction (1)	(2)	(3)	(4)	unrestricted
w_L market					
Male	-0.2668	-0.2670	-0.2658	-0.2678	-0.2689
	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)	(-0.38,-0.17)
Black	-0.0031	-0.0025	0.0029	0.0016	0.0002
	(-0.13,0.09)	(-0.12,0.09)	(-0.12,0.09)	(-0.12,0.09)	(-0.12,0.09)
Hispanic	-0.1927	-0.1933	-0.1875	-0.1898	-0.1903
	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)	(-0.33,-0.07)
Education	0.0074	0.0072	0.0092	0.0089	0.0075
	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)	(-0.03,0.04)
High School	0.1034	0.1030	0.0945	0.0929	0.0948
	(-0.02,0.24)	(-0.02,0.24)	(-0.03,0.23)	(-0.03,0.24)	(-0.03,0.24)
College	-0.1896	-0.1839	-0.1958	-0.1901	-0.1843
	(-0.48,0.14)	(-0.48,0.14)	(-0.48,0.12)	(-0.48,0.14)	(-0.48,0.15)
Urban	-0.1303	-0.1311	-0.1277	-0.1287	-0.1294
	(-0.25,0.01)	(-0.25,0.00)	(-0.24,0.01)	(-0.24,0.01)	(-0.24,0.01)
Age	-0.2090	-0.2089	-0.2083	-0.2086	-0.2090
	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)	(-0.23,-0.19)
UI	-1.0611	-1.0619	-1.0614	-1.0600	-1.0620
	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.82)	(-1.32,-0.81)	(-1.32,-0.82)
Searching	0.4115	0.4203	0.4118	0.4199	0.4201
	(0.31,0.51)	(0.32,0.52)	(0.31,0.51)	(0.32,0.52)	(0.32,0.52)
w_M market					
Male	0.2444	0.2145	0.2425	0.2120	0.2127
	(0.18,0.32)	(0.15,0.29)	(0.18,0.32)	(0.15,0.29)	(0.15,0.29)
Black	-0.3397	-0.3486	-0.3341	-0.3406	-0.3432
	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)	(-0.43,-0.25)
Hispanic	-0.1420	-0.1383	-0.1515	-0.1469	-0.1466
	(-0.25,-0.04)	(-0.24,-0.04)	(-0.25,-0.05)	(-0.25,-0.05)	(-0.24,-0.05)
Education	0.0920	0.0915	0.0920	0.0913	0.0920
	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)	(0.07,0.12)
High School	0.3058	0.3032	0.3021	0.2953	0.2965
	(0.18,0.43)	(0.18,0.43)	(0.18,0.43)	(0.17,0.42)	(0.17,0.42)
College	-0.4170	-0.4210	-0.4152	-0.4183	-0.4215
	(-0.59,-0.24)	(-0.59,-0.25)	(-0.59,-0.24)	(-0.59,-0.24)	(-0.59,-0.24)
Urban	0.1255	0.1115	0.1295	0.1034	0.1039
	(0.04,0.22)	(-0.00,0.21)	(0.04,0.22)	(-0.01,0.20)	(-0.01,0.20)
Age	0.0013	0.0017	0.0008	0.0003	0.0012
	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)	(-0.01,0.01)
UI	-0.7301	-0.8037	-0.7312	-0.7042	-0.7945
	(-0.83,-0.64)	(-0.93,-0.68)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.92,-0.68)
Searching	0.0189	0.2053	0.0266	0.1989	0.2080
	(-0.04,0.08)	(0.13,0.27)	(-0.03,0.08)	(0.13,0.27)	(0.14,0.28)
w_H market					
Male	0.7198	0.7680	0.7363	0.7955	0.7942
	(0.57,0.85)	(0.63,0.90)	(0.59,0.89)	(0.65,0.94)	(0.65,0.94)
Black	-0.9742	-0.9468	-1.0099	-0.9761	-0.9638
	(-1.13,-0.80)	(-1.11,-0.78)	(-1.17,-0.81)	(-1.14,-0.79)	(-1.13,-0.78)
Hispanic	-0.1737	-0.1641	-0.2175	-0.2006	-0.1954
	(-0.33,0.01)	(-0.34,0.01)	(-0.36,0.03)	(-0.37,0.02)	(-0.38,0.03)
Education	0.1875	0.1926	0.1901	0.1917	0.1955
	(0.15,0.24)	(0.15,0.24)	(0.15,0.25)	(0.15,0.25)	(0.15,0.25)
High School	0.4109	0.4014	0.5206	0.5168	0.5063
	(0.15,0.66)	(0.15,0.66)	(0.20,0.75)	(0.21,0.75)	(0.21,0.75)
College	0.5449	0.5331	0.4983	0.5116	0.5101
	(0.02,0.81)	(0.05,0.82)	(0.02,0.81)	(0.04,0.79)	(0.04,0.81)
Urban	0.1255	0.1581	0.1295	0.1834	0.1798
	(0.04,0.22)	(-0.05,0.41)	(0.04,0.22)	(-0.01,0.45)	(-0.01,0.44)
Age	0.1251	0.1243	0.1284	0.1293	0.1273
	(0.11,0.14)	(0.10,0.14)	(0.11,0.15)	(0.11,0.15)	(0.11,0.15)
UI	-0.7301	-0.5135	-0.7312	-0.7042	-0.5288
	(-0.83,-0.64)	(-0.70,-0.33)	(-0.84,-0.63)	(-0.80,-0.60)	(-0.74,-0.33)
Searching	0.0189	-0.4354	0.0266	-0.3902	-0.4224
	(-0.04,0.08)	(-0.55,-0.32)	(-0.03,0.08)	(-0.51,-0.28)	(-0.54,-0.31)

Note: 95% bootstrap intervals in parenthesis.

Table 2.12: Wage Distributions by Eduction

	Standard Data		Inclusive Data	
	High School	College	High School	College
Mean	12.59	17.22	16.45	20.00
Std. Dev.	24.43	15.50	142.83	37.46
25^{th} Percentile	7.33	10.00	7.5	10.7
75^{th} Percentile	12.36	19.17	13.24	21.63
Observations	3,343	384	10,617	1,362

Table 2.13: Likelihood Ratio Tests by Education: Weibull Hazard

	Specification				
	(1)	(2)	(3)	(4)	unrestricted
Standard data: Highschool					
$\ln L$	-14254.8164	-14248.9368	-14250.9355	-14249.8313	-14245.6054
LR test	18.4221	6.6628	10.6602	8.4517	
p-value	0.0010	0.0357	0.0048	0.0036	
Standard data: College					
$\ln L$	-1572.5371	-1571.9408	-1572.7105	-1571.8639	-1571.8331
LR test	1.4081	0.2156	1.7548	0.0617	
p-value	0.8428	0.8978	0.4159	0.8038	
Inclusive data: Highschool					
$\ln L$	-51367.6426	-51318.8019	-51356.6103	-51310.4165	51308.9126
LR test	117.4601	19.7785	95.3954	3.0078	
p-value	0.0000	0.0001	0.0000	0.0829	
Inclusive data: College					
$\ln L$	-5680.1866	-5675.2052	-5673.9313	-5669.8700	-5669.7648
LR test	20.8437	10.8809	8.3330	0.2104	
p-value	0.0009	0.0043	0.0396	0.6465	

Table 2.14: Likelihood Ratio Tests by Education: Piecewise Exponential Hazard

	Specification				
	(1)	(2)	(3)	(4)	unrestricted
Standard data: Highschool					
$\ln L$	-14209.8386	-14204.9645	-14208.4759	-14207.8358	-14201.4364
LR test	16.8043	7.0560	14.0789	12.7986	
p-value	0.0021	0.0294	0.0009	0.0003	
Standard data: College					
$\ln L$	-1584.1900	-1583.1533	-1584.1869	-1583.2134	-1583.1533
LR test	2.0733	0.0001	2.0673	0.1201	
p-value	0.7223	1.0000	0.3557	0.7289	
Inclusive data: Highschool					
$\ln L$	-51109.3769	-51070.3267	-51098.9918	-51063.9213	-51062.2604
LR test	94.2329	16.1327	73.4629	3.3218	
p-value	0.0000	0.0003	0.0000	0.0684	
Inclusive data: College					
$\ln L$	-5626.4299	-5621.3700	-5626.3282	-5621.3424	-5621.3360
LR test	10.1878	0.0680	9.9844	0.0127	
p-value	0.0701	0.9666	0.0187	0.9102	

Table 2.15: Kullback-Leibler Divergence

Sub-Market	$D_{KL}(p\|\|q)$	H(p)
Black High-School Non-completers	0.0589	3.5677
Black High-School Graduates	0.0764	2.9850
Black College Non-completers	0.0597	2.3401
White High-School Non-completers	0.0657	3.0358
White High-School Graduates	0.0626	2.4240
White College Non-completers	0.046	1.7345
White College Graduates	0.0905	1.6845

Chapter 3

Quality Hours: Measuring Labor Input

Joint with Finn Kydland, and Peter Rupert

3.1 Introduction

Not all hours are created equal. In this paper we present a method for adjusting aggregate hours to account for changes in the quality of hours worked. Average human capital has rapidly increased since 1980 as better educated cohorts enter the workforce and the baby boomers continue to work and gather experience. The neoclassical production function, when using hours in place of labor input, treats all hours as equal, and so measures of growth and productivity can be clouded by changes in the education and experience level of the workforce. In order to account for these changes in the quality of labor provided, we use data on individual workers from the Current Population Survey's Outgoing Rotation Groups to construct a measure of labor input. We scale each individual's hours worked by a weight, created from hourly wages, that reflects education-experience level and an individual residual to measure relative labor input.

