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Abstract

This paper presents a model of occupational choice in a labor market characterized by moral hazard. The model demonstrates that in such a labor market, workers' occupational choices are determined by not only their comparative advantage but also their effort decisions in each occupation. The estimation results, based on data from the National Longitudinal Survey of Youth, suggest that workers' self-selection into white collar and blue collar occupations leads to higher wages and lower dismissal rates in both occupations. Furthermore, analysis results reveal that these effects of self-selection diminish as the labor market becomes increasingly characterized by moral hazard.

1 Introduction

A common finding among studies of involuntary job loss is that blue collar workers experience substantially higher dismissal rates than white collar workers. Displaced Worker Surveys data show that production workers consistently had higher involuntary job loss rates than any other occupational category between 1981 and 1995. The job loss rate for craft workers, operatives and laborers in the 1993-1995 period was 13.5 percent, while the job loss rate for professionals was 7.8 percent and 5.9 percent for managers (Farber, 1997). Data from the National Longitudinal Survey of Youth also indicate that blue collar workers are on average twice as likely to be dismissed over the first 11 years of their job tenure as white collar workers (Figure 1).

In this paper, I investigate the extent to which self-selection of workers into occupations in the presence of moral hazard can generate the occupational differences in dismissal rates that are observed in the data. I present a two-sector model of self-selection, in which each sector is characterized by imperfect monitoring on the part of firms and incentives to shirk on the part of workers. Dismissals in this model occur when workers are caught to be shirking during the firm's random monitoring of workers. Workers, endowed with two-dimensional ability bundles, choose occupations based on their comparative advantage, wages and monitoring intensity in each occupation. The pattern of self-selection causes the distribution of worker abilities in an occupation to differ from the population distribution. As a result, occupational self-selection leads to systematic differences in average productivity, shirking propensity and consequently dismissal rates across occupations.

The model of occupational choice presented in this paper draws key elements from Roy's model of self-selection (1951). Roy's model rests on the intuition that tasks in different occupations require different types of skills. Therefore, when making occupational choices, workers consider their relative skill levels, their comparative advantages, in different occupations. The model has been applied to explain various labor market issues, including sectoral choice and wage distribution (Heckman and Sedlacek, 1985), wage inequality (Gould, 2002), and patterns of schooling, employment and occupational choice (Keane and Wolpin, 1997). However, studies investigating the impact of occupational self-selection on observed patterns of labor turnover are few.

The main papers that model the relationship between occupational choice and turnover behavior are those by Miller (1984), McCall (1990) and Neal (1999). Although these studies focus on and explain differ-

ent aspects of labor mobility, all three formulate the turnover behavior within a search-matching framework. More recently, Moscarini has shown the implications of comparative advantage in a frictional search model (2001). As in any model based on the job search-matching tradition, in these studies, turnover is driven by the uncertainty regarding the match productivity; therefore, quits and dismissals are behaviorally equivalent.

The main contribution of this paper is to analyze the implications of occupational sorting on dismissal rates across occupations when dismissals are caused by poor performance or malfeasance. This study shows that when the labor market is characterized by moral hazard, selection into occupations is driven not only by workers' comparative advantage but also by the underlying differences in their effort decisions in each occupation. While comparative advantage plays an important role in the occupational choice decisions of workers who do not shirk, workers who shirk on the job take into consideration the monitoring intensities in the two occupations.

The sources of occupational self-selection in this model can be traced back to the dual roles played by the occupation-specific worker abilities, which determine both disutility of effort and propensity to shirk in this model. First, conditional on not shirking, a worker's occupation-specific ability determines the disutility that the worker receives from exerting effort in a given occupation. Workers with high ability in an occupation complete the required tasks with minimal effort, thus they receive relatively low disutility from working in that occupation. On the other hand, low-ability workers have to exert relatively more effort to complete the tasks and thus receive higher disutility from working in a given occupation. Second, the occupation-specific worker ability affects the probability that a worker shirks in a given occupation. High-ability workers tend to have a lower propensity to shirk because the disutility that they receive from exerting effort and completing the tasks in an occupation is relatively low. In contrast, workers with low ability are more likely to shirk since they have a greater incentive to avoid the large disutility that would result if they exert effort and complete the required tasks.

Because of its dual role as determinant of disutility of effort and as a factor in propensity to shirk, workers' skill endowments affect their selection into occupations in two distinct ways. First, among non-shirkers, occupational choice is determined to a large extent by the relative disutility associated with employment in the two occupations, and thus on the worker's relative abilities in the two occupations. What derives the sorting in this case, is workers' comparative advantage; therefore, the intuition behind this type of self-selection is similar to that depicted in other comparative advantage self-selection models[1]. Second, a worker's effort

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[1]See Sattinger (1993) for a discussion of comparative advantage and its role in occupational choice.

decision plays an important role in his occupational choice decision because it determines which factors are taken into account by the worker in his occupational decision. For instance, for a worker who exerts effort in both occupations, his relative disutility of effort in the two occupations plays an important role in his occupational decision. In contrast, disutility of effort does not enter a shirker's decision-making process since he exerts no effort and thus receives no disutility from it. Instead, a shirker considers how closely he will be monitored in each occupation in order to assess his probability of dismissal. Therefore, workers' occupational sorting depends in part on the sequence of work/shirk decisions that they will make in the two occupations and consequently on their relative abilities in these occupations. Through its impact on the worker's effort decisions, the worker's skill bundle determines the relative importance of disutility of effort, firm's monitoring intensity and wages in worker's occupational decision.

I extend a shirking model developed by Flinn to describe the moral hazard problem and the resulting dismissals in the two sectors of the economy (1997). The model shares key components with the Shapiro-Stiglitz model and many of its extensions (Shapiro and Stiglitz, 1984). However, it also has two properties that are not simultaneously present in most standard Shapiro-Stiglitz type shirking models. First, the model generates an equilibrium in which shirking exists. This property is crucial in studying the impact of shirking propensity on workers' self-selection pattern because it generates variation in shirking probability among workers[2]. Second, the shirking model used in this paper is a dynamic model; therefore, it allows one to compare the pattern of wages, dismissal rates and average productivity in each occupation over time. By nesting a shirking model in a general self-selection framework, the model presented in this paper allows one to study the relationship between a worker's occupational decision and his effort decision. More specifically, it allows one to determine the relative importance of comparative advantage and information problems in determining workers' selection of occupations.

I estimate the structural parameters of the model using data from the National Longitudinal Survey of Youth. The estimation results suggest that self-selection of workers increases expected worker productivity in both blue collar and white collar occupations as average worker ability in each occupation is estimated to be above the population mean. Consequently, workers' selection into occupations leads to higher wages and lower dismissal rates in both occupations compared to an economy in which workers are randomly assigned to each occupation. The monitoring rate in the white collar occupation is estimated to be higher than the

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[2]Albrecht and Vroman (1998) extend the Shapiro-Stiglitz model by adding worker heterogeneity and consequently generate an equilibrium in which some workers shirk. However, their model does not include a dynamic process.

monitoring rate in the blue collar occupation, suggesting that white collar workers are monitored more closely than blue collar workers. Findings also indicate that the difference between the rates of dismissal for cause between the two occupations is driven by the higher expected productivity in the white collar sector. Higher wages and higher monitoring rate in the white collar occupation seem to provide stronger incentives to exert effort than those in the blue collar occupation, causing the white collar workforce to have a smaller proportion of shirkers than the blue collar workforce.

In addition, the estimation results suggest that there is only a small degree of positive selection into the white collar occupation as workers with high ability in the white collar occupation have a slightly higher probability of choosing that occupation. There is evidence of a more substantial degree of selection into the blue collar occupation although the selection is mixed as workers at both ends of the ability distribution tend to choose the white collar occupation. The analysis results also show that if the occupational sorting took place in a labor market without a moral hazard problem, workers in both occupations would predominantly come from the higher ability end of the population distribution. A comparison of the post-selection marginal distributions that result under moral hazard with those that come about in the no moral hazard case suggests that the existence of moral hazard mitigates the degree of positive selection into both occupations. This difference can be explained by the behavior of low ability workers who tend to be the potential shirkers when there is moral hazard in the labor market. When compared to the case without moral hazard, workers in the moral hazard case have a higher probability of choosing an occupation in which they have low ability since they now have the option of shirking and avoiding the disutility of effort.

Finally, I present results of comparative statics exercises, which investigate the effects of a higher monitoring rate and a higher output price on labor market outcomes. Results reveal that a higher monitoring rate in the blue collar occupation leads to higher wages and lower dismissal rates in the blue collar occupation and lower wages and higher dismissal rates in the white collar occupation. While an increase in the blue collar monitoring rate decreases the propensity to shirk in the blue collar occupation, it makes the white collar occupation relatively more attractive to those workers, who have low ability and are potential shirkers in both occupations. On the other hand, a higher white collar output price leads to higher wages and lower dismissal rates in both occupations. These findings illustrate how a change in the parameters of a given occupation may have positive or adverse effects on the labor market outcomes in the other occupation depending on its impact on the workers' selection pattern.

This paper is organized as follows: The next section discusses alternative approaches to modeling dis-

missals in the literature, Section 3 presents the model and results of representative simulations, Section 4 describes the estimation methodology, and Section 5 discusses identification issues. Sections 6 and 7 present the description of the dataset and the discussion of the results, respectively, and Section 8 includes concluding remarks.

2   Alternative Approaches to Occupational Differences in Dismissal Rates

National Longitudinal Survey of Youth data indicate that the rate of dismissals differs substantially between white collar and blue collar occupations. Figure 1 shows involuntary separation rates by occupation against the number of years in occupation[3]. These statistics indicate that blue collar workers are on average more than twice as likely to experience a firm-initiated separation as white collar workers during the first 11 years in occupation.

Models of labor turnover provide different explanations for the variation in dismissal rates across occupations, based on differing interpretations of dismissals. The job matching model, which is frequently used to explain labor turnover behavior, argues that there exists uncertainty regarding the value of a worker-firm match (Jovanovic, 1979). Both the worker and the firm learn about the match value through worker's output over his tenure, and matches whose values are revealed to be low end in worker-firm separations. The life-cycle implication of this model is that young workers are more likely to change jobs since typically they have not had enough time in the labor market to find a good match (Topel and Ward, 1992). As a result, occupations that are predominantly occupied by young workers will exhibit high rates of worker-firm separations. Miller extends the job matching model to incorporate differences in the level of matching uncertainty between occupations (1984). According to his model, occupations with higher levels of uncertainty regarding the match value exhibit higher turnover rates as workers in these occupations learn about their match value fairly quickly and move on to other jobs in case of bad matches.

Matching-search models can also be used in conjunction with the human capital theory to explain the observed differences in dismissal rates between occupations. According to the human capital model, job-specific human capital accumulation increases the value of the worker-firm match relative to the outside alternatives. Therefore, occupations with more opportunities for on-the-job training or a higher rate of learning-by-doing exhibit lower rates of separations.

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[3]Involuntary separations are those that are involuntary to the worker and include both firings and lay-offs.

Although the matching-search framework is successful in explaining several regularities observed in labor turnover behavior, it implies that worker-initiated and firm-initiated separations are behaviorally equivalent. Empirical evidence suggests that there may be underlying differences between the two types of separations. For example, previous research has shown that workers who experience an involuntary separation earn lower wages on their next job following the separation than workers who report a voluntary from their previous jobs (Bartel and Borjas, 1981; Gibbons and Katz, 1991).