We show that the cyclical behavior of labor input differs from aggregate hours: labor input is less volatile and has a slightly smaller contemporaneous correlation with real gross domestic product. Further, the measured average annual growth rate of labor productivity differs substantially when using labor input instead of aggregate hours. The average annual growth rate of labor productivity since 2004 is 0.75% when using aggregate hours, whereas labor productivity measured using labor input has an average growth rate of only 0.22%, implying that 70% of the growth of labor productivity since 2004 has been through an increase in education and experience. That is, the "productivity slowdown" is more severe when using labor input compared to aggregate hours, the decline is understated by 23 percentage points. Similarly, when using labor input instead of aggregate hours, the annual growth rate of total factor productivity (TFP) decreases from 0.63 to 0.16, implying that 75% of the growth in TFP since 1979 can be explained by increases in the quality of the workforce. We calculate the Solow residual using both our measures of labor input and aggregate hours and find that the cyclical component of the output residual remains almost unchanged. The autocorrelation of the Solow residual drops from 0.96 to 0.94 when using labor input and the standard deviation of the error component is unchanged at 0.007. Overall, accounting for changes in the quality if the workforce has a large effect on the trend of productivity but a rather small effect on the cyclical component of productivity.

With respect to Real Business Cycle (RBC) models for the economy, the volatility of labor input in these models is lower than that of aggregate hours in data from the U.S., see for example Hall (1997) and Christiano and Eichenbaum (1992), spurring the need to either reevaluate the model or the data. Several adjustments for changes in the quality of hours of work have been suggested in the past. Jorgenson et al. (1987), Hansen (1993), and Denison (1957) create labor input series by weighting hours by earnings at broad age-sex groups. Although this does adjust hours for quality across age-sex groups, it does not adjust for within group heterogeneity. Kydland and Prescott (1993) attempt to solve this problem by using the Panel Study of Income Dynamics (PSID) to weight hours at the individual level. The unit of time across these proposed series varies from yearly (Jorgenson et al. (1987),Denison (1957),Kydland and Prescott (1993)), to monthly (Hansen (1993)) thus comparing the cyclical behavior across the different series is difficult. The benefit of using the Current Population Survey is that hours can be weighted at the individual level and the resulting labor input series is monthly. The series can be updated tin a timely manner and aggregated to any level for use in further analysis - thus combining the best of all current measures of labor input.

Recent literature commenting on the volatility of key economic series, has come to the consensus that there has been a significant drop in the volatility of these series in the post-war economy, typically citing 1984 as the turing point.[1] These papers focus on aggregate hours instead of compositionally adjusted series for labor input; however, the series proposed in this paper does not lend itself well to studying the post 1984 reduction in volatility since it can only be constructed beginning in 1979.

3.2 Measuring Labor Input

In this section we present a model of labor input and estimate labor input using data from the Current Population Survey Outgoing Rotation Group since January 1979 for private and government workers. The data include information about an individual's usual weekly hours worked in the previous month, hourly earnings, education and other individual characteristics. Details of the data processing can be found in section A.2.

[1]See for example Stock and Watson (2003), Hall (2007), Gal and van Rens (2008) and cites there within.

3.2.1 Model

In order to account for differences in worker's productivity, we start start by modeling worker $i's$ labor input at time t, l_{it}, as:

$$l_{it} = \gamma_i h_{it}. \tag{3.1}$$

where h_{it} is hours worked and γ_i is the worker's individual productivity of an hour. The aggregate labor input at time t is

$$\begin{aligned} L_t &= \sum_i l_{it} \\ &= \sum_i \gamma_i h_{it}. \end{aligned} \tag{3.2}$$

We model aggregate output at time t, Y_t, as a Cobb-Douglas production function with two inputs: labor input, L_t and capital, K_t. The production function is given by:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha} \tag{3.3}$$

where z_t is an aggregate shock at time t and α is capital's share of output. Assuming markets are competitive, worker i's hourly wage is given by his marginal product of output. The natural log of worker i's wage is:

$$\ln w_{it} = \ln \frac{\partial Y_t}{\partial h_{it}} = \ln \left[(1-\alpha) z_t K_t^{\alpha} L_t^{-\alpha} \right] + \ln \gamma_i. \tag{3.4}$$

Notice that the first part of the right hand side of Equation 3.4 is common to all workers and can be interpreted as the aggregate labor market conditions at time t, and the second part of the right hand side of Equation 3.4 is the component of interest.

3.2.2 Empirical Specification

Ultimately, we are after estimating a reduced form version of Equation 3.4 to get an estimate of γ_i. Using the estimate of the worker's individual productivity, $\hat{\gamma}_i$, we can estimate labor input at time t using Equation 3.2. Our reduced form model for a worker's wage is as follows:

$$\ln w_{it} = \ln A_t + \ln \gamma_i + \nu_i \tag{3.5}$$

where A_t are the aggregate labor market conditions at time t and ν_i are individual demographic characteristics. To account for the aggregate labor market conditions we include time fixed effects which we allow to vary at the industry level, δ_{tj}, where j is one of 14 industries specified in section A.2.

We assume that the individual demographic characteristics are observable characteristics of the worker that may affect his wage but not the productivity of an hour of work. Specifically, we assume that ν_i is composed of race, sex and marital status:

$$\nu_i = \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \tag{3.6}$$

where male_i, hisp_i, black_i, and married_i are dummies for if the worker is male, hispanic, black or married. The assumption that these characteristics do not affect the labor input of the worker, and that we will ultimately not weight hours by these characteristics warrants some discussion. Ideally we would like to give more weight to more productive individuals; however, differences in wage reflected by, for example sex, may not reflect differences in productivity of the individual but instead an occupational choice.[2] Consequently, if hours are weighted by sex, then men and women within the same occupation whose labor input may be identical will have different weights. Similarly, we do not weight hours by race since difference in wages across race may be a reflection of discrimination and not differences in labor input. This assumption stands in contrast to earlier work by Hansen (1993) and Jorgenson et al. (1987) who weight hours by demographic

[2] For example, Blau et al. (2013) find that there still exist significant segregation of employment for men and women across occupations and Blau and Kahn (2017) show that about one third of the gender wage gap can be explained by differences in the occupational choices of men and women.

characteristics.

As noted by Kydland and Prescott (1993) however, wages are cyclical and may be a noisy signal of productivity if a worker's wage is only observed once. For example, a college educated worker with 10 years of experience may have a different wage depending on whether he is observed during a boom or a recession. Therefore, weighting hours by raw wages is problematic since wages may be distorted by when a worker is observed. To avoid such distortions, we include time by industry fixed effects into our reduced form specification of the natural-log wage.

We choose the weight to be composed of education, experience and an unobservable component ϕ_i, thus our specification for the parameter of interest, γ_i is:

$$\ln \gamma_i = \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \phi_i \tag{3.7}$$

where $\mathbb{1}\{edu_i = E_k\}$ is an indicator function that takes on the value 1 if a worker's education is in one of 5 categories: high school drop out (HSD), high school graduate (HSG), some college (SMC), college graduate (CLG), and greater than college (GTC) such that $E_j \in \{HSD, HSG, SMC, CLG, GTC\}$. Our final empirical specification of the wage is:

$$\begin{aligned} \ln w_{ijt} &= \delta_{tj} + \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \\ &\quad + \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \varepsilon_{ijt} \end{aligned} \tag{3.8}$$

Using the estimated coefficients from Equation 3.8 the estimate of worker i's weight is:

$$\hat{\gamma}_i = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_i = E_k\} + \hat{\beta}_5 exp_i + \hat{\beta}_6 exp_i^2 + \hat{\beta}_7 exp_i^3 + \hat{\beta}_8 exp_i^4 + \hat{\phi}_i \right). \tag{3.9}$$

The individual component, $\hat{\phi}_i$, is the within industry-time normalized regression residual from Equation 3.8:

$$\hat{\phi}_i = \hat{\varepsilon}_{ijt} - \frac{1}{N_{jt}} \sum_i \hat{\varepsilon}_{ijt} \tag{3.10}$$

where N_{jt} is the number of workers in industry j at time t. The weight is time invariant and workers with identical observable characteristics will have almost identical weights over time. Only the unobservable characteristics differ across observably identical workers and therefore their weight will not be identical. However, more educated workers or workers with more experience will be weighted higher than their less educated or experienced counterparts in every year.

3.3 Findings

The standard measure of aggregate monthly hours calculated from the CPS is:

$$H_t = \sum_i (4.17 * h_{it})(orgwt_{it}). \tag{3.11}$$

where h_{it} are the usual weekly hours reported by person i in year t and $orgwt_{it}$ is the Outgoing Rotation Group weight for person i at time t. Weekly hours are multiplied by 4.17 to get usual monthly hours. Using the estimated weight, Equation 3.9, aggregate monthly labor input is:

$$L_t = \sum_i (4.17 * \hat{\gamma}_i * h_{it})(orgwt_{it}) \tag{3.12}$$

Given the measure of labor input, we can find a summary statistic of the quality of the employed labor force by dividing labor input by aggregate hours. We define this statistic as workforce quality:

$$WQ_t = \frac{L_t}{H_t} \tag{3.13}$$

Workforce quality tracks changes in the average labor input per hour worked. In this section we analyze the sectoral and cyclical behaviors of aggregate hours, labor input, workforce quality as well as labor productivity measured using both aggregate hours (Y_t/H_t) and labor input (Y_t/L_t).

3.3.1 Labor Input

Figure 3.1 plots seasonally adjusted labor input and aggregate hours derived from the CPS as well as the hours series from the Current Employment Statistics (CES) for comparison. As the units of the labor input series is not the same as hours from the CPS or CES, the series are indexed to January 1979. The standard measure of hours from the CPS and hours reported by the Bureau of Labor Statistics in the CES track each other closely. Labor input has a larger trend and diverges from the standard measure of hours.

Figure 3.1: Labor Input and Hours

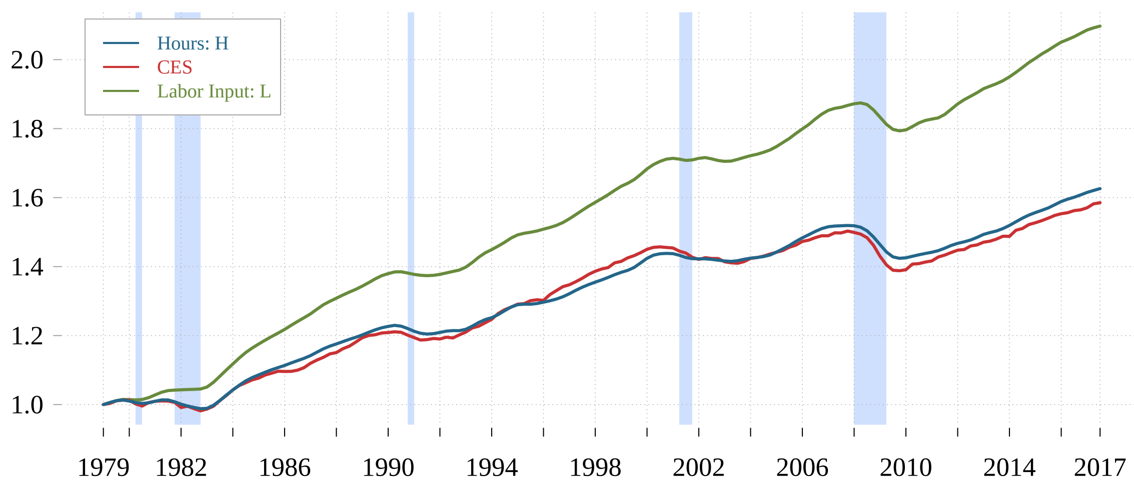


Table 3.1 shows the average yearly growth rate of the labor input and aggregate hours over the entire sample and between each recession. Over all, the yearly growth rate of labor input is 0.5 percentage points higher than that of aggregate hours. The growth rate of both series display similar trends, with high growth rates from the early 1980's until the 2001 recession, after which both growth rates fell by nearly 1 percentage point. After the great recession, both the growth rate of labor input and aggregate hours has increased, although not returned to their pre-2000 levels. The largest difference in growth rate was

Table 3.1: Yearly Growth Rates of Hours and Labor Input

Years	Hours	Labor Input
1980-2016	1.27	1.97
1983-1990	2.66	3.58
1992-2000	1.93	2.38
2002-2007	1.00	1.42
2010-2016	1.51	1.90

Table 3.2: U.S. 1979Q1–2016Q4: Selected Moments

	Standard Deviation	Cross Correlation of Real Gross Domestic Product With								
		x_{t-4}	x_{t-3}	x_{t-2}	x_{t-1}	x_t	x_{t+1}	x_{t+2}	x_{t+3}	x_{t+4}
Real Gross Domestic Product	1.29	0.25	0.46	0.68	0.87	1.00	0.87	0.68	0.46	0.25
Employment	0.99	0.02	0.22	0.43	0.65	0.80	0.88	0.85	0.76	0.62
Aggregate Hours	1.27	0.03	0.22	0.44	0.66	0.82	0.89	0.86	0.76	0.61
Hours Per Worker	0.33	0.04	0.21	0.40	0.59	0.73	0.79	0.75	0.64	0.47
Labor Input	1.13	0.01	0.19	0.40	0.61	0.77	0.85	0.83	0.75	0.62
Labor Input Per Worker	0.31	-0.04	0.01	0.08	0.17	0.26	0.30	0.33	0.32	0.28
Workforce Quality	0.27	-0.10	-0.25	-0.41	-0.54	-0.60	-0.62	-0.55	-0.41	-0.26
GDP/Hour	0.77	0.37	0.40	0.39	0.36	0.31	-0.02	-0.29	-0.49	-0.59
GDP/Labor Input	0.83	0.38	0.45	0.50	0.51	0.49	0.18	-0.09	-0.32	-0.47

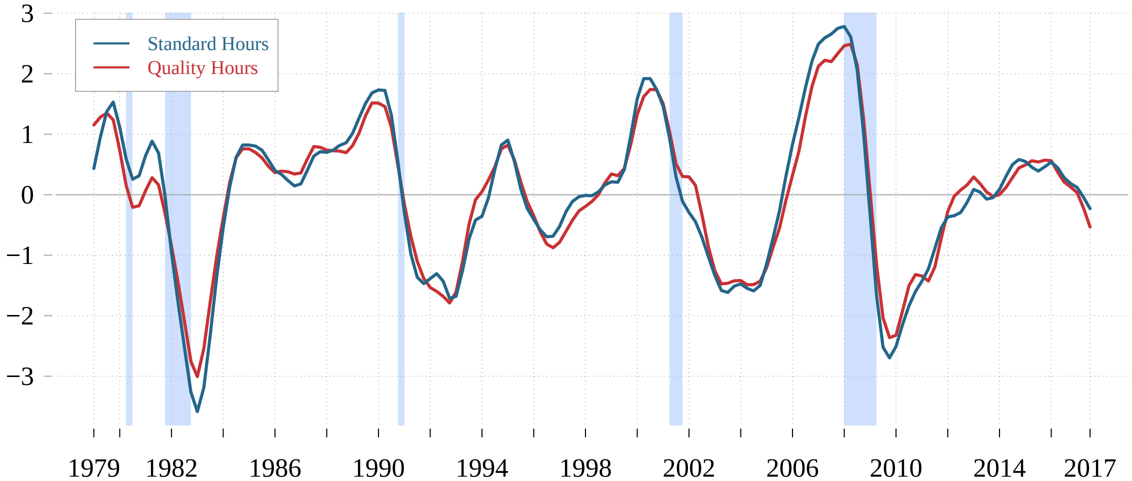
during 1983-1990, when the growth rate of labor input was 0.92 percentage points higher than that of aggregate hours. These differences in growth rates are driven by a rapid increase in the education and experience level of the workforce beginning in the 1980's.

As well as differences in secular trends, labor input and aggregate hours display differences in cyclical behavior. Statistics for comparing the cyclical behavior of the two series are created by logging and detrended the series using the Hodrick and Prescott (1997) filter. Table 3.2 shows the standard deviation and cross correlation of real gross domestic product (GDP) with labor input, aggregate hours and other labor market indicators. Labor input and aggregate hours lag the cycle; however, the contemporaneous correlation and first lag correlation of labor input with real GDP are less than those of aggregate hours. The contemporaneous correlations of aggregate hours and employment with real GDP are 0.82 and 0.80. The contemporaneous correlation of labor input with GDP falls to 0.77. These results are in line with Kydland and Prescott (1993), who find that the contemporaneous correlation of gross national product (GNP) with labor input is 0.75, in contrast to 0.8 for aggregate hours. These findings are contrary to Hansen (1993), who finds that the contemporaneous correlation of labor input with GNP is only slightly lower than that of aggregate hours.

The first column of Table 3.2 shows also that labor input is less volatile than aggregate hours. Figure 3.2 plots the percent deviations from trend of aggregate hours and labor input. The standard deviation of labor input is 1.13 whereas the that of aggregate hours is 1.27, which constitutes an 11% decrease in volatility. This decrease is between those found in Hansen (1993) and Kydland and Prescott (1993), who find a decrease in volatility of 5% and 23%, respectively. However, the volatility of aggregate hours is much higher in previous papers since the data used ends in the mid to late 1980's before the beginning of the great moderation. As mentioned by Hansen (1993) the difference in results about volatility of labor input versus aggregate hours (from those presented here and in Kydland and Prescott (1993)) may be driven by the unit of observation. Here, hours are weighted at the individual level whereas Hansen (1993) weights hours at relatively broad age-sex subgroups. The contrasting results from weights constructed from individual data versus broader groups suggest that the cyclical properties of hours among workers within sex-age groups differ substantially.

Additionally, Table 3.2 contains statistics about hours per worker and labor input per worker. Although the two series have similar standard deviations, their contemporaneous correlations with GDP differ. Hours per worker is highly correlated with GDP, 0.73, whereas labor input per worker has a contemporaneous correlation with GDP of 0.26. These differences may arise from the types of workers laid off during recessions. If, for

Figure 3.2: Percent Deviation from Trend: Hours



example, workers with the lowest labor input are laid off first, labor input per worker would be less positively correlated with GDP over the business cycle.

3.3.2 Workforce Quality

Given the measure of labor input, we derive a summary statistic of the quality of the labor market by dividing labor input by aggregate hours, Equation 3.13. Workforce quality shows changes in the average labor input per hour; Figure 3.3 plots the series. The figure illustrates that the quality of hours worked has risen gradually since 1979. This is consistent with the rise in the average level of experience and education of the labor force over the past 35 years. The figure shows that the quality of the employed workforce has risen about 30% since 1979.

Figure 3.4 plots the percent standard deviations from trend of workforce quality. The figure reveals that the quality of the employed workforce is countercyclical and