Another approach to explaining dismissals is to treat them as an outcome of labor demand fluctuations, which are in turn caused by shocks to preferences or technology. To the extent that different sectors of the economy experience different labor demand fluctuations and that the prevalence of occupational groups varies across sectors, involuntary separations due to firms' operating decisions will cause dismissal rates to differ between occupations. Even when all sectors of the economy are equally affected by fluctuations in labor demand, different occupations may still experience higher rates of dismissals due to the heterogeneity in the population. For instance, if dismissal rates depend on certain socioeconomic characteristics, then the socioeconomic make-up of the workforce in an occupation would determine the rate of dismissals in that occupation. Idiosyncratic shifts in labor demand, however, fail to explain certain features of the dismissal data. The finding that most turnover takes place within sectors instead of between sectors and the result that the conditional probability of being dismissed decreases over one's tenure in the job or in the occupation cannot be explained solely by this framework. Furthermore, Jovanovic and Moffitt present empirical evidence that demand shifts do not explain the majority of the labor turnover in the labor market (1990).

This paper presents a third approach to explaining the dismissal rate differences between occupations. According to this approach, involuntary separations are dependent on workers' effort decisions. Firms dismiss workers due to poor performance on the job or malfeasance. In this case, differences in dismissal rates across occupations arise when (1) workers in different occupations display intrinsically different performance and effort levels and/or (2) the intensity with which workers are monitored varies across occupations. If we abstract from firms' monitoring rate decisions, then the pressing question is why workers exhibit different effort levels and consequently different levels of productivity across occupations.

In this paper, I demonstrate that workers' self-selection into occupations can lead to differences in average worker productivity between occupations, which in turn bring about differences in dismissal rates. Using a structural model of occupational choice and moral hazard in the labor market, I investigate the extent to which occupational self-selection explains why white collar workers have a lower probability of

dismissal than blue collar workers. I also test whether the model's implications for the wage profiles of workers in different occupations are consistent with the patterns observed in the data.

The structural model presented in this paper has advantages over more reduced form approaches. The primary advantage is that it allows one to examine the direct and indirect roles played by the model's structural parameters in bringing about equilibrium wages, average worker productivity and dismissals. Furthermore, through comparative static exercises, one can study how the existence of moral hazard affects workers' selection into occupations and also assess the implications of changes to the structural parameters, such as the monitoring rate and the output price. The identification of these parameters requires assumptions that are detailed later in the paper.

Before discussing the specifics of the model, one should note its focus and its boundaries. First, the model presented here explains dismissals that are due to workers' lack of effort. Therefore, the model abstracts from other factors that influence dismissals, such as poor worker-firm matches and exogenous shocks to labor demand. Second, this model involves a single source of wage growth, which is the systematic dismissal of unproductive workers from the firm. Demiralp (2007) incorporates other sources of wage growth, particularly the human capital accumulation. By focusing primarily on the implications of occupational self-selection and moral hazard, this paper is aimed to investigate the extent to which the equilibrium wage and dismissal dynamics that are generated by occupational selection with moral hazard are consistent with the patterns observed in the data.

3 The Model

3.1 The Set-up

The labor market consists of a primary and a secondary sector, both of which are made up of perfectly competitive firms. The primary sector is characterized by the moral hazard problem. This problem stems from the assumption that primary sector firms cannot perfectly observe their workers' effort levels, possibly due to the lack of an employee-specific output measure, which is necessary for observing effort through output. The utility flow to a worker in each period is given by $w_t - e_t$, where w_t is the wage that he receives and e_t is the amount of effort that he exerts in period t. Due to the disutility of effort, workers have an incentive to shirk. I assume that firms randomly monitor their workers in an attempt to detect shirking in their workforce. The punishment for shirking is dismissal from the firm.

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The primary sector, in turn, consists of two subsectors, denoted by j and k where $j, k = 1, 2$ and $j \neq k$. Firms in primary sector j have monitoring rate π_j, and output price ρ_j, both of which are taken as exogenous. The monitoring rate is a measure of the intensity with which firms provide supervision of employees. It means that a worker in firm j faces a constant probability, π_j, of being monitored by the firm. Differences in monitoring rates reflect differences in monitoring technologies and monitoring costs across firms. Workers who are detected to be shirking and are therefore dismissed, find jobs in the secondary sector of the labor market.

In the secondary sector, firms perfectly observe effort via employee-specific output; therefore, there is no moral hazard. Since firms are competitive, the secondary sector wage equals the output price. Furthermore, the amount of effort needed to produce one unit of output in this sector equals the output price, so the utility flow for each worker is zero. The secondary sector consists of two types of firms. Workers who are dismissed from primary sector firm j find employment in the secondary sector firm j and earn wage given by w_j^s. The secondary sector is an absorbing state; workers in this sector cannot be rehired in the primary sector[4]. As I will show below, workers in the primary sector receive a positive utility flow in each period; thus, workers voluntarily start their labor market careers in the primary sector.

The two types of primary sector firms, firm j and firm k, require their workers to perform a unique task. Each worker is endowed with two productive inefficiency indices, ξ_j and ξ_k, which determine the amount of effort needed to complete the firm-specific task in firms j and k, respectively. Workers are heterogeneous with respect to their productive inefficiency indices. In particular, ξ_j and ξ_k are distributed according to a bivariate population distribution, denoted by the cdf $H(\xi_j, \xi_k)$, and the corresponding marginal distributions are given by $H_j(\xi_j)$ and $H_k(\xi_k)$. The marginal distribution of $\log \xi_j$ has mean, μ_j, and standard deviation, α_j, and the covariance of $\log \xi_j$ and $\log \xi_k$ is α_{jk}. Furthermore, workers know their own endowments of productive inefficiency indices in the beginning of the labor market careers.

The production function for a worker of type ξ_j in the primary sector firm j in period t is

$$y_j(e_t; \xi_j) = \left\{ \begin{array}{l} 1 \text{ iff } e_t \geq \xi_j \\ 0 \text{ otherwise} \end{array} \right\} \tag{1}$$

---

[4]This condition has two parts. First, workers who are detected and dismissed in primary sector firm j cannot be rehired by firm j. This condition is an outcome and not an assumption of the model. This result is explained in Flinn (1997). I add the assumption that workers who are dismissed in primary sector firm 1 cannot be hired by primary sector 2. Combined with the above-mentioned result, this assumption yields that secondary sector is an absorbing state.

where e_t is the amount of effort exerted in period t. Therefore, a worker's productive inefficiency index, ξ_j, can be interpreted as the minimum amount of effort that the worker has to exert in order to produce one unit of output. Since workers receive disutility from putting forth effort, they either exert the minimum effort possible to produce output (i.e. ξ_j) or they exert no effort at all and shirk[5]. Finally, workers have infinite horizon, and they discount the future by a factor, β.

The structure of the model carries several assumptions. First, the monitoring rate is exogenous. Therefore, firms are assumed to have already made decisions on monitoring rates before workers choose their occupations, and they cannot change their monitoring decisions in the duration covered by this model[6]. Second, workers are assumed to perfectly observe their productive inefficiency indices in each firm, eliminating the case in which workers learn about their productive inefficiencies. Finally, I assume that workers who are dismissed from firm primary sector firm j cannot be hired by primary sector firm k. Due to this assumption, the model abstracts from the inter-occupational mobility of workers after dismissal.

The following subsections discuss the worker's decision, the primary sector firm's decision, and the equilibrium of the model, respectively. In subsection 3.5, I discuss in more detail the implications of the model regarding self-selection properties and present results of representative simulations.

3.2 Worker's Decision

Workers in this model make two types of decisions: 1) at the beginning of their labor market careers, they decide for which primary sector firm to work, 2) in each period of their employment in the primary sector, they decide whether to work or shirk. I first explain the work/shirk decision of the worker conditional on his employment in firm j. Then, I discuss worker's decision regarding the type of primary sector firm for which to work.

Consider worker i in firm j. As explained above, a worker will either choose to exert effort in the amount of his productive inefficiency index, ξ_{ij}, or no effort. Therefore, his work/shirk decision in each period is based on the following maximization problem. The value of employment in firm j in period t by worker i is

$$V_{ijt}(\xi_{ij}) = \max\left\{w_{jt} - \xi_{ij} + \beta V_{ij,t+1}(\xi_{ij}); w_{jt} + \beta(1 - \pi_j)V_{ij,t+1}(\xi_{ij})\right\} \tag{2}$$

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[5]The production function can be equivalently interpreted as stochastic in the following way:

$$y_j(e_t;\xi_j) = \left\{ \begin{array}{l} 1 \text{ with probability } 1 \text{ if } e_t \geq \xi_j \\ 1 \text{ with probability } 1 - \pi_j \text{ if } e_t < \xi_j \\ 0 \text{ with probability } \pi_j \text{ if } e_t < \xi_j \end{array} \right\}$$

[6]The monitoring rate could be endogenous if firms adjust their monitoring rates in response to workers' productivity.

where the first argument is the value of working, and the second argument is the value of shirking. This function reflects the assumption that worker's utility flow in the secondary sector is zero.

If we assume that the wage sequence is monotonically increasing over time, a worker of type ξ_{ij} will

$$\text{work if } \xi_{ij} \leq \xi_{jt} \tag{3}$$

$$\text{shirk otherwise}$$

where the threshold level of productive inefficiency in firm j in period t, ξ_{jt}, equals

$$\xi_{jt} = \frac{\beta \pi_j (1 - \beta)}{1 - \beta + \beta \pi_j} \left(\sum_{s=t+1}^{\infty} \beta^{s-t+1} w_{js} \right)$$

Furthermore, in the beginning of his labor market history, the worker makes a one-time decision about which firm to work for based on his likelihood of dismissal and the wages offered by different firms. Given Equation 3, Equation 2 can be expressed as

$$V_{ijt} = I(\xi_{ij} < \xi_{jt}) \cdot (w_{jt} - \xi_{ij} + \beta V_{i,j,t+1}) + I(\xi_{ij} \geq \xi_{jt}) \cdot (w_{jt} + \beta(1 - \pi_j) V_{i,j,t+1}) \tag{4}$$

Worker i chooses the firm that maximizes his value of employment in the beginning of period 1, $(V_{ijt=1})$. Therefore, worker i chooses firm j iff $V_{i,j,t=1} > V_{i,k,t=1}$. This condition can equally be expressed in terms of the worker's productive inefficiency as follows: Worker chooses firm j iff

$$\xi_{i,j} < \xi_j^*(\xi_{ik}; \{w_j\}_{t=1}^{\infty}, \{w_k\}_{t=1}^{\infty}, \pi_j, \pi_k) \tag{5}$$

ξ_j^* is a function of worker's productive inefficiency in firm k, ξ_{ik}, therefore, the marginal distribution of ξ_j in period 1 among workers who choose firm j is given by

$$f_{j,t=1}(\xi_j) = \int_0^{\infty} \frac{h_j(\xi_j)}{H_j(\xi^*(\xi_k))} dH_k(\xi_k) \tag{6}$$

The marginal distribution of ξ_j in firm j changes over time in a systematic way as a constant proportion of shirking workers are detected and dismissed in each period. In particular, if we consider a cohort of workers who start to work in firm j at the same time, the marginal distribution of workers remaining in the

cohort changes over time with the mass point of the distribution moving toward lower levels of productive inefficiency. The cdf of worker types remaining in the cohort at the end of period t in firm j can be expressed in terms of the cdf of worker types in firm j in period one. When the sequence of the ξ_{jt} is increasing, the relationship between $F_{jt}(\xi_{jt})$ and $F_{j,t=1}(\xi_j)$ is given by the following equation (Flinn, 1997).

$$F_{jt}(\xi_{jt}) = 1 - \left(1 - F_{j,t=1}(\xi_{jt})\right) A_{jt}\left(\{\xi_{js}\}_{s=1}^{t-1}\right)$$

where

$$A_{jt}\left(\{\xi_{js}\}_{s=1}^{t-1}\right) = \left\{1 + \frac{\pi_j}{(1-\pi_j)^{t-1}}F_{j,t=1}(\xi_{j,t=1}) + \cdots + \frac{\pi_j}{1-\pi_j}F_{j,t=1}(\xi_{j,t-1})\right\}^{-1}$$

3.3 Firm's Decision

In this subsection, I will continue to consider the labor market experiences of a cohort of workers, who enter the firm at the same time. The firm cannot observe the productive inefficiency index of each worker in the cohort, so it cannot observe whether each worker is working or shirking. However, the firm observes the marginal distribution of productive inefficiencies within the cohort, $f_{jt}(\xi_j)$, the threshold level of productive inefficiency in each period, ξ_{jt}, and thus the expected productivity in a cohort, given by $F_{jt}(\xi_{jt})$.

Due to the zero profit condition, the firm pays cohort members the value of the expected productivity in the cohort. Therefore, the wage that firm j offers to the members of a cohort in period t of their employment is given by Equation 7[7].

$$w_{jt} = \rho_j F_{jt}(\xi_{jt}) \tag{7}$$

As a result, everyone in the cohort earns the same wage although they make different effort decisions based on their productive inefficiency indices.

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[7]The wage contracts described in this paper are individual wage contracts. Wage contracts that depend on group output are not considered.

3.4 Equilibrium

The Nash equilibrium wage sequence is defined as the fixed point of the following operator:

$$
T(\{w_{jt}\}) = \begin{bmatrix} \rho_j F_{j,t=1}(\xi_{j,t=1}) \\ \rho_j F_{j,t=2}(\xi_{j,t=2}) \\ \vdots \\ \rho_j F_{j,t=\tau}(\xi_{j,t=\tau}) \\ \vdots \end{bmatrix} \tag{8}
$$

where ξ_{jt} is given by Equation 3. The fixed point of $T(\{w_{jt}\})$ gives the equilibrium wage sequence in firm j *conditional* on $F_{j,t=1}$, which is the post-selection marginal distribution of ξ_j in firm j. Let ν_j and ω_j be the parameters that characterize $F_{j,t=1}$. The parameters of $F_{j,t=1}$ and $F_{k,t=1}$, are in turn fixed points of the operator given in Equation 9, which completes the characterization of the equilibrium in this model.

$$
\begin{bmatrix} F_{j,t=1}(\nu_j, \omega_j) \\ F_{k,t=1}(\nu_k, \omega_k) \end{bmatrix} = \begin{bmatrix} \int_0^\infty \frac{h_j(\xi_j)}{H_j(\xi^*(w_1(F_{j,t=1}(\nu_j,\omega_j)), w_2(F_{k,t=1}(\nu_k,\omega_k))))} dH_k(\xi_k) \\ \int_0^\infty \frac{h_k(\xi_k)}{H_k(\xi^*(w_1(F_{j,t=1}(\nu_j,\omega_j)), w_2(F_{k,t=1}(\nu_k,\omega_k))))} dH_j(\xi_j) \end{bmatrix} \tag{9}
$$

Every iteration in solving the fixed point problem in Equation 8 involves the computation of the equilibrium wage sequence; therefore, the algorithm to compute the fixed points of $T(\{w_{jt}\})$ is nested within the fixed point algorithm to compute the parameters of $F_{j,t=1}(\xi_j)$ and $F_{k,t=1}(\xi_k)$.

This equilibrium has several important features. First, the equilibrium wage sequence in firm j depends not only on the output price, worker distribution and monitoring rate in firm j, but also on the wages and parameters in firm k. Intuitively, this result captures the fact that when workers select firm types, they take into account the wages and monitoring rates in both types of firms. Therefore, the marginal distribution of workers in a given firm depends on the wages and monitoring rates observed in the entire primary sector.

The second feature of this equilibrium is that the equilibrium wage sequence is monotonically increasing over time due to the systematic dismissal of relatively inefficient workers. In each period, a proportion of relatively inefficient workers are dismissed. Therefore, the remaining cohort is made up of a lower proportion of relatively inefficient workers. As the expected productive inefficiency in the cohort falls, the

expected worker productivity and wages rise. Furthermore, a worker's effort decision is not constant over time. With wages monotonically increasing over time, different workers stop shirking at different times depending on their productive inefficiency index with high productivity workers (low productive inefficiency workers) deciding to put forth effort earlier than others.

Finally, the system in Equation 8 is not recursive. Although ξ_{jt} depends only on the wage sequence starting in period $t + 1$, F_{jt} depends on the entire wage sequence, $\{w_{jt}\}_{t=1}^{\infty}$. The computation of the equilibrium wage sequences is discussed in the appendix.

3.5   Simulations

As shown in the previous section, one of the key determinants of the pattern of selection into occupations is the variance-covariance structure of the population distribution of worker types. In this section, I present results of representative simulations, demonstrating how the correlation between ξ_j and ξ_k in the population affects the direction of self-selection in the labor market. In particular, I compare the outcome when the two random variables have a high positive correlation to the case when they are negatively correlated.

I assume that the population distribution of worker types is characterized by a bivariate lognormal distribution. ξ_1 and ξ_2 denote the workers' productive inefficiencies in firms 1 and 2, respectively. The population marginal distribution of $\log \xi_1$ has a mean and variance of 2 and 1.8, and the corresponding parameters for the population marginal distribution of $\log \xi_2$ are 1.2 and 0.8, respectively. The full set of parameters used in the simulation are given in Table 1.

Figures 2 and 3 present the population marginal distributions of $\log \xi_1$ and $\log \xi_2$ as well as the post-selection marginal distributions in each firm when $\log \xi_1$ and $\log \xi_2$ have a correlation coefficient of 0.83. These results show that the pdf of $\log \xi_1$ among people who choose firm 1 lies above the lower tail of the population distribution and below the upper tail of the population distribution, indicating a positive selection into firm 1. Therefore, workers with lower productive inefficiency indices that are relevant in firm 1 (i.e. higher levels of the type of ability used in firm 1) have a higher tendency to choose firm 1. In contrast, simulation results in Figure 3 show that workers in firm 2 come disproportionately from the right tail of the population distribution of ξ_2. Therefore, workers with relatively high levels of productive inefficiency in firm 2 (i.e. lower level of the type of ability relevant in firm 2) exhibit a relatively higher tendency to choose firm 2. Figure 3 also reveals that workers with the highest levels of ξ_2 are likely to choose firm 1; nevertheless, the majority of the firm 2 workforce consists of workers with relatively high levels of ξ_2.

These results are consistent with those of the previous research which has applied Roy's model and examined its properties in labor markets with symmetric information (Willis, 1987; Sattinger, 1993; Borjas, 1987). When ξ_1 and ξ_2 have a strong positive correlation, as in the standard Roy's model, self-selection tends to lead to higher average productivity in firm 1, and lower average productivity in firm 2. Since workers with low productive inefficiency in one firm also tend to have low productive inefficiency in the other firm, positive selection into firm 1 is associated with negative selection into firm 2.

When the correlation coefficient between $\log \xi_1$ and $\log \xi_2$ in the population distribution is -0.4, self-selection leads to positive selection into both firms as given in Figures 4 and 5. The post-selection marginal distributions of worker types in both firms lie above the lower tail of the population distribution and below the higher tail of the population distribution. These results indicate that in the case of a negative correlation between ξ_1 and ξ_2, workers are likely to choose firms in which they have lower productive inefficiency. Similar to the results for selection under symmetric information, when self-selection occurs in the presence of moral hazard, negative correlation between ξ_1 and ξ_2 tends to lead to an outcome in which each firm contains the best workers.

4   Estimation

I estimate the structural parameters of the model using maximum likelihood. The data used in the estimation procedure consist of workers' occupational choices, wages, and information on whether they were dismissed in each period. Before specifying the likelihood function, I will discuss several empirical issues that are addressed in mapping the theoretical model to the data.

First, I translate workers' selection of firm types in the model to the selection of occupations in the estimation by assuming that firm j employs only white collar workers and firm k employs only blue collar workers. This characterization applies to a labor market in which the white collar and blue collar workers employed in a firm produce separate goods and have no interaction in the production process. Furthermore, the monitoring technology involved in monitoring white collar workers are different from the monitoring technology for blue collar workers.

Second, the model predicts that workers with the same tenure in a given occupation earn the same wage. In order to account for the variation in wages observed among workers with the same tenure in an

occupation, I add measurement error to wages. The measurement error takes on the following form:

$$\ln w_{ijt} = \ln w_{jt}^* + \varepsilon_t$$

$$\ln w_{ijt} = \ln ws_j + \varepsilon_t \tag{10}$$

where w_{ijt} is the reported wage, w_{ijt}^* the primary sector wage predicted by the model, and ws_j is the secondary sector wage of a worker dismissed from primary sector firm j. ε_t is independently and identically distributed over time according to a normal distribution with mean zero and standard deviation, σ_ε.

Another issue that should be addressed in the estimation is the number of dismissals per worker. According to the model, a worker experiences only one dismissal due to malfeasance in his labor market career. Yet, roughly 26 percent of the sample report having more than one dismissal. In cases of multiple dismissals over one's labor market career, I assume that the first dismissal experienced by the worker during the sample period is due to shirking. Dismissals that occur after the first one are assumed to occur due to labor demand shocks when the worker is in the secondary sector. Furthermore, workers are assumed to find a new job immediately when they are dismissed in the secondary sector. Thus, they do not face any repercussions of subsequent dismissals that occur after the first one.

Finally, I assume that worker types in the population are distributed according to a bivariate lognormal distribution, characterized by the following parameters: $\mu_j, \mu_k, \alpha_j, \alpha_k$, and α_{jk}. The existence of a unique equilibrium wage sequence among the class of increasing wage sequences requires the distribution function of productive inefficiency indices to be concave. The lognormal distribution satisfies the concavity condition.

The likelihood function requires the numerical computation of equilibrium wages based on the model's parameters, according to the algorithm included in the appendix. The equilibrium wage sequence, together with the parameters of the model, can then be used to calculate the likelihood function.

Let θ be the set of the model's parameters. Then, the likelihood contribution of sample member i working in sector j is given by

$$L_i = \Pr(V_j > V_k, \{\ln w_{ijt}\}_{t=1}^T, \{d_{ijt}\}_{t=1}^T; \theta) = \Pr(V_j > V_k, \{\ln w_{ijt}\}_{t=1}^T | \{d_{ijt}\}_{t=1}^T; \theta)$$

$$\cdot \Pr(\{d_{ijt}\}; \theta) \quad (11)$$

where V_j is the value of working in occupation j, $\{w_{ijt}\}_{t=1}^{T}$ is the worker's reported wage sequence, and $\{d_{ijt}\}_{t=1}^{T}$ is his dismissal sequence, indicating whether the worker was dismissed or not in occupation j in period t. The full specification of the likelihood function is given in the appendix.