Figure 3.3: Quality of the Employed Workforce

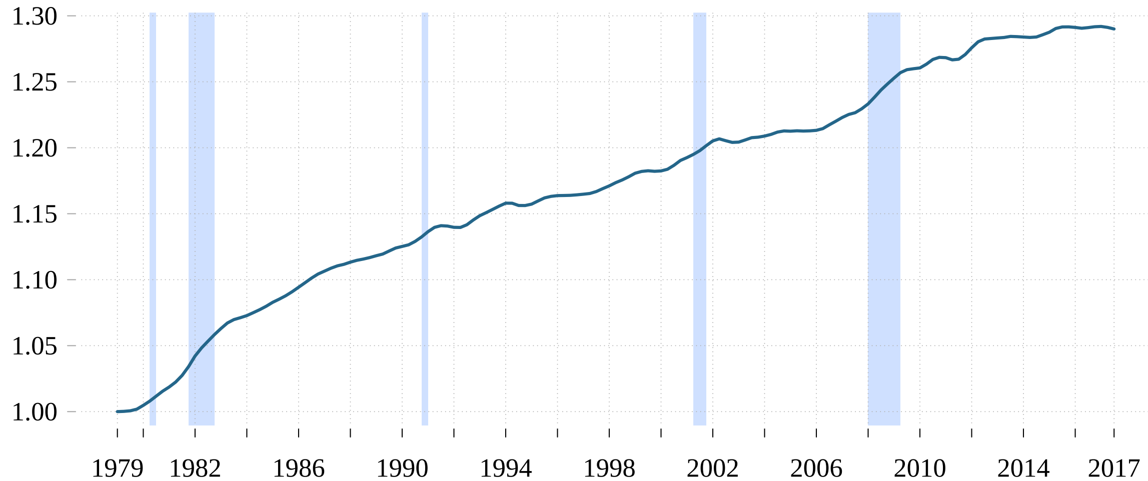
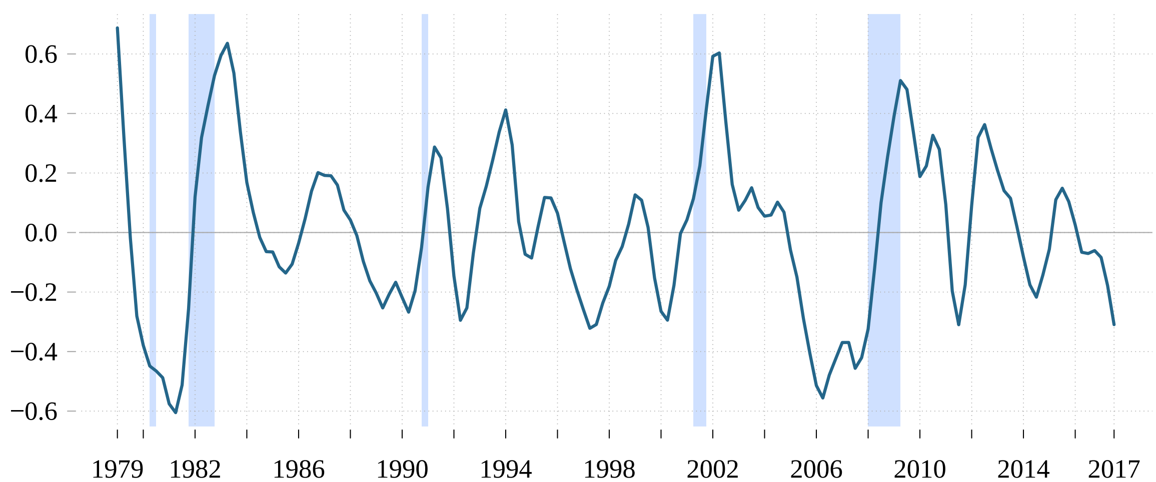


Figure 3.4: Percent Standard Deviations from Trend: Labor Quality

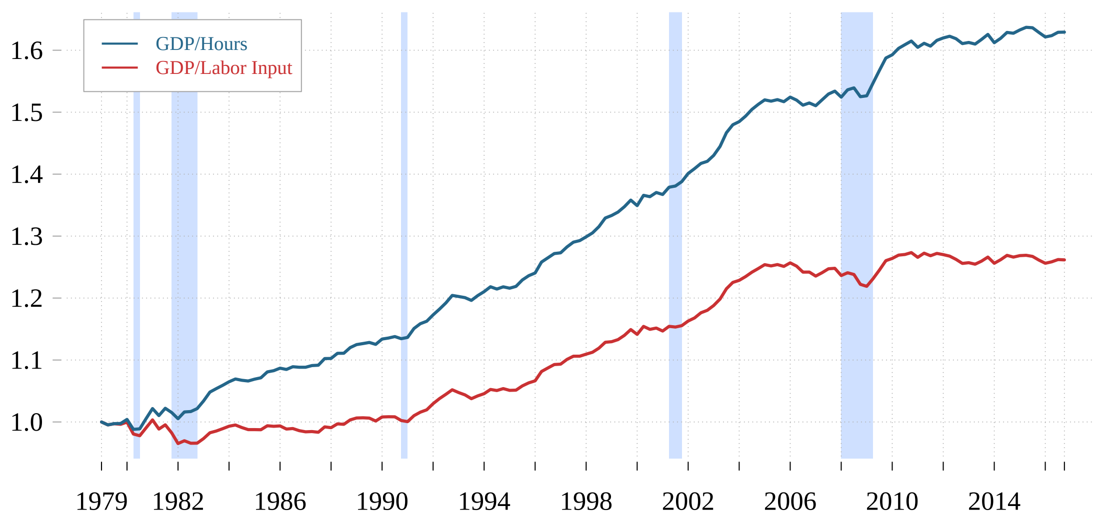


has a slight phase shift in the direction of lagging the cycle. Table 3.2 gives the cross correlations of GDP with workforce quality. The contemporaneous correlation between the quality of the labor force and real GNP is -0.6. The rise of labor quality during recessions suggests that less educated and experienced workers lose their jobs first and the fall during booms suggests they become rehired last. The rise in the quality hours measures during recessions can also be attributed to how workers and firms sort over the business cycle as modeled in Lise and Robin (2017). The counter-cyclical behavior of workforce quality is in line with the large decrease in the contemporaneous correlation of labor input per worker with GDP.

3.3.3 Labor Productivity

Figure 3.5 plots labor productivity using labor input and aggregate hours. Both series are indexed to January 1979. It is well known that the growth of labor productivity, measured as GDP per aggregate hours, has fallen since the mid 2000's, see Byrne et al. (2016) for example. But as Figure 3.5 demonstrates, labor productivity measured using labor input has grown even substantially more slowly. In fact, GDP per labor input was nearly flat between 1980-1990 and 2004-2016. Table 3.3 gives the annualized growth rate of quarterly labor productivity for both measures. Over the entire sample GDP per hour grew at an annualized rate of 1.32 percent whereas GDP per labor input grew at an annualized rate of 0.63 percent per year. Furthermore, Table 3.3 shows the average annualized growth rates for 3 different time periods. First, from 1979 to 1989 the average annual growth rate of GDP per hour was 1.14%, and the average annual growth rate of GDP per labor input was 0.05%. This implies that the majority of productivity growth from 1979 to 1989 came from increases in education and experience of the workforce. Second, the average annual growth rate from 1990 to 2003 was nearly 2% for GDP per hour and 1.47% for GDP per labor input. Although the average education and experience of the workforce continued to increase over this period, a substantial part of the increase in labor productivity is attributed to other factors. Lastly, when looking at the most recent time period, 2004 to 2016, the average annual growth rate of both measures has decreased. The annual growth rate of GDP per hour has fallen by 62%, from 2% to 0.75% and the annual growth rate of GDP per labor input has fallen by 85% from 1.47% to 0.22%. Again, the low growth rate of GDP per labor input implies that increases in education and experience of the workforce account for about 70% of the growth in productivity since 2004.

Figure 3.5: Labor Productivity



We argue that both GDP per hour and GDP per labor input are important measures for assessing economic growth. Since GDP per hour includes all factors that make workers more productive, it gives a general sense of how productive the workforce is, and growth in GDP per hour is what ultimately leads to economic growth. On the other hand, if one is interested in what may be driving an increase in productivity, GDP per hour alone falls short. GDP per labor input is constructed such that hours of workers with the same years of eduction and experience are weighted the same across time. Therefore, changes

Table 3.3: Annualized Growth Rate of Quarterly Labor Productivity

Years	GDP/Hours	GDP/Labor Input
1979-2016	1.32	0.63
1979-1989	1.14	0.05
1990-2003	1.99	1.47
2004-2016	0.75	0.22

in GDP per labor input can be attributed to factors other than changes in experience and education. Together, GDP per hour and GDP per labor input can give some insights into what factors are driving increases in labor productivity.

Table 3.2 shows the cyclical behavior of GDP per hour and GDP per labor input. Both series lead the cycle, however GDP per labor input has a higher contemporaneous correlation with GDP, 0.49, than GDP per hour, 0.31. This stands in contrast to Gal and van Rens (2008) who argue that the pro-cyclicality of labor productivity with output has decreases substantially post-1984. Similarly the standard deviation the cyclical component of GDP per labor input, 0.83, is higher than that of GDP per hour, 0.77.

3.3.4 Total Factor Productivity

Given the Cobb-Douglas structure in aggregate production, Equation 3.3, and our measure of labor input, we can calculate total factor productivity (TFP), z_t, as the Solow residual. We measure the capital stock and capital's share of output, α, as described in Gomme and Rupert (2007). The average annual capital share of output since 1979 is $\alpha = 0.312$ and the measurement of the real capital stock from 1979 is plotted in Figure A.1 in section A.2.

Figure 3.6 shows the normalized total factor productivity since 1979 calculated using both aggregate hours and labor input. The result is similar to labor productivity. Table 3.4 shows that the average annual growth rate of TFP since 1979 is 0.63 when measured using aggregate hours and 0.16 when measured using labor input.

Figure 3.6: Total Factor Productivity

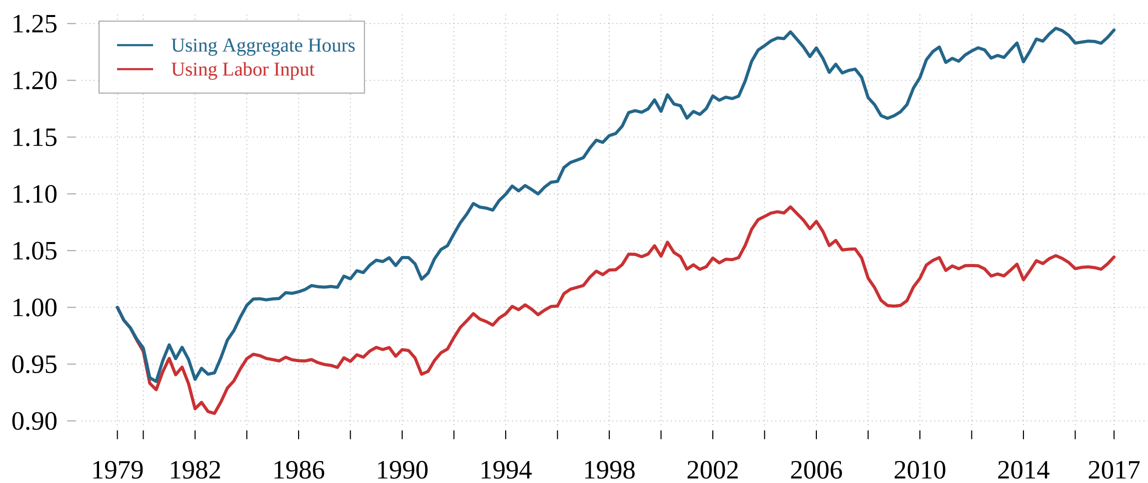


Table 3.4: Yearly Growth Rate of Total Factor Productivity

	Measured Using	
Years	Hours	Labor Input
1979-2016	0.63	0.16
1979-1989	0.56	-0.22
1990-2003	1.07	0.71
2004-2016	0.21	-0.14

Since our measure of labor input is slightly less volatile than aggregate hours over the business cycle, TFP must capture more of the volatility in output. To see the extent to which TFP volatility increases when using labor input instead of aggregate hours, we run the following AR(1) process on the estimated Solow residuals:

$$\ln z_t = \rho_1 + \rho_2 \ln z_{t-1} + \rho_3 t + \epsilon_t \tag{3.14}$$

using both the residuals when using labor input and aggregate hours.