4.1 Identification

The identification of the model's parameters is obtained using data on workers' occupational choices, wages and the empirical hazard rates of dismissal in each occupation over the sample period. The parameters to be estimated are the occupation-specific monitoring rates (π_j, π_k), output prices (ρ_j, ρ_k), the parameters of the population heterogeneity distribution $(\mu_j, \alpha_j, \mu_j, \alpha_k, \alpha_{jk})$, and the secondary sector wages for workers who are dismissed from each occupation (ws_j, ws_k). As described in the Model section, $H_j(\xi_j)$ and $H_k(\xi_k)$ denote the marginal distribution of worker types in the population while $F_j(\xi_j)$ and $F_k(\xi_k)$ indicate the marginal distributions in occupations j and k[8]. In the following discussion, I will first explain how $\rho_j, \rho_k, \pi_j, \pi_k, \beta$ and the parameters of $F_j(\xi_j)$ can be identified from wage and dismissal rate data for the two occupations.

Wages and dismissal rates observed in occupation j are used in identifying the output price and the monitoring rate in occupation j as well as the parameters of $F_j(\xi_j)$ in the following fashion. Equations 12 and 13 give the wage and hazard rate of dismissal in occupation j in period t.

$$w_{jt} = \rho_j F_{jt}(\xi_{jt}) \tag{12}$$

$$h_{jt} = \pi_j \left(1 - F_{jt} \left(\xi_{jt} \right) \right) \tag{13}$$

$F_j(\xi_{jt})$ indicates the percentage of workers who choose to exert effort in the cohort in period t. Then, according to Equation 12 , when everyone in the cohort chooses to work, the wage reaches its upper limit at ρ_j. Although this threshold case helps with the identification of ρ_j as the limiting wage, we do not actually observe it in the data, and therefore, we have to consider identifying the parameters of the model when $F_{jt}(\xi_{jt})$ is between 0 and 1 for all t. It is clear that one cross-section of the wage and dismissal rate data for occupation j would not be sufficient to identify ρ_j, π_j, and $F_{jt}(\xi_{jt})$ since in that case there would be two equations and three unknowns. In order to disentangle ρ_j and π_j from $F_{jt}(\xi_{jt})$, observations from more

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[8]$F_j(\xi_j)$ and $F_k(\xi_k)$ are previously noted as $F_{j,t=1}(\xi_j)$ and $F_{k,t=1}(\xi_k)$ above. I drop the subscript $t = 1$ in order to shorten the notation.

time periods are needed. Since $F_{jt}(\xi_{jt})$ is a function of $F_j(\xi_{jt=1})$, we can increase the number of equations by considering more time periods without increasing the number of unknowns. The feature of the model that is crucial in identification is that the time-path of wages and dismissal rates are determined solely by $F_{jt}(\xi_{jt})$. Therefore, the panel nature of the data can be exploited to identify the time-variant component, $F_{jt}(\xi_{jt})$, and the time-invariant factors, ρ_j and π_j, can be identified given $F_{jt}(\xi_{jt})$ and Equations 12 and 13. For example, consider having data on two time periods, t and $t+1$. In that case, the ratio of $\frac{w_{jt}}{w_{jt+1}}$ identifies $F_{jt}(\xi_{jt})$, and then ρ_j and π_j can be backed out from Equations 12 and 13. The parametric assumption on $F_{jt}(\xi_{jt})$ is critical in identifying these parameters. Thus, occupation-specific parameters, $\rho_j, \pi_j, \nu_j, \omega_j$, can be identified given information on wages and hazard rates of dismissal only in occupation j.

The identification of the parameters of $H\left(\xi_j, \xi_k\right)$ is obtained through the set of equilibrium conditions in Equation 9 given the parameters of $F_{jt}(\xi_{jt})$ and $F_{kt}(\xi_{kt})$. Therefore, the identification of the parameters of $H\left(\xi_j, \xi_k\right)$ require data in *both* occupations. As in the case of $F\left(\xi_j, \xi_k\right)$, a parametric assumption on $H\left(\xi_j, \xi_k\right)$ is needed to identify its parameters.

In order to check the performance of the estimator, I generate data based on a fixed value of the parameter vector, θ. The estimator was able to recover the parameters, providing evidence that the model's parameters are identified. In the estimation of the model, I fixed the discount rate at 0.95.

5 Data

5.1 The Sample

The sample used in the estimation is constructed from the National Longitudinal Survey of Youth (NLSY), which is a survey of individuals who were between the ages of 14 and 22 when they were first interviewed in 1979. Since then, the respondents have been interviewed annually until 1994 and once every two years after 1994. 19 waves of the NLSY were available from 1979 to 2000 are used in the analysis.

One of the strengths of the NLSY compared to other longitudinal datasets is the detailed employment information that it collects. It includes the beginning and end dates of up to five jobs that the respondent has had in a year. Therefore, a relatively more accurate date of transition into the labor market can be established and job tenure can be fully captured. In addition, it includes data on usual hours worked, number of weeks worked, the hourly rate of pay, the three-digit industry and occupation codes, and the reason for separation from the job.

The model makes certain predictions about wages and dismissal rates among workers who have worked the same number of years in their first occupation. Therefore, the beginning of one's labor market career needs to be determined for the empirical analysis. Following Farber (1994), I assume that a worker's labor market career starts when he makes a permanent transition into the labor force. According to this definition, a permanent labor market transition occurs in the beginning of the first 3-year spell of "primarily working," following at least one year in which the worker was "not primarily working"[9]. A worker is defined to be primarily working if he has worked at least half of the weeks since the last interview and averaged at least 30 hours per week during the weeks in which he worked. The sample includes only workers who have made a permanent transition into the labor force during the sample period. Consequently, people who have never worked primarily for three consecutive years during the sample period and those who were primarily working in the first year in which they were observed in the dataset are excluded from the sample. Restricting the sample to those who have made a long-term transition into the labor market during the sample period not only mitigates the initial condition problem, but also allows one to focus on the labor market experiences of those workers who have formed a long-term attachment to the labor market. Furthermore, I exclude workers who have started their labor market careers before the age of 16.

Only jobs that start after the worker's permanent labor market transition are included in the sample. In addition, jobs without valid data on wage, occupation and reason for separation are excluded. The occupation data are collected for jobs that last for at least 9 weeks; as a result, jobs with shorter tenure are excluded from the sample.

The discrete period of analysis is an interview year, which spans the time between two consecutive interviews and is approximately equal to one calendar year. The sample includes the first 8 years of a worker's labor market history beginning with his permanent transition into the labor force. Since the dataset has information on up to 5 jobs per year and the job tenure is in weeks, I use the following rules to construct the variables used in the analysis.

Occupation: I categorize occupations into blue collar or white collar, based on one-digit census codes[10]. The worker's occupation in a given year is the one in which he has worked the most number of hours. For multiple job holders, the jobs that are not in the worker's assigned occupation are excluded from the

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[9]Farber (1994) and Farber and Gibbons (1991) show that the definition of permanent labor force entry is able to define a sharp transition from non-work to work.

[10]White collar occupations are 1) professional, technical, and kindred; 2) managers, officials, and proprietors; 3) sales workers; 4) farmers and farm managers; and 5) clerical and kindred. Blue collar occupations are 1) craftsmen, foremen, and kindred; 2) operatives and kindred; 3) laborers, except farm; 4) farm laborers and foremen; and 5) service workers.

analysis. For example, if a multiple job holder has worked the most number of hours in the white collar occupation in a given year, any blue collar job that he may have had during that year is excluded. Formulating the two types of primary sectors as white collar and blue collar occupations in the estimation carries the underlying assumption that workers use different types of skill sets in different occupations and that jobs within each occupation are homogeneous with respect to their output prices and monitoring rates. Increasing the number of occupational categories would probably capture skill heterogeneity and firm heterogeneity more accurately; however, the computational burden would also increase.

Wages: I use hourly wages in 2000 dollars. For multiple job holders, I calculate the weighted average of wages in the worker's occupation by multiplying each wage by the number of hours worked in each job and dividing the total earnings by the total number of hours worked in occupation.

Dismissals: If the worker has reported a firing or lay-off during an interview year, he is considered to have experienced a dismissal at the end of that year. I consider layoffs as dismissals in this analysis because there might be arbitrariness involved in a worker's self-reporting. He may choose to report a firing as lay-off due to the stigma that might be associated with a firing. Furthermore, the firm might choose to dismiss its least productive workers during a lay-off instead of firing them since firing may increase the probability that the worker will be disgruntled and possibly challenge the firm's decision. Although it is quite difficult to accurately measure dismissals, this is arguably the best definition given the available data. If the worker reports a quit and takes on another job in the same occupation following the separation, I treat the tenure in that occupation as uninterrupted. If the worker becomes unemployed during the sample period, I only consider his experience until he enters unemployment.

Furthermore, about 20 percent of the individuals in the sample report switching to jobs in a different occupation before their first dismissal. The theoretical model does not include inter-occupational moves while in the primary sector; therefore, I make the following assumptions in mapping the data to the model. If the occupation switch occurs while the worker is in the primary sector, i.e. before he experiences his first dismissal, I include only his labor market experience until he switches occupations in the analysis sample.

5.2 Descriptive Statistics

After I impose the criteria described in the previous subsection, the resulting sample includes 5391 individuals. 2059 (38%) of these individuals are employed in the white collar occupation in the first year of their labor market careers; and they remain in the white collar sector until their first dismissal or occupation

switch. The remaining 3332 (62%) are employed in the blue collar sector.

Table 2 shows the observable sample heterogeneity in terms of age and education at the start of the labor market career. These statistics suggest that blue collar workers start their long-term labor market careers earlier than white collar workers. 45 percent of blue collar workers make a permanent transition into the labor market between the ages of 16-18 while only 32 percent of white collar workers start their labor market careers before they turn 19. A related statistic is the educational composition of the labor force in the two occupations. Approximately 83 percent of the blue collar workers have at most a high school degree at the beginning of their permanent labor market careers. On the other hand, white collar employees are relatively more educated when they start their careers, with 41 percent having more than a high school degree.

Dismissal rates and average log wages in each occupation conditional on the sample period are given in Table 3[11]. Dismissal rates in both occupations follow a general downward trend over tenure in occupation, except for the second period of employment among blue collar workers. This pattern is consistent with the model's prediction that dismissal rates fall in the primary sector because over time a smaller proportion of the people remaining in the cohort choose to shirk. The blue collar sector has higher dismissal rates over the first eight years in the occupation. The average white collar dismissal rate during this period is about 5 percent while the average blue collar dismissal rate is roughly 10 percent. Table 3 also shows that the wage in each occupation is monotonically increasing over tenure. Blue collar wages are lower than white collar wages at all tenure levels.

Table 4 presents ordinary least squares (OLS) regression results that show the effect of dismissals on subsequent wages. These results support several basic implications of the theoretical model. First, the statistically insignificant coefficient on the "dismissed in t-1" dummy variable suggests that dismissals in the secondary sector do not significantly affect wages[12]. This result is consistent with the model's assumption that workers, who are dismissed in the secondary sector, immediately find another job with the same wage. On the other hand, dismissals in the primary sector seem to have a negative effect on wages although the effect is statistically insignificant among white collar workers (the sum of the coefficients on "dismissed in $t - 1$" and "(dismissed in $t - 1$)*(never dismissed until $t - 1$)"). This result supports the model's implication that workers dismissed in the primary sector find work in the secondary sector where they earn lower wages.

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[11]The statistics presented in this table are different from those shown in Figure 1 because the samples used in generating Table 3 and Figure 1 are slightly different in terms of the workers who switch occupations. The sample used in computing the dismissal rates in Table 3 does not include the observations after a worker switches occupations whereas the Figure 1 sample includes all observations on a worker regardless of the occupation switch.

[12]Statistical significance is calculated at the 5% level.

Finally, the regression results show that there is a significant difference between primary and secondary sector wages of workers who were not dismissed in the previous period. In particular, the positive and statistically significant coefficient on "never dismissed until $t-1$" suggests that primary sector workers earn higher wages than secondary sector workers conditional on tenure. (A worker, who has never been dismissed until period $t-1$ and is not dismissed in $t-1$, is in the primary sector in period t.)

6 Results

6.1 Parameter Estimates

Table 5 presents the maximum likelihood estimates of the model's structural parameters and their associated asymptotic standard errors. The estimates of the output prices are similar in the two occupations. The output price is \$14.44 in the white collar occupation and \$14.77 in the blue collar occupation. The output price can be interpreted as the upper limit on the wage sequence since it equals the wage that would be earned if there were no shirking. The secondary sector wage is \$11.47 for workers who have been dismissed from a white collar job and \$10.65 for those who have been dismissed from a blue collar job. This result suggests that blue collar workers, who have been dismissed, earn less on their next jobs than the dismissed white collar workers. Furthermore, monitoring rate in the white collar sector is estimated to be 32 percent while the estimate for the blue collar sector is 25 percent. According to these findings, white collar workers face a higher probability of being monitored than blue collar workers.

The marginal population distribution of $\log \xi_1$ has an estimated mean of 2.02 and a variance of 1.2, while the estimates for the mean and variance of $\log \xi_2$ are 2.5 and 0.9, respectively[13]. Therefore, the population distribution of blue collar productive inefficiency (ξ_2) has a larger mass at high inefficiency levels and is more concentrated around its mean when compared to the population distribution of white collar inefficiency index (ξ_1). Finally the covariance between $\log \xi_1$ and $\log \xi_2$ is estimated to be 0.89, which translates into a correlation coefficient of 0.86 between the two random variables. This result supports the hypothesis that the abilities relevant in blue collar and white collar occupations are highly correlated, indicating that the skills needed in the two occupations might be similar to each other.

Figures 6 and 7 compare the population marginal distributions with the post-selection marginal distribution in each occupation. The parameters of the post-selection distributions of worker types in each

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[13] In the discussion of results, I will refer to the white collar inefficiency index as ξ_1 and the blue collar inefficiency index as ξ_2.

occupation are estimated by using maximum likelihood of fitting the post-selection distributions to lognormal distributions. As shown in Figure 6, the distribution of worker types in the white collar occupation is very close to the population distribution. The estimates of the mean and the variance of $\log \xi_1$ among white collar workers are 1.96 and 1.2, resulting in a post-selection distribution of $\log \xi_1$ in the white collar occupation that is very close to the distribution of $\log \xi_1$ in the population. The distribution of $\log \xi_1$ in the white collar sector has slightly higher mass in the lower tail and a slightly smaller mass in the upper tail, compared to the population distribution. Therefore, workers with low values of ξ_1 have a higher tendency to become white collar workers while those with high values of ξ_1 have a slightly lower probability of choosing the white collar occupation. Since lower values of the inefficiency index (ξ_1) indicate higher ability in the white collar occupation, these results can be interpreted as evidence of a small degree of positive selection into white collar occupation.

The pattern of selection into the blue collar occupation is more complicated as shown in Figure 7. The estimates for the mean and variance of the distribution of $\log \xi_2$ among blue collar workers are 2.43 and 0.42, respectively. As shown in Figure 7, the marginal distribution of $\log \xi_2$ among blue collar workers lies below the population distribution at low levels of $\log \xi_2$, indicating that workers with low productive inefficiency in the blue collar sector tend to choose the white collar sector. The post-selection distribution also has a smaller mass at high levels of $\log \xi_2$ than the population distribution. Therefore, workers with high levels of productive inefficiency in the blue collar sector also have a higher probability of choosing the white collar occupation. The tendency of both high inefficiency and low inefficiency workers to avoid the blue collar sector would have opposite effects on the expected worker productivity in that sector. The forces behind this mixed pattern of selection and its impact on equilibrium wages and dismissal rates in the two occupations are discussed in the following subsections.

Table 6 lists the dismissal rates and the hourly wage sequences that result in an equilibrium characterized by the parameter estimates given in Table 5. Dismissal rates in both occupations fall over tenure as dictated by the model. blue collar workers face higher dismissal rates than white collar workers during the first eight years in the occupation. The high rate of dismissals in the blue collar sector is driven by the result that relative to the white collar sector, the blue collar workforce is composed of a higher proportion of workers who are likely to shirk. In fact, the estimated average productivity in the blue collar sector over the sample period is 0.69, indicating that almost 31 percent of blue collar workers are shirking on average during the sample period. On the other hand, the average white collar productivity over 8 periods is 0.86. Although

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the dismissal rates are lower in the white collar occupation, they fall faster than blue collar dismissal rates, especially in the first few years in the occupation. This result suggests shirkers are detected and dismissed faster due to the higher monitoring rate in that sector. Since the monitoring rate is lower in the blue collar occupation, it takes firms longer to eliminate shirkers in the blue collar occupation.

Table 6 also shows that the predicted wages in the white collar occupation are higher than those in the blue collar occupation. The white collar occupation exhibits higher wages in spite of a lower output price in comparison to the blue collar occupation primarily because of the high level of productivity in that sector. By the 8th period, 97 percent of the white collar workforce chooses to exert effort, and consequently, their wage approaches the upper limit of $14.44. Furthermore, the theoretical model implies that wage growth occurs as inefficient workers are eliminated from the primary sector so that the remaining workers in the cohort become more efficient on average. Therefore, it is not surprising to see that the blue collar sector, which has higher dismissal rates, also has a higher wage growth. blue collar wages rise at a higher rate than white collar wages primarily because there are higher productivity gains in the blue collar sector due to the systematic dismissal of shirkers.

6.2   Model's Fit to the Data

Figures 8-13 graphically depict how well the model fits the observed data on dismissal rates and hourly wages. The data points labeled "actual" represent the dismissal rates and average wages that are reported in Table 3. The points labeled "estimated" represent the model's predictions for the dismissal rates and wages as listed in Table 6. Figures 10 and 13 show the ratio of the estimated to the actual outcomes.

The results depicted in Figure 8 reveal that the model's fit to the white collar dismissal rates is quite good. The ratio of estimated to actual dismissal rates is very close to 1 in several periods, and in other periods, the estimated white collar dismissal rate is slightly lower than the actual. The blue collar dismissal rates estimated by the model are lower than the observed dismissal rates, except in the first year of employment. However, the predicted blue collar dismissal rates exhibit a similar rate of decrease as the observed dismissal rates. These results seem to suggest that dismissals for cause, as modeled in this paper, can explain most of the dismissals observed in the white collar occupation. However, relative to the white collar occupation, a greater proportion of dismissals in the blue collar occupation may be due to reasons not included in the model, such as exogenous demand shocks.

The hourly wages predicted by the self-selection model and those observed in the data are plotted in

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Figures 11-13. In the white collar occupation, the model overestimates the wages in the earlier years and underestimates them at later years in the occupation. In the blue collar occupation, the opposite pattern is evident as the estimated to the actual wage ratio is higher than one in earlier periods and less than one in later periods. While the model explains wage levels over one's tenure in the occupation, it does not fully explain the rate of wage growth. In particular, the estimated wage-tenure profiles are concave, which causes the gap between the estimated and actual wages. The concavity of the wage-tenure profile is an implication of the structural model, in which wage growth is generated by systematic dismissals of unproductive workers. As the dismissal rate falls over time, the rate at which wage grows also decreases, leading to the concave shape of the wage-tenure profile.

6.3 The Implications of Self-Selection on Wages and Dismissal Rates

I use the parameter estimates to evaluate the impact of self-selection on wages and dismissal rates in the two occupations. In particular, I compare the wages and dismissal rates that are predicted by the self-selection model with those that would result if workers were randomly assigned to each occupation. In the latter case, the workforce in each sector would be a random draw from the population. Therefore, the equilibrium wages and dismissal rates in this case are calculated by setting the marginal distribution parameters in each occupation to the population parameters. Table 7 lists the equilibrium wages that would result in a random assignment economy. Results indicate that the random assignment of workers leads to lower wages in both white collar and blue collar occupations when compared to the case with self-selection. Higher wages in both occupations under self-selection indicate that workers' selection into occupations increases the expected productivity in both occupations. These results provide further evidence for the finding indicated earlier that there is positive selection into white collar occupation in the sense that the expected worker productivity in the white collar occupation rises as a result of self-selection. The previous subsection also documents the evidence of negative selection into the blue collar occupation at low levels of ξ_2 and positive selection at high levels of ξ_2. The net effect of this type of sorting into blue collar occupation is higher wages in the blue collar occupation compared to the case of random assignment.

Self-selection also affects the dismissal rates observed in the labor market. Findings in Table 8 suggest that dismissal rates resulting in an economy with self-selection are lower than those that would result when workers are randomly assigned to occupations. Lower dismissal rates as a result of self-selection provide further support for the finding that workers' selection into occupations leads to higher expected productivity

in both occupations.

6.4 The Effects of Moral Hazard on the Pattern of Self-Selection

In order to investigate the effects of moral hazard on the selection pattern, I compare the outcome under moral hazard to the outcome in a labor market in which effort is perfectly observed by the firm. As described in the "model" section, utility flow to a worker in a given period is the wage less the disutility of effort, which equals the productive inefficiency index of the worker. When there is no moral hazard and thus every worker in a cohort exerts effort, wage equals it upper bound, which is the output price. Therefore, worker chooses primary sector firm j if $\rho_j - \xi_{ij} > \rho_k - \xi_{ik}$, provided that $\rho_j - \xi_{ij} > 0$ or $\rho_k - \xi_{ik} > 0$. The worker chooses the secondary sector if $\rho_j - \xi_{ij} < 0$ and $\rho_k - \xi_{ik} < 0$.

In order to observe the self-selection properties in a labor market without moral hazard, I simulate data using the estimates for the population distribution parameters and output prices given in Table 5[14]. Figure 14 shows the marginal distribution of worker types in the population and in the white collar occupation when there is no moral hazard. The comparison of these two densities reveal that white collar workers are drawn disproportionately from the lower tail and are less likely to come from the upper tail of the population distribution. Comparison of Figure 14 to Figure 6, which shows the outcome under moral hazard, suggests that the existence of moral hazard in the labor market significantly mitigates the degree of positive selection into the white collar occupation.

Furthermore, blue collar workers are positively selected into the blue collar occupation when there is no moral hazard in the labor market, as revealed in Figure 15. This result stands in contrast to the outcome under moral hazard when workers at both ends of the population distribution are discouraged from entering the blue collar occupation (Figure 7).