Table 3.5 shows the estimated coefficients from Equation 3.14 using the residuals from labor input and aggregate hours. Since labor input is less cyclical, the variance of the error terms is slightly lower. However, the estimate is still in line with what authors have used in the literature to calibrate models. The autocorrelation term of the residual also drops when using labor input, but this drop is not statistically significant. In total, including labor input into the production function instead of aggregate hours has a large and significant effect on measured growth of productivity. The effects on the cyclical component of output, however, are almost unchanged.

Table 3.5: Solow Residual Regressions

	Measured Using	
Years	Hours	Labor Input
Lag	0.964 (0.022)	0.946 (0.022)
Constant	-0.388 (0.241)	-0.599 (0.256)
Time ($\times 10^{-3}$)	0.006 (0.005)	0.005 (0.002)
SD(ϵ_t)	0.0072	0.0073

3.4 Alternative Measures

For completeness, in this section we compare our measure of labor input to commonly used quantity indices. We use our method of weighting hours at the individual level and compute the Laspeyres, Paasche and Fisher quantity indices.

3.4.1 Laspeyres Quantity Index

Our measure of labor input is most closely related to the Laspeyres quantity index. Diewert (1976) suggests the following calculation as the the Laspeyres quantity index:

$$S_t^Q = \frac{\sum_i q_{it} p_{i0}}{\sum_i q_{i0} p_{i0}} \tag{3.15}$$

where q_{it} and p_{it} are the quantity and price of good i at time t. Note that the Laspeyres quantity index requires only information on prices at time 0 but quantities in all time periods. Relating back to our measure of Labor Input, quantities q_{it} are equivalent to hours worked by individual i at time t, h_{it}.

Our measure differs slightly from the Laspeyres quantity index in its measure of prices, p_{i0}. While the Laspeyres quantity index uses period-0 prices to weight quantities, our measure of labor input uses a measure of the average relative price of individuals over the entire sample, $\hat{\gamma}_i$. For comparison we calculate the standard Laspeyres quantity index as follows:

$$S_t^Q = \frac{\sum_g \hat{\gamma}_{g0} h_{gt}}{\sum_j \hat{\gamma}_{g0} h_{g0}} \tag{3.16}$$

where $t = 0$ is January of 1979. Since we do not observe the same individual over the entire sample, g indexes education-experience groups where education can fall into one of the five categories defined above and experience is binned into single year categories. The estimated price for each group $\hat{\gamma}_{g0}$ as before,

$$\hat{\gamma}_{g0} = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_{g0} = E_k\} + \hat{\beta}_5 exp_{g0} + \hat{\beta}_6 exp_{g0}^2 + \hat{\beta}_7 exp_{g0}^3 + \hat{\beta}_8 exp_{g0}^4\right) \tag{3.17}$$

where the coefficients on education and experience are estimated from wages using only observations from January 1979, i.e. $t = 0$. The regression on wages is as follows:

$$\ln w_{ij0} = \delta_j + \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \\ + \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \varepsilon_{ij} \quad (3.18)$$

where δ_j are industry fixed effects. The main difference between the estimated prices $\hat{\gamma}_{g0}$ from Equation 3.17 and prices used in our measure of labor input, $\hat{\gamma}_i$ from Equation 3.9, is the inclusion of the regression residual ϕ_i which makes our labor input price vary at the individual level instead of the group level.

3.4.2 Paasche Quantity Index

Diewert (1976) suggests the following calculation as the Paasche quantity index:

$$P_t^Q = \frac{\sum_i q_{it} p_{it}}{\sum_i q_{i0} p_{it}} \quad (3.19)$$

where q_{it} and p_{it} are the quantity and price of good i at time t. The Paasche quantity index requires information about both prices and quantities in every time period. We estimate prices in every period by regressing log wages on education, experience, demographics and an industry fixed effect as in Equation 3.18. This gives an estimate on education and experience for every month since January 1979. Figure 3.7 shows the yearly average of the education coefficients over time. The figure indicates that most of the increase in the return to education occurred in the 1980's with college graduates earning about 80% more than high school dropouts and workers with more than sixteen years of education earning almost double that of high school dropouts since the mid 1990's. We use these coefficients, along with those on experience, to calculate an estimated price $\hat{\gamma}_{gt}$ for each education-experience group, g, for each time period, t as follows:

$$\hat{\gamma}_{gt} = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_{gt} = E_k\} + \hat{\beta}_5 exp_{gt} + \hat{\beta}_6 exp_{gt}^2 + \hat{\beta}_7 exp_{gt}^3 + \hat{\beta}_8 exp_{gt}^4 \right) \quad (3.20)$$

We calculate the Paasche quantity index as:

$$P_t^Q = \frac{\sum_g \hat{\gamma}_{gt} h_{gt}}{\sum_g \hat{\gamma}_{gt} h_{g0}} \tag{3.21}$$

where h_{gt} are the aggregate hours of group g at time t.

Figure 3.7: Education Coefficients

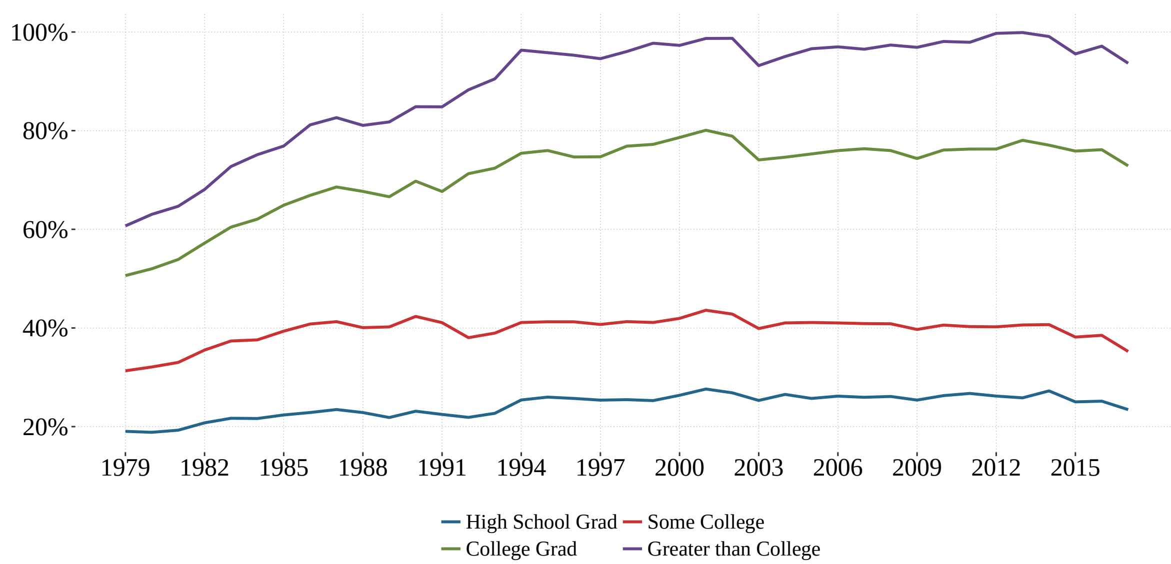
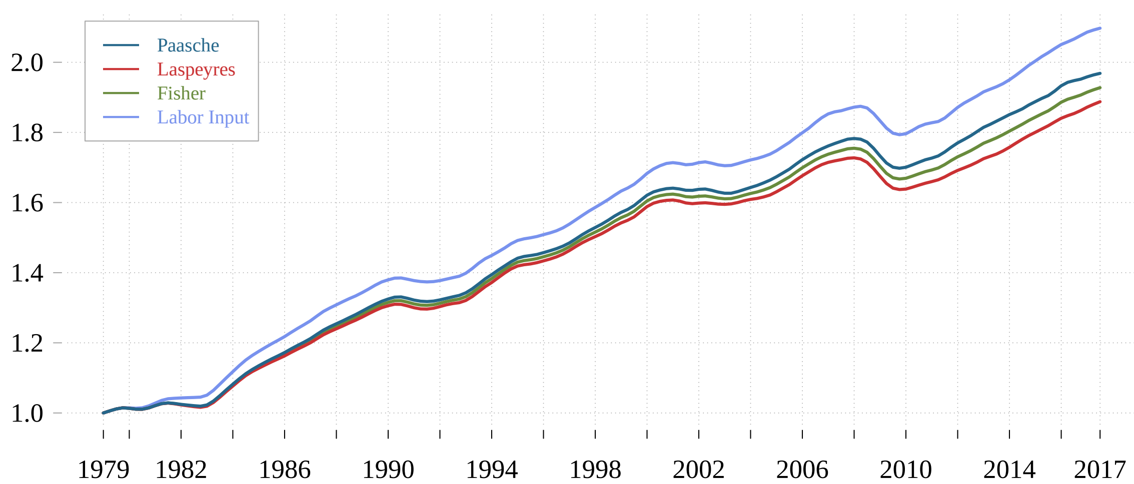


Figure 3.8 plots the seasonally adjusted Paasche and Laspeyres quantity indices along with our measure of labor input and the Fisher quantity index defined as the geometric mean of the Paasche and Laspeyres indices:

$$F_t^Q = \sqrt{P_t \times S_t}. \tag{3.22}$$

All four series follow a similar pattern, having increased between 90 to 110 percent since 1979. Our measure of labor input has grown more than the alternative measures because the individual weight used in our measure includes the regression residual. It is well known that residual wage inequality has increased in the U.S. since the 1980's therefore, by weighting at the individual level, i.e. including the regression residual, accounts for the within education-experience group heterogeneity leading to a higher level of labor input.[3]