There might be several explanations for why the moral hazard in the labor market affects the selection patterns in this fashion. First, let's consider workers with high values of ξ_2. Given the relatively high positive correlation between ξ_1 and ξ_2, workers with high values of ξ_2 tend to have high values of ξ_1 and thus are likely to shirk in both occupations. The results suggests that when the labor market moves from the no-moral-hazard to the moral-hazard case, these workers become more likely to choose the white collar

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[14]The simulation exercise involves generating a dataset of worker types, computing each worker's occupation decision based on the value of employment in each occupation, and then finding the parameters of the post-selection marginal distributions based on the worker types in each occupation. The post-selection distribution parameters are found by fitting the post-selection distribution of $\xi's$ to a lognormal distribution using maximum likelihood.

occupation , increasing the mass at the right tail of the log ξ_1 distribution in the white collar occupation and decreasing the mass at the right tail of the log ξ_2 distribution in the blue collar occupation. Workers who would potentially shirk in either occupation seem to choose the white collar occupation because white collar wages are substantially higher than the blue collar wages, and the white collar monitoring rate is not high enough to discourage shirkers from choosing this occupation.

In addition, differences in the selection patterns in labor markets with and without moral hazard can also be explained by the behavior of workers with high ξ_1 and low ξ_2. These workers are likely to shirk in the white collar occupation and exert effort in the blue collar occupation. A marginal worker, who has high ξ_1 and low ξ_2 and is indifferent between the two occupations when there is no moral hazard, might choose the white collar occupation when moral hazard exists if the monitoring rate in the white collar occupation is not sufficiently high to discourage him from entering this occupation.

6.5   The Impact of an Increase in the Monitoring Rate

In this section, I present results of a comparative static exercise that aims to investigate the effects of an increase in the blue collar sector's monitoring rate on the equilibrium wages and dismissal rates in the labor market. As shown in Table 9, a 50 percent increase in the monitoring rate of the blue collar occupation leads to lower wages and higher dismissal rates in the white collar occupation and higher wages and lower dismissal rates in the blue collar occupation. A higher monitoring rate has two effects on the blue collar workforce. First, it makes this sector less attractive for some of the workers who have high productive inefficiency and are likely to shirk in a blue collar job. Second, it provides a bigger incentive to the remaining workforce not to shirk. As a result, average productivity in the blue collar sector goes up, leading to a similar increase in the wages of blue collar workers. A higher monitoring rate in the blue collar occupation also leads to lower dismissal rates in that occupation through its impact on the direction of selection in the labor market. Since the higher monitoring rate discourages both relatively inefficient workers from choosing the blue collar occupation and the remaining workforce from shirking, the blue collar workforce consists of proportionately more efficient workers. As a result, the percentage of workers shirking in the blue collar occupation decreases, bringing about a similar decrease in the blue collar dismissal rates. The results also indicate that an increase in the monitoring rate has implications for the profile of dismissal rates over time. Table 9 shows that under a higher monitoring rate, dismissal rate in period 1 is 27 percent less than the original rate while the dismissal rate in period 10 is about 90% less than the original, indicating that blue

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collar dismissal rates fall much faster as a result of a higher monitoring rate. This finding is consistent with the implications of the model. A higher monitoring rate causes unproductive workers in the blue collar occupation to be dismissed faster and thus the blue collar dismissal rate to fall much more rapidly.

The effect of an increase in the monitoring rate of the blue collar occupation on the equilibrium outcomes of the white collar occupation are also consistent with the explanation given above. Since the higher monitoring rate discourages workers with high productive inefficiency in the blue collar occupation from choosing the blue collar occupation, these workers have a higher probability of choosing the white collar occupation compared to the original case. However, due to the relatively high positive correlation between ξ_1 and ξ_2 in the population, workers who have high productive inefficiency in the blue collar occupation also tend to have high productive inefficiency as white collar workers. As a result, the proportion of relatively inefficient workers in the white collar occupation increases, and the average productivity in the white collar occupation decreases. This adverse effect on the composition of the white collar workforce results in lower wages and higher dismissal rates in this occupation as given in Table 9.

6.6 The Impact of an Increase in the Output Price

This section investigates the effects of a 10 percent increase in the output price in the white collar sector. According to the findings presented in Table 10, a 10 percent increase in the white collar output price leads to higher wages and lower dismissal rates in the white collar occupation. A higher output price in the white collar sector brings about an increase in white collar wages through two channels. First, an increase in output price has a direct positive effect on wages since it raises the value of workers' marginal product. Furthermore, higher wages due to a higher output price provide work incentives, decrease shirking and thus increase expected productivity in that occupation. This increase in expected productivity further increases the wages in the white collar occupation, resulting in an average of 11 percent increase in white collar wages over 10 periods. Results in Table 10 also indicate that a higher white collar output price brings about lower dismissal rates in that occupation. These findings support the explanation that an increase in the white collar output price leads to a decrease in the proportion of shirking workers in the white collar occupation due to its direct positive effect on wages.

The bottom part of Table 10 shows the effects of an increase in the white collar occupation's output price on the equilibrium outcomes in the blue collar occupation. According to these results, wages rise and dismissal rates fall in the blue collar occupation when the output price in the white collar occupation

increases. This result suggests that an increase in the white collar output price affects the selection pattern in such a way that it brings about a blue collar workforce that is on average more productive and less likely to shirk. Higher wages in the white collar occupation can attract both workers with low productive inefficiency indices as well as those with high productive inefficiency indices in the blue collar occupation. The results of this exercise suggest that when the white collar output price increases by 10 percent, it is the movement of workers with high blue collar productive inefficiency indices out of the blue collar occupation and into the white collar occupation that has a dominating effect on the blue collar wages and dismissal rates. As more workers, who would potentially shirk in the blue collar sector, are attracted to the white collar occupation due to the higher wages, the blue collar workforce consists of disproportionately more productive workers. Consequently, as the propensity of shirking decreases in the blue collar occupation, wages rise along with expected productivity, and dismissal rates fall in that occupation as shown in Table 10. Therefore, a higher output price leads to a lower incidence of shirking and higher wages not only in the white collar sector but also in the blue collar sector.

7 Conclusion

In this paper, I present the structural estimation of a model of occupational self-selection in a labor market characterized by moral hazard. The model demonstrates that in such a labor market, workers' occupational choices are determined by not only their comparative advantage but also their effort decisions in each occupation. Conditional on not shirking, a worker chooses an occupation in which he has a comparative advantage in terms of the amount of disutility that he receives from working in each occupation. On the other hand, conditional on shirking, the worker takes into account the monitoring rate in the occupation instead of his disutility of effort in making an occupational choice. Therefore, in this model, worker types affect the selection pattern through their impact on worker's relative ability in each occupation and through their effect on the worker's work/shirk decision.

The model is estimated using data from the National Longitudinal Survey of Youth. The estimation results suggest that self-selection of workers increases expected worker productivity in both blue collar and white collar occupations. In particular, workers' selection into occupations leads to higher wages and lower dismissal rates in both occupations compared to an economy in which workers are randomly assigned to each occupation. Findings also indicate that the difference between the rates of dismissal for cause between the

two occupations is driven by the higher expected productivity in the white collar sector. Higher wages and higher monitoring rate in the white collar occupation provide stronger incentives to exert effort than those in the blue collar occupation, causing the white collar workforce to have a smaller proportion of shirkers than the blue collar workforce. The prevalence of shirking in the labor market ultimately determines the degree to which the pattern of self-selection is affected by the occupational choices of potential shirkers.

Furthermore, analysis results reveal that the positive effects of self-selection in terms of higher expected productivity, higher wages and lower dismissal rates diminish as the labor market becomes increasingly characterized by moral hazard. If the occupational sorting took place in a labor market without a moral hazard problem, workers in both occupations would predominantly come from the higher ability end of the population distribution. This difference can be explained by the behavior of low ability workers who are also potential shirkers when there is moral hazard in the labor market. When compared to the case without moral hazard, workers in the moral hazard case have a higher probability of choosing an occupation in which they have low ability since they now have the option of shirking and avoiding the disutility of effort.

Finally, results reveal that a higher monitoring rate in the blue collar occupation leads to higher wages and lower dismissal rates in the blue collar occupation and lower wages and higher dismissal rates in the white collar occupation. While an increase in the monitoring rate in the blue collar occupation decreases the propensity to shirk in the blue collar occupation, it makes the white collar occupation relatively more attractive to those workers, who have low ability and are potential shirkers in both occupations. On the other hand, a higher white collar output price leads to higher wages and lower dismissal rates in both occupations. These analyses demonstrate that an exogenous shock in one occupation can have positive or adverse effects on the other occupation's economic outcomes depending on its impact on the pattern of workers' selection into occupations.

The model presented in this paper can be extended in different directions. First, the model can be extended to incorporate other sources of wage growth, such as learning-by-doing or human capital investment, in order to enhance the model's ability to explain the rate of wage growth over tenure in occupation. This extension is considered in Demiralp (2007). Second, the model presented here abstracts from firms' decisions on monitoring intensity by taking the monitoring rate as exogenous. The model can be extended to explain the firms' monitoring decision by specifying the monitoring technology and monitoring costs, thus allowing one to study how the firm changes its monitoring rate in response to other variables, such as worker productivity. Finally, the model presented here focuses only on dismissals that are due to shirking

or malfeasance. The model can also be formulated to include other causes of dismissals, such as exogenous demand fluctuations and low worker-firm match value. This addition would allow one to study of the relative importance of different causes of dismissals in the labor market.

8 Appendix

8.1 Computation of the Equilibrium Wage Sequence

The computation of the equilibrium wage contract consists of two sets of fixed point iterations, one nested within the other. Let (ν_j, ω_j) be the set of parameters that characterize the post-selection marginal distribution of ξ_j in occupation j. Then, (ν_j, ω_j) and (ν_k, ω_k) are the fixed points of the following operator:

$$
\begin{bmatrix} (\nu_j, \omega_j) \\ (\nu_k, \omega_k) \end{bmatrix} = \begin{bmatrix} \int_0^\infty \frac{h_1(\xi_1)}{H_1(\xi^*(w_1(\theta_1,\theta_2),w_2(\theta_1,\theta_2)))} dH_2(\xi_2) \\ \int_0^\infty \frac{h_2(\xi_2)}{H_1(\xi^*(w_1(\theta_1,\theta_2),w_2(\theta_1,\theta_2)))} dH_1(\xi_1) \end{bmatrix} \tag{14}
$$

Embedded in this fixed point algorithm is a second fixed point algorithm that computes the wage sequence in each occupation, *conditional on* (ν_j, ω_j) and (ν_k, ω_k). The wage sequence in primary sector firm j, *conditional on* (ν_j, ω_j), is the fixed point of the following operator:

$$
T(\{w_{jt}\}) = \begin{bmatrix} \rho_j F_{j,t=1}(\xi_{j,t=1}) \\ \rho_j F_{j,t=2}(\xi_{j,t=2}) \\ \vdots \\ \rho_j F_{j,t=\tau}(\xi_{j,t=\tau}) \\ \vdots \end{bmatrix} \tag{15}
$$

The finite approximation of this infinite horizon problem is given by the following mapping:

$$
T_S(\{w_{jt}\}) =
\begin{bmatrix}
\rho_j F_{j,t=1}(\xi_{j,t=1}) \\
\vdots \\
\rho_j F_{j,t=S}(\xi_{j,t=S}) \\
\rho_j \\
\rho_j \\
\vdots
\end{bmatrix}
\tag{16}
$$

The fixed points of $T_S(\{w_{jt}\})$ gives the wage sequence in firm j *conditional* on the marginal distribution of ξ_j in firm j. Every iteration in solving the fixed point problem in Equation 16 involves the computation of the conditional equilibrium wage sequence; therefore, the algorithm to compute the fixed points of $T_S(\{w_{jt}\})$ is nested within the algorithm to compute the parameters of $f_j(\xi_j)$.

The procedure to calculate the equilibrium wages and marginal distribution parameters in each firm are explained below. The execution of the following procedure relies on parametric assumptions regarding both the marginal distribution of worker types in the population and the marginal distribution of types in each occupation. $H(\xi_j, \xi_k)$, which describes worker heterogeneity in the population, is assumed to be a bivariate lognormal distribution. $F_{j,t=1}(\xi_j)$ is the marginal distribution of ξ_j in firm j in the beginning of period 1, and it is also assumed to be a lognormal distribution. The algorithm to compute the equilibrium wage sequence in each firm is as follows:

Step 1: Choose positive constants κ and ψ, and set S to a large positive integer.

Step 2: Randomly draw N observations from the bivariate population distribution, $H(\xi_j, \xi_k)$.

Step 3: Choose initial values for the wage sequence and denote them $\{w_{jt}\}^0$ and $\{w_{kt}\}^0$.

Step 4: Using the operator $T(\{w_{jt}\})$, iterate until Equation 17 is satisfied.

$$
d_\infty\left(\{w_{jt}\}^{K+1}, \{w_{jt}\}^K\right) \leq \kappa
\tag{17}
$$

The value of the wage sequence at the final iteration is $\{w_{jt}\}^*$. Do the same for firm k and compute $\{w_{kt}\}^*$.

Step 5: Using $\{w_{jt}\}^*$, $\{w_{kt}\}^*$ and the parameters of the model, calculate $V_{i,j,t=1}$ and $V_{i,k,t=1}$ according to Equation 4, and determine which of the N (ξ_j, ξ_k) pairs choose firm j and which ones choose firm k. Recall that a worker chooses firm j if $V_{i,j,t=1} > V_{i,k,t=1}$.

Step 6: Compute $\nu_j, \omega_j, \nu_k,$ and ω_k by fitting the post-selection marginal distributions that are generated in Step 5 to lognormal distributions using maximum likelihood.

Step 7: Denote parameters estimated in Step 6, $(v_j, \omega_j)^0$ and $(v_k, \omega_k)^0$.

Step 8: Repeat steps 4-6. Denote the parameter estimates $(v_j, \omega_j)^*$. Compute $D_j = d_\infty \left((v_j, \omega_j)^* , (v_j, \omega_j)^0 \right)$ for firm j and k. Iterate (repeat steps 4-6) by setting $(v_j, \omega_j)^0 = (v_j, \omega_j)^*$ and $(v_k, \omega_k)^0 = (v_k, \omega_k)^*$ until $D_j \leq \psi$ and $D_k \leq \psi$. If $D_j \leq \psi$ and $D_k \leq \psi$, the approximate equilibrium wage sequence in firm j is $\{w_{jt}\}^*$ and the parameter estimates of the distribution of ξ_j in firm j is $(v_j, \omega_j)^*$.

8.2 The Likelihood Function

Let θ be the set of the model's parameters. Then, the likelihood contribution of sample member i working in sector j is given by

$$L_i = \Pr(V_j > V_k, \{\ln w_{ijt}\}_{t=1}^T, \{d_{ijt}\}_{t=1}^T; \theta) \tag{18}$$

or equivalently

$$L_i = \Pr(V_j > V_k, \{\ln w_{ijt}\}_{t=1}^T | \{d_{ijt}\}_{t=1}^T; \theta) \cdot \Pr(\{d_{ijt}\}; \theta) \tag{19}$$

where V_j is the value of working in occupation j, $\{w_{ijt}\}_{t=1}^T$ is the worker's reported wage sequence, and $\{d_{ijt}\}_{t=1}^T$ is his dismissal sequence, indicating whether the worker was dismissed or not in occupation j in period t. Conditional on $\{d_{ijt}\}_{t=1}^T$, worker i's productive inefficiency vector (ξ_j, ξ_k) and the measurement error in wages (ε_t) are independent. Therefore worker i's likelihood contribution can be stated as

$$L_i = \Pr(V_j > V_k | \{d_{ijt}\}_{t=1}^T; \theta) \cdot \Pr(\{\ln w_{ijt}\}_{t=1}^T | \{d_{ijt}\}_{t=1}^T; \theta) \cdot \Pr(\{d_{ijt}\}_{t=1}^T; \theta) \tag{20}$$

The probability that a worker has chosen occupation j, conditional on having no dismissals over T periods is given by

$$\Pr(V_j > V_k | \sum_{t=1}^T d_{ijt} = 0) = (1 - \pi_j)^T \iint I(\xi_j^*(\xi_k) \geq \xi_j > \xi_{j,t=T} | \xi_k) \cdot dH(\xi_j, \xi_k)$$

$$+ (1 - \pi_j)^{T-1} \iint I(\xi_j^*(\xi_k) \geq \xi_j | \xi_k) I(\xi_{j,t=T} < \xi_j \leq \xi_{j,t=T-1}) \cdot dH(\xi_j, \xi_k)$$

$$+ \cdots + \iint I(\xi_j^*(\xi_k) \geq \xi_j | \xi_k) * I(\xi_j < \xi_{j,t=1}) dH(\xi_j, \xi_k) \tag{21}$$

The probability that a worker has chosen occupation j, conditional on being dismissed in period T is expressed as

$$\Pr(V_j > V_k | d_{ij,t=T} = 1) = (1 - \pi_j)^{T-1} \pi_j \iint I(\xi_j^*(\xi_k) \geq \xi_j > \xi_{j,t=T} | \xi_k) dH(\xi_j, \xi_k) \qquad (22)$$

The bivariate integral in the above equation is numerically evaluated for each individual in the sample using the trapezoid rule.

The probability of a worker's reported wage sequence conditional on having no dismissals over T periods is

$$\Pr(\{\ln w_{ijt}\}_{t=1}^T | \sum_{t=1}^T d_{ijt} = 0) = \sigma_\varepsilon^{-T} \prod_{t=1}^T \phi \left(\frac{\ln w_{ijt} - \ln w_{ijt}^*}{\sigma_\varepsilon} \right) \qquad (23)$$

where ϕ is the pdf of a standard normal variable. The probability of the wage sequence of a worker who has been dismissed at the end of period T and has spent T^s periods in the secondary sector is given by

$$\begin{aligned} \Pr(\{\ln w_{ijt}\} | d_{ij,t=T} = 1) &= \sigma_\varepsilon^{-T} \prod_{t=1}^T \phi \left(\frac{\ln w_{ijt} - \ln w_{ijt}^*}{\sigma_\varepsilon} \right) \\ &\cdot \prod_{t=T+1}^{T^s} \phi \left(\frac{\ln w_{ijt} - \ln ws_{ij}}{\sigma_\varepsilon} \right) \end{aligned} \qquad (24)$$

Finally, the probability of the dismissal sequence, $\{d_{ijt}\}_{t=1}^T$ is

$$\Pr(\sum_{t=1}^T d_{ijt} = 0) = F_j(\xi_{j,t=1}) + (1 - \pi_j) \left[F_j(\xi_{j,t=2}) - F_j(\xi_{j,t=1}) \right] + \cdots \qquad (25)$$

$$+ (1 - \pi_j)^{T-1} \left[F_j(\xi_{j,t=T}) - F_j(\xi_{j,t=T}) + (1 - \pi_j)^T \left[1 - F_j(\xi_{j,t=T}) \right] \right]$$

and

$$\Pr(d_{ijt} = 1) = \pi_j (1 - \pi_j)^{t-1} \left[1 - F_j(\xi_{jt}) \right] \qquad t = 1, \ldots T - 1 \qquad (26)$$

As shown in the equations above, the post-selection marginal distributions of worker types in each occupation, $F_j(\xi_j)$ and $F_k(\xi_k)$, are needed for the construction of the likelihood function. The parameters of these distributions are evaluated numerically by means of simulations because the truncation point in Equation 6, $\xi^*(\xi_{i,k})$, cannot be solved analytically. The parameters of $F_j(\xi_j)$ and $F_k(\xi_k)$ are computed

according to the fixed point algorithm that is explained in the previous subsection of the appendix.

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Table 1: Parameters Used in Figures 2-5

Parameter	Description	Value
ρ_1	Output price in firm 1	30
π_1	Monitoring rate in firm 1	0.15
μ_1	Mean of $\log(\xi_1)$	2
α_1^2	Variance of $\log(\xi_1)$	1.8
ρ_2	Output price in firm 2	25
π_2	Monitoring rate in firm 2	0.15
μ_2	Mean of $\log(\xi_2)$	1.2
α_2^2	Variance of $\log(\xi_2)$	0.8
α_{12}	$Cov(\xi_1,\xi_2)$	0.9

Table 2: Age and Education Distribution of the Sample

	White Collar	Blue Collar	Total
Age at the start of labor market career			
16-18	652 (32%)	1488 (45%)	2140 (40%)
19-21	795 (39%)	1168 (35%)	1963 (36%)
21-25	384 (19%)	390 (12%)	774 (14%)
26-30	146 (7%)	174 (4%)	320 (6%)
31-42	82 (4%)	112 (3%)	194 (4%)
Total	2059	3332	5391
Education at the start of labor market career			
Less than high school	545 (26%)	1690 (51%)	2235 (41%)
High school	658 (32%)	1071 (32%)	1729 (32%)
Some college	619 (30%)	521 (16%)	1140 (21%)
College	189 (9%)	45 (1%)	234 (4%)
More than college	48 (2%)	5 (0.2%)	53 (1%)

Column percentages are given in parentheses.

Table 3: Dismissal Rates and Log Wages by Period

	Dismissal Rates			Hourly Wage		
Period	White Collar	Blue Collar	Total	White Collar	Blue Collar	Total
1	9.47%	13.30%	11.83%	9.16	7.97	8.43
2	8.47%	14.59%	12.12%	9.04	8.17	8.52
3	7.95%	12.55%	10.51%	10.19	8.80	9.41
4	4.45%	11.14%	7.93%	11.03	8.99	9.97
5	4.32%	8.33%	6.28%	13.28	9.27	11.32
6	2.71%	8.10%	5.12%	13.21	10.13	11.83
7	1.63%	6.21%	3.60%	15.64	10.77	13.54
8	1.62%	3.97%	2.59%	15.50	13.03	14.47

Table 4: OLS Regressions of Wages

Dependent variable: log(wage)	Entire Sample	White Collar	Blue Collar
Dismissed in t-1	0.016	0.013	0.041
	(0.017)	(0.030)	(0.021)
Never dismissed until t-1	0.059*	0.049*	0.038*
	(0.007)	(0.011)	(0.010)
(Dismissed in t-1) * (Never dismissed until t-1)	-0.083*	-0.063	-0.086*
	(0.025)	(0.039)	(0.032)
Tenure in occupation	0.065*	0.079*	0.057*
	(0.002)	(0.002)	(0.002)
Constant	1.889	1.935	1.863
	(0.006)	(0.009)	(0.008)

Huber-White standard errors are in parentheses. (*) indicates significance at 5% level.