Figure 3.8: Indicies



3.4.3 Chain-Weighted Indices

We construct the the chain weighted Paasche quantity and Laspeyres quantity index as follows:

$$CS_t^Q = \frac{\sum_g \hat{\gamma}_{g0} h_{g1}}{\sum_j \hat{\gamma}_{g0} h_{g0}} \times \frac{\sum_g \hat{\gamma}_{g1} h_{g2}}{\sum_j \hat{\gamma}_{g1} h_{g1}} \times \cdots \times \frac{\sum_g \hat{\gamma}_{gt-1} h_{gt}}{\sum_j \hat{\gamma}_{gt-1} h_{gt-1}} \tag{3.23}$$

$$CP_t^Q = \frac{\sum_g \hat{\gamma}_{g1} h_{g1}}{\sum_g \hat{\gamma}_{g1} h_{g0}} \times \frac{\sum_g \hat{\gamma}_{g2} h_{g2}}{\sum_g \hat{\gamma}_{g2} h_{g1}} \times \cdots \times \frac{\sum_g \hat{\gamma}_{gt} h_{gt}}{\sum_g \hat{\gamma}_{gt} h_{gt-1}} \tag{3.24}$$

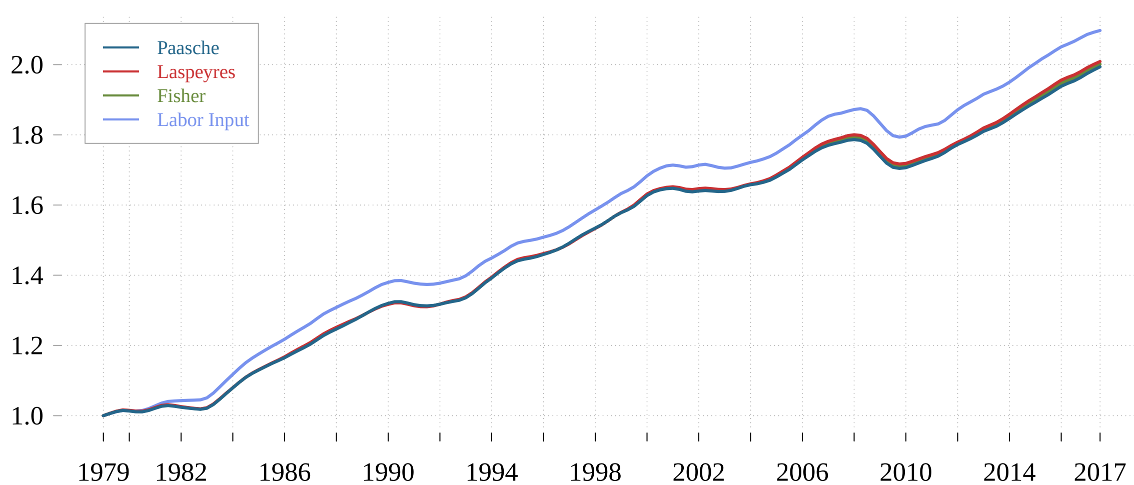
[3] See for example Autor et al. (2008) or Lemieux (2006)

where $\hat{\gamma}_{gt}$ are calculated as in Equation 3.20 and h_{gt} are the aggregate hours of education-experience group g at time t. The chain weighted Fisher quantity index is:

$$CF_t^Q = \sqrt{CS_t^Q \times CP_t^Q}. \tag{3.25}$$

Figure 3.9 plots the seasonally adjusted Paasche, Laspeyres, and Fisher quantity index as well as our measure of labor input. Again the series show similar growth, increasing between 100 and 110% since 1979, in contrast to standard aggregate hours, that increased only 60% since 1979.

Figure 3.9: Chain Weighted Indices



3.5 Conclusion

We construct an aggregate labor input series since 1979 using the Current Population Survey. We model each individual's contribution to labor input as their hours worked times an individual weight. We use a Mincer-type regression of wages on education, experience, demographics and industry to estimate the average education and experience premium over the sample. Using the estimated education and experience premiums as well as the regression residual we construct the individualized weights. The series for labor input presented in this paper is a considerable improvement over past series: it is constructed from data on individuals at a monthly frequency and updated easily with the newest release of the CPS.

We show that labor input is less volatile over the business cycle and has a lower contemporaneous correlation with Gross Domestic Product (GDP) than aggregate hours. These results stem from the fact that workforce quality is countercyclical, i.e. less educated and less experienced workers leave employment first during recessions. We show that workforce quality, or the average labor input per hour of work, has increased by 30% since 1979. We calculate labor productivity as GDP per labor input and show that the average annual growth rate of labor productivity has decreased by 85% since 2004 in contrast to 62% when using GDP per hour as a measure of labor productivity. Comparing labor productivity measured using GDP per labor input and GDP per hour reveals that the increase in education and experience accounts for about 70% of growth in labor productivity since 2004, whereas increases in education and experience account for only 26% of growth in labor productivity between 1990 and 2003.

Appendix A

Supplementary Materials

A.1 Crime and the Minimum Wage

A.1.1 Proofs

Proposition 2.1 *If $a \geq a^*$ then $\phi_e(a, \lambda) = 0$ for all $\lambda \geq \lambda^R(a)$. Where $\lambda^R(a)$ is the workers reservation job productivity defined as $V_e(\lambda^R(a), a) = V_u(a)$.*

Proof. If $a \geq a^*$ then $V_u(a) > V_u(a)^*$, thus $\phi_u(a) = 0$. From (1.3) this implies $g + \pi V_p(a) \leq \pi V_u(a)$. The definition of $\lambda^R(a)$ implies that $g + \pi V_p(a) \leq \pi V_e(\lambda^R(a), a)$. Since (1.6) is strictly increasing in λ it must be the case that $g + \pi V_p(a) \leq \pi V_e(\lambda, a)$ for all $\lambda \geq \lambda^R(a)$. Thus from (1.4), $\phi_e(a, \lambda) = 0$ for all $\lambda \geq \lambda^R(a)$. □

Proposition 2.2 *If $(r + \delta)/\mu_e \pi \leq (1 - \beta)/\beta$ then,*

a. If $\phi_u(a) = 0$ then for all $\lambda \geq \lambda^R(a)$ the worker accepts the job and $\phi_e(a, w(a, \lambda)) = 0$.

b. If $\phi_u(a) = 1$ then for all $\lambda^R(a) \leq \lambda \leq \lambda^{D1}(a)$ the worker accepts the job and $\phi_e(a, w(a, \lambda)) = 1$.

c. *If* $\phi_u(a) = 1$ *then for all* $\lambda \geq \lambda^{D1}(a)$ *the worker accepts the job and* $\phi_e(a, w(a, \lambda)) = 0$.

Proof.

a. If $\phi_u(a) = 0$ then $V_u(a) \geq V_u(a)^*$, therefore the wage offered to the worker is

$$w(a, \lambda) = \beta a\lambda + (1 - \beta)w_R(a).$$

If $\lambda > \lambda^R(a) = w_R(a)/a$ then $w(a, \lambda) > \beta a\lambda^R(a) + (1 - \beta)w_R(a) = w_R(a)$ since $w(a, \lambda)$ is increasing in λ. Then $V_e(w(a, \lambda), a) > V_u(a)$ since $V_e(w, a)$ is increasing in w. Therefore the worker accepts the job. By Proposition 1, the worker forges crime opportunities while employed, i.e. $\phi_e(a, w(a, \lambda)) = 0$.

b. If $\phi_u(a) = 1$ then $V_u(a) < V_u(a)^*$ and the wage function is given by Equation 1.25. If $\lambda^R(a) < \lambda < w_C(a)/a$ then the wage is given by:

$$w(a, \lambda) = \beta a\lambda + (1 - \beta)w_R(a)$$

Since $w(a, \lambda)$ is increasing in λ,

$$\beta a\lambda^R(a) + (1 - \beta)w_R(a) < w(a, \lambda) < \beta w_C(a) + (1 - \beta)w_R(a)$$

Plugging in for $\lambda^R(a) = w_R(a)/a$ and simplifying:

$$w_R(a) < w(a, \lambda) < \beta w_C(a) + (1 - \beta)w_R(a)$$

Since $w_R(a) < w_C(a)$ we get

$$w_R(a) < w(a, \lambda) < w_C(a)$$

If $w_C(a)/a < \lambda < \lambda^{D1}(a)$ then wage is

$$w(\lambda, a) = \frac{\beta(r + \delta + \mu_e\pi)[a\lambda - (\chi L + rV_u(a))]}{r + \delta} + w_R(a).$$

Pluggin in $w_C(a)/a$,

$$\begin{aligned} w(w_C(a)/a, a) &= \frac{\beta(r+\delta+\mu_e\pi)[w_C(a) - (\chi L + rV_u(a))]}{r+\delta} + w_R(a) \\ &= \frac{\beta(r+\delta+\mu_e\pi)r[V_u(a)^* - V_u(a)]}{(r+\gamma)} + w_R(a) \\ &> w_R(a) \end{aligned}$$

since $V_u(a) < V_u(a)^*$. Plugging in Equation 1.24 for $\lambda^{D1}(a)$,

$$w(\lambda^{D1}(a), a) = \frac{\beta(r+\delta+\mu_e\pi)w_C(a) + \mu_e\pi w_R(a)}{\mu_e\pi + \beta(r+\delta+\mu_e\pi)} - \frac{\mu_e\pi r(V_u(a)^* - V_u(a))}{[\mu_e\pi + \beta(r+\delta+\mu_e\pi)](r+\delta)(r+\gamma)} \tag{A.1}$$

Now assume for contradiction that the right hand side of Equation A.1 is greater than the crime reservation wage, $w_C(a)$, then after some algebra we get:

$$-(r+\delta)(r+\gamma)\mu_e\left[g + \pi\left(\frac{z - rV_u(a)}{(r+\gamma)}\right)\right] - r((r+\delta)^2 + \mu_e\pi)(V_u(a)^* - V_u(a)) > 0$$

Since the worker commits crimes while unemployed, $V_u(a) < V_u(a)^*$ and $\mu_e\left[g + \pi\left(\frac{z-rV_u(a)}{(r+\gamma)}\right)\right] > 0$, therefore we get a contradiction. So it must be the case that $w(\lambda^{D1}(a), a) < w_C(a)$. Since the wage is larger than the reservation wage the worker accepts the job and since the wage is less than the crime reservation wage, the worker commits crimes on the job when given the opportunity, i.e. $\phi_e(a, w(a, \lambda)) = 1$.

c. If $\phi_u(a) = 1$ then $V_u(a) < V_u(a)^*$ and the wage function is given by Equation 1.25. If $\lambda > \lambda^{D1}(a)$ then there are two possible wage equations. First if $\lambda^{D1}(a) < \lambda < \lambda^{D2}(a)$ then the wage is equal to the crime reservation wage, $w_C(a)$. In this case the worker accepts the jobs since $w_R(a) < w_C(a)$ and forges crime opportunities since his wage is equal to the crime reservation wage. Second if $\lambda > \lambda^{D2}(a)$ the his wage is given by

$$w(a, \lambda) = \beta a\lambda + (1-\beta)w_C(a)$$

Since $w(a,\lambda)$ is increasing in λ:

$$w(a,\lambda) > \beta a\lambda^{D2}(a) + (1-\beta)w_C(a)$$

Plugging in for $\lambda^{D2}(a)$ given by Equation 1.13 and simplifying:

$$w(a,\lambda) > \frac{\beta(r+\delta)[w_C(a)-w_R(a)]}{\mu_e\pi} + w_C(a)$$

Since $w_R(a) < w_C(a)$ it must be the case that $w(a,\lambda) > w_C(a)$. So the worker accepts the job and forges crime opportunities while employed, i.e. $\phi(a, w(a,\lambda)) = 0$.

□

A.1.2 Steady State Distributions

Equating the flows from Figure 1.4 gives the following steady state distributions:

$$u(a) = \begin{cases} \dfrac{\delta\gamma(\mu_e\pi+\delta)}{\Omega(a)} & \text{if } a < a^* \\ \dfrac{\delta}{\mu_j B(a)+\delta} & \text{if } b \geq b^* \end{cases} \tag{A.2}$$

$$e_{nc}(a) = \begin{cases} \dfrac{\mu_j A(a)\gamma(\mu_e\pi+\delta)}{\Omega(a)} & \text{if } a < a^* \\ \dfrac{\mu_j B(a)}{\mu_j B(a)+\delta} & \text{if } a \geq a^* \end{cases} \tag{A.3}$$

$$e_c(a) = \begin{cases} \dfrac{\delta\gamma\mu_j D(a)}{\Omega(a)} & \text{if } a < a^* \\ 0 & \text{if } a \geq a^* \end{cases} \tag{A.4}$$

$$p(a) = \begin{cases} \dfrac{\delta\pi[\mu_u(\mu_e\pi+\delta)+\mu_e\mu_j D(a)]}{\Omega(a)} & \text{if } a < a^* \\ 0 & \text{if } a \geq a^* \end{cases} \tag{A.5}$$

where $\Omega(a) = (\mu_e\pi+\delta)[\delta(\mu_u\pi+\gamma)+\gamma\mu_j A(a)] + \delta\mu_j D(a)(\mu_u\pi+\gamma)$.

A.1.3 Welfare

The average values $\bar{V}_i$ for $i \in \{uc, unc, ec, enc, p\}$ are defined as:

$$\bar{V}_{uc} = \int^{a^*} V_(a) \frac{dF(a)}{F(a^*)} \tag{A.6}$$

$$\bar{V}_{unc} = \int_{a^*} V_u(a) \frac{dF(a)}{1 - F(a^*)} \tag{A.7}$$

$$\bar{V}_p = \int^{a^*} V_p(a) \frac{dF(a)}{F(a^*)} \tag{A.8}$$

$$\bar{V}_{ec} = \int^{a^*} E_\lambda \big[V_e(a, \lambda) | \phi_e(a, \lambda = 1) \big] \frac{dF(a)}{F(a^*)} \tag{A.9}$$

$$\bar{V}_{enc} = \int^{a^*} E_\lambda \big[V_e(a, \lambda) | \phi_e(a, \lambda = 0) \big] dF(a) + \int_{a^*} E_\lambda \big[V_e(a, \lambda) \Big] dF(a) \tag{A.10}$$

A.1.4 Data

National Longitudinal Survey of Youth 1997

The sample is restricted to individuals who are between the ages of 16 and 19 in 1998. Employment status in the NLSY97 is reported in weekly arrays; employment status consists of an employer ID if employed and one of several categories, including unemployed, if not associated with an employer. First employment status is recoded to equal 1 if associated with an employer in a given week and 0 if unemployed, all other categories are coded as NA's. Weekly employment status is aggregated to a monthly status by taking the mean employment status over the month. Labor force participation status for 1998 is calculated as the sum of months that an individual is either working or unemployed. Individuals with labor force participations of less than 6 months are dropped from the sample.

Individuals report usual weekly hours and an hourly wage for up to nine jobs worked between interview periods. Usual weekly hours from only the first job are used to calculate the average weekly hours worked in the sample. Average hourly wage for each individual is calculated as the weighted average of hourly wages reported for each job; the weights are the fraction of hours worked at each job. Individuals with an average hourly wage less than the minimum wage in 1998, $5.15, are dropped from the sample.

At each interview, individuals are asked if they have committed a crime since their last interview; specifically, they are asked if they have stolen something worth more than $50 or have committed any other property crime such fencing, receiving, possessing or selling stolen property, and if so, how many times. The responses to the frequency of crime are top coded at 99. Nine top coded individuals are dropped from the sample, corresponding to about 0.1% of the sample. The aggregate yearly crime rate for the sample is constructed as the sum of all times individuals stole more the $50 and committed other property crimes divided by the number of individuals in the final sample (2,356). The monthly crime rate is the yearly crime rate divided by 12.

The job finding rate is calculated as the average number of transitions from unemployment to employment, without exiting the labor force in any two consecutive months over all individuals over the 12 months in 1998. Similarly the job destruction rate is calculated as the average number of transitions from employment to unemployment in any two consecutive months over all individuals and months in 1998.

During round 1, individuals participated in the administration of the computer-adaptive form of the Armed Services Vocational Aptitude Battery (CAT-ASVAB) which measures the respondents ability in 12 categories: arithmetic reasoning, electronics information, numerical operations, assembling objects, general science paragraph comprehension, auto information, mathematics knowledge, shop information, coding speed, mechanical comprehension, and word knowledge. An aggregated measure of ability is constructed for each individual as the sum of their scores in the arithmetic reasoning, paragraph comprehension and word knowledge categories. Sampling weights are used in all calculations.

Uniform Crime Reports

The county level data from the Uniform Crime Reports come from the National Archive of Criminal Justice Data[1]. The data include counts of arrests and offenses of Part I offenses (murder, rape, robbery, assault, burglary, larceny, auto theft, and arson) and Part II offenses (forgery, fraud, embezzlement, vandalism, weapons violations, sex offenses, drug and alcohol abuse violations, gambling, vagrancy, curfew violations, and runaways) at the county level. The crime rate for each county is calculated as the number of offenses for each category in each county divided by the population of each county divided by $100,000$. The property crime rate in each county is calculated as the sum of all burglaries, larcenies and motor vehicle thefts divided by the population, divided by $100,000$.

County Demographics and Minimum to Median Wage Ratios

The county level demographic data come from the Survey of Epidemiology and End Results (SEER) that provides estimates of the total population, and estimates of the population by 19 age groups, sex and 3 race groups - white, black and other. The age groups are aggregate to 6 groups: 0 to 14, 15 to 24, 25 to 39, 40 to 59, 60 to 79 and 80 plus. Data on the poverty rate and average household income of each county come from

[1] U.S. Dept. of Justice, Federal Bureau of Investigation. UNIFORM CRIME REPORTING PROGRAM DATA [UNITED STATES]: COUNTY-LEVEL DETAILED ARREST AND OFFENSE DATA, 1995-2014. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor].

the Census' Small Area Income and Poverty Estimates.

The minimum to median wage ratios are calculated at the state level using data from the Current Populations Outgoing Rotation Groups from 1995 to 2014. The data come from the National Bureau of Economic Research[2]. The sample is restricted to individuals between the ages of 16 and 19. The hourly wages are calculated as reported hourly wage for hourly wage workers and weekly wages divided by usual hours worked per week for individuals who report not working as hourly wage workers. The binding minimum wage in each state in each year is calculated as the maximum of the state and federal minimum wage.

A.1.5 Simulations

Panel Data Set

This data set is constructed by simulating data for 1,000 "individuals" at each unique realization of the real binding minimum wage. The real binding minimum wage is the maximum of the state and federal minimum wage in 1998 dollars; from 1990 to 2011 there were 204 unique levels of the real binding minimum wage across states in the US. An individual in this simulation consists of a single draw from the estimated ability distribution, $F(\hat{\mu}_a, \hat{\sigma}_a)$.

For each of the 204 minimum wages, the probability of unemployment, employment and prison for each worker is calculated. To simulate the workers expected wage, 50 realizations from the estimated productivity distribution, $G(\hat{\mu}_\lambda, \hat{\sigma}_\lambda)$, are drawn. For each realization the wage is calculated and the expected wage for each individual at each minimum wage is calculated as the mean wage across realizations of job productivities. This process produces the final data set which includes an expected wage and unemployment

[2] http://www.nber.org/cps/

probability for each of the 1,000 individuals at each unique minimum wage.

Aggregate Data Set

The aggregate data set consists of observations of the average unemployment probability and average expected wage of all individuals in the economy. The aggregate economy consists of 1,000 individuals and is simulated at every observed real binding minimum wage from 1990 to 2011; there were 1,122 observed real binding minimum wages, 50 states and Washington D.C. times 22 years. For each minimum wage, 1,000 individuals are drawn from the estimated ability distribution, $F(\hat{\mu}_\lambda, \hat{\sigma}_\lambda)$. For each individual, the probability of unemployment and expected wage are calculated. The expected wage for each individual is calculated as the average wage resulting from 100 draws from the estimated job productivity distribution. The aggregate unemployment probability and aggregate expected wage is calculated as the weighed average across individuals; the weights are the estimated probability of observing each type of individual, $f(a|\hat{\mu}_\lambda, \hat{\sigma}_\lambda)$.

A.1.6 Robustness

As a robustness check for the result of the U-shaped relationship between the minimum to median wage ratio on the crime rate, Table A.1 gives the estimated coefficients from Equation 1.46 without the lagged dependent variable. The results are consistent with those found when including the lagged dependent variable in both the OLS and IV specifications.

The lagged dependent variable is included in the main specifications to control for county level time varying unobservables. As a robustness check for the dependence of controlling for county level time varying unobservables I re-estimate Equation 1.46 and replace the lagged dependent variable with four different time trends: (1) aggregate linear

Table A.1: Non-Parametric Specification without Lagged Dependent Variable

	(1) Property Crimes	(2) Burglary	(3) Larceny	(4) Motor Vehicle Theft	(5) Robbery
Quintile of Min-to-Median Ratio					
2nd.	-15.83	7.659	8.089	-10.47***	0.474
	(11.15)	(3.927)	(7.286)	(1.536)	(0.487)
3rd.	-127.3***	-8.751*	-19.17*	-17.66***	-2.438***
	(13.60)	(3.833)	(9.454)	(1.897)	(0.518)
4rd.	-177.2***	14.00***	-10.24	-28.85***	-2.163***
	(16.19)	(4.203)	(11.19)	(2.045)	(0.586)
5th.	-116.0***	24.37***	12.68	-24.16***	-0.441
	(15.62)	(4.211)	(11.01)	(2.029)	(0.538)
N	54,780	54,780	54,780	54,780	54,780

Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income and poverty levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

time trend, (2) aggregate quadratic time trend, (3) state level linear time trends, (4) state level quadratic time trends. Table A.2 shows that the U-shaped relationship between the minimum to median wage ratio and the crime rate is robust to the inclusion of more aggregated trends.

As a final robustness check, I specify a parametric relationship between the minimum to median wage ratio and the crime rate:

$$\text{crime}_{ct} = \beta_1 + \beta_2 MM_{st} + \beta_3 MM_{st}^2 + \beta_3 X_{ct} + \beta_4 \text{crime}_{ct-1} + \gamma_c + \varepsilon_{ct} \qquad \text{(A.11)}$$

Specifying a quadratic relationship between the minimum to median wage ratio and the

Table A.2: Inclusion of Time Trends

	(1) Property Crimes	(2) Property Crimes	(3) Property Crimes	(4) Property Crimes
Quintile of Min-to-Median Ratio				
2nd.	-27.27*	-20.75	-37.38***	-21.88*
	(11.11)	(11.00)	(10.98)	(10.31)
3rd.	-116.9***	-106.1***	-131.5***	-86.64***
	(13.54)	(13.08)	(13.16)	(11.90)
4th.	-133.6***	-119.8***	-168.2***	-116.6***
	(15.33)	(14.27)	(13.83)	(12.15)
5th.	-96.97***	-86.95***	-114.0***	-74.12***
	(15.33)	(14.42)	(14.32)	(12.93)
Linear Time Trend	✓			
Quadratic Time Trend		✓		
State Level Linear Time Trend			✓	
State Level Quadratic Time Trend				✓
N	54,780	54,780	54,780	54,780

Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income and poverty levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

crime rate is more restrictive on the data than the non parametric relationship in the main specifications since it can only deliver one of three outcomes - no relationship, a linear relationship or a quadratic relationship - whereas the nonparametric specification can deliver any result. Table A.3 gives the estimates on the linear and squared term of the minimum to median wage ratio. The table shows a U-shaped relationship between the minimum to median wage ratio and the burglary, motor vehicle and robbery crime rates since the squared term is positive and significant. The squared term on the total property crime rate is significant at the 15% level. Table A.4 gives the estimated coefficients when not including a lagged dependent variable. The table shows a U-shaped relationship for all crime categories except the larceny crime rate.

Table A.3: Robustness Check: Parametric Specification with Lagged Dependent Variable

	(1) Property Crimes	(2) Burglary	(3) Larceny	(4) Motor Vehicle Theft	(5) Robbery
MM	-1442.0*	-1447.1***	-552.4	-327.5***	-97.67***
	(635.7)	(198.7)	(422.5)	(83.00)	(26.73)
MM^2	541.5	904.8***	319.9	152.9**	55.52***
	(376.0)	(118.4)	(249.7)	(48.55)	(15.76)
N	51,418	51,418	51,418	51,418	51,418

Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income, poverty levels and a lagged dependent variable. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Robustness Check: Parametric Specification without Lagged Dependent Variable

	(1) Property Crimes	(2) Burglary	(3) Larceny	(4) Motor Vehicle Theft	(5) Robbery
MM	-4658.2***	-1420.3***	-1168.6	-702.1***	-94.17**
	(974.2)	(279.1)	(680.6)	(141.1)	(35.56)
MM^2	2372.8***	898.3***	703.5	345.4***	53.38*
	(572.1)	(167.1)	(399.6)	(82.06)	(21.15)
N	54,780	54,780	54,780	54,780	54,780

Standard errors clustered at the county level. All specifications include demographic controls, county fixed effects, household income and poverty levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Quality Hours: Measuring Labor Input

A.2.1 Sample Selection and Data Cleaning

We use the Merged Outgoing Rotation Group files from the National Bureau of Economic Research (NBER).[3] We restrict the sample to private and government workers wage 16 or older. We construct a consistent education variable using the method described in Jaeger (1997) and compute experience as the maximum of zero and age minus education minus six.

We use the weekly wage variable provided by the NBER, *earnwke*, which includes overtime, tips and commissions. The variable is constructed from the census variable *a-werntp* from 1979 to 1993, *prernwa* from 1994 to 1997, and *pternwa* from 1998 onward.

[3] http://www.nber.org/cps/

All top coded values are multiplied by 1.3. We use the usual hours worked variable provided by the NBER, *uhourse*, which is constructed from the census variable *a-uslhrs* from 1979 to 1993 and *peernhro* from 1994 onward. Between 1998 and 2002 there exist 823 observations which have a positive value for usual weekly hours and missing weekly earnings. For these observations we impute the weekly wage. In each year we regress log weekly earnings on a quartic in experience, dummy variables for the education groups, high school dropout, high school graduate, some college, college graduate, and greater than college, and dummy variables for sex, martial status, race, and state. For each year we replace the missing weekly earnings variable with the predicted weekly wage. We construct real hourly wages by dividing weekly earnings by usual hours per week and deflate using the Chain-type Personal Consumption Expenditures Price Index to deflate wages. We replace zeros with 0.01 and log real hourly wages.

We use the industry wage variable *dind* from 1979 to 2002 and *dind02* provided by the NBER for a consistent industry classification. We then construct 14 broad industries: agriculture and mining, construction, utilities, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, finance and real estate, professional and business services, education and health services, arts and entertainment, and government.

A.2.2 Removing Jumps in Series

Due to the 1994 redesign of the CPS, all aggregate hours and labor input series have a discontinuous jump up from December 1993 to January 1994. To remove this jump we first find the average change in each series from December to January for all year expect 1993-1994. We then multiply the first part of each series (January 1979 through December 1993) by a constant such that the change from December 1993 to January

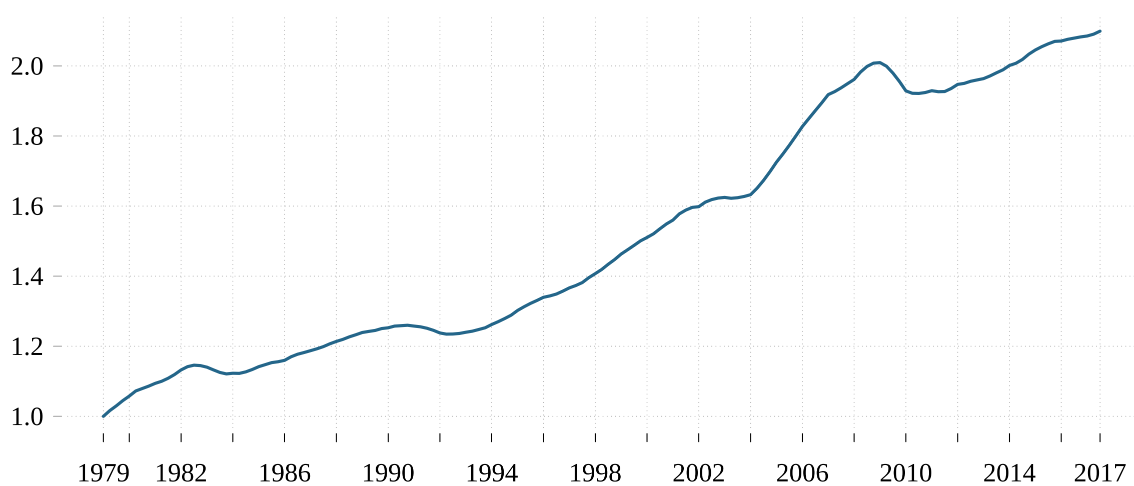
1994 is equal to the average December-January jump of all other years. We implement this procedure on unfiltered, not seasonally adjusted data.

A.2.3 Seasonal Adjustment and HP Filtering

To seasonally adjust the aggregated series created from the CPS by decomposing the series into a trend, seasonal, and irregular component. The irregular component corrects sampling error.[4] Next we aggregate the seasonally adjusted series to a quarterly frequency and filter it into a trend and business cycle component using the Hodrick-Prescott filter with smoothing component $\lambda = 1600$.

A.2.4 Capital Stock

Figure A.1: Real Capital Stock



[4]See Tiller and Natale (2005) for details about including an irregular component into the decomposition. See Cleveland et al. (1990) for details about the decomposition.

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