Table 5: Maximum Likelihood Estimates of the Parameters

Parameter	Description	ML Estimates	Asymptotic Standard Errors
ρ_1	WC output price	14.444	0.153
π_1	WC monitoring rate	0.320	0.013
ws_1	WC sec sector wage	11.467	0.079
μ_1	mean of $\log(\xi_1)$	2.024	0.034
α_1	var of $\log(\xi_1)$	1.201	0.016
ρ_2	BC output price	14.774	0.245
π_2	BC monitoring rate	0.249	0.007
ws_2	BC sec sector wage	10.649	0.054
μ_2	mean of $\log(\xi_2)$	2.491	0.103
α_2	var of $\log(\xi_2)$	0.899	0.043
σ_ε	std dev of ε	0.471	0.001
α_{12}	$cov(\xi_1,\xi_2)$	0.890	0.090

Table 6: Equilibrium Dismissal Rates and Hourly Wages

	Dismissal Rates			Hourly Wage		
Period	*White Collar*	*Blue Collar*	*Total*	*White Collar*	*Blue Collar*	*Total*
1	10.85%	13.68%	11.11%	9.55	6.67	9.27
2	8.18%	11.62%	8.61%	10.75	7.89	10.49
3	6.01%	9.67%	5.72%	11.74	9.04	11.48
4	4.32%	7.91%	3.85%	12.50	10.09	12.27
5	3.05%	6.36%	2.62%	13.07	11.01	12.87
6	2.14%	5.04%	1.80%	13.48	11.79	13.32
7	1.48%	3.95%	1.23%	13.78	12.43	13.65
8	1.02%	3.07%	0.85%	13.98	12.96	13.88

Simulations are performed using 10,000 draws.

Table 7: Equilibrium Wages under Random Assignment

	White Collar		Blue Collar	
Period	*With Self-Selection*	*Random Assignment of Workers*	*With Self-Selection*	*Random Assignment of Workers*
1	9.55	9.28	6.67	6.45
2	10.75	10.52	7.89	7.62
3	11.74	11.55	9.04	8.75
4	12.50	12.36	10.09	9.80
5	13.07	12.96	11.01	10.74
6	13.48	13.41	11.79	11.55
7	13.78	13.72	12.43	12.23
8	13.98	13.95	12.96	12.79

Table 8: Dismissal Rates under Random Assignment

	White Collar		Blue Collar	
Period	*With Self-Selection*	*Random Assignment of Workers*	*With Self-Selection*	*Random Assignment of Workers*
1	10.85%	11.46%	13.68%	14.04%
2	8.18%	8.69%	11.62%	12.06%
3	6.01%	6.41%	9.67%	10.15%
4	4.32%	4.63%	7.91%	8.38%
5	3.05%	3.28%	6.36%	6.81%
6	2.14%	2.30%	5.04%	5.44%
7	1.48%	1.60%	3.95%	4.29%
8	1.02%	1.10%	3.07%	3.35%

Table 9: Effect of a 50% Increase in Blue Collar Occupation's Monitoring Rate

	Percentage change in hourly wage	Percentage change in dismissal rate	Percentage change in hourly wage	Percentage change in dismissal rate
Period	*White Collar*		*Blue Collar*	
1	-5.99%	5.76%	61.17%	-27.35%
2	-4.53%	6.56%	52.04%	-41.63%
3	-3.34%	7.33%	42.83%	-53.60%
4	-2.41%	7.78%	34.39%	-63.25%
5	-1.71%	8.23%	27.12%	-70.93%
6	-1.20%	8.26%	21.12%	-76.84%
7	-0.83%	8.12%	16.30%	-81.35%
8	-0.57%	9.09%	12.50%	-85.07%

Table 10: Effect of a 10% Increase in White Collar Occupation's Output Price

	Percentage change in hourly wage	Percentage change in dismissal rate	Percentage change in hourly wage	Percentage change in dismissal rate
Period	*White Collar*		*Blue Collar*	
1	13.74%	-11.61%	1.92%	-4.06%
2	12.78%	-12.77%	1.48%	-5.31%
3	12.02%	-13.73%	1.14%	-6.40%
4	11.44%	-14.47%	0.88%	-7.40%
5	11.01%	-14.94%	0.68%	-8.52%
6	10.70%	-15.65%	0.52%	-9.19%
7	10.49%	-16.25%	0.39%	-9.79%
8	10.33%	-15.45%	0.30%	-10.45%

Figure 1: Involuntary Separation Rates by Occupation
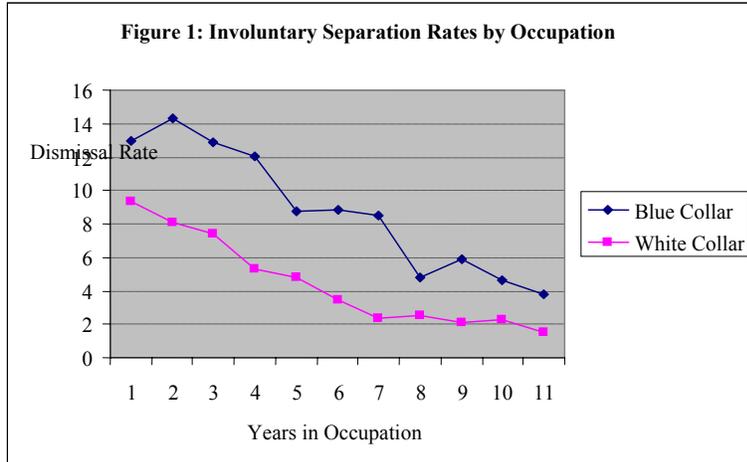
**Figure 2: Marginal Pdfs of ξ1 in Population and in Firm 1
When the Correlation Coefficient is 0.83**
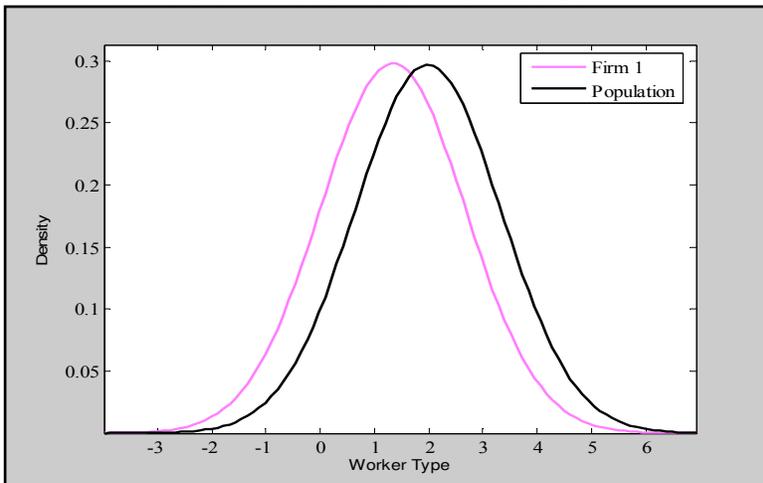
**Figure 3: Marginal Pdfs of ξ2 in Population and in Firm 2
When the Correlation Coefficient is 0.83**
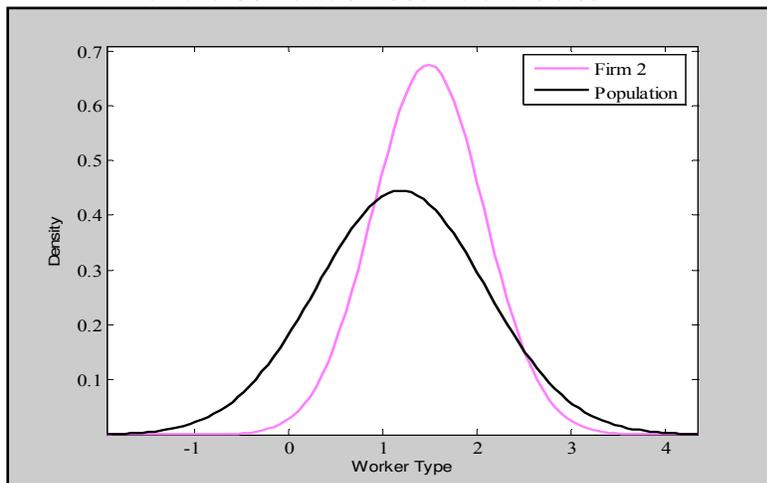
Figure 4: Marginal Pdfs of ξ1 in Population and in Firm 1 When the Correlation Coefficient is -0.4
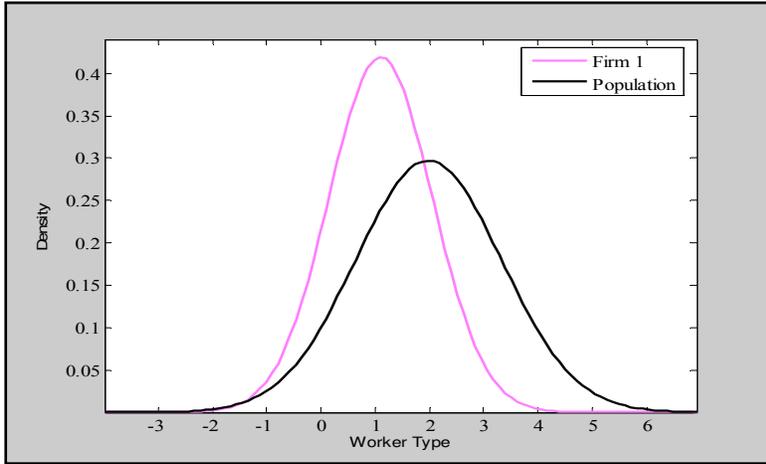
Figure 5: Marginal Pdfs of ξ2 in Population and in Firm 2 When the Correlation Coefficient is -0.4
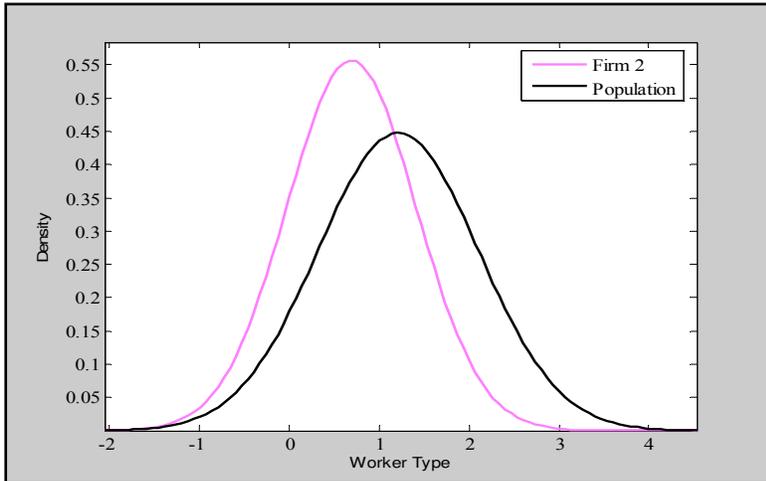
Figure 6: Marginal Distributions of ξ1 in the Population and Among White Collar Workers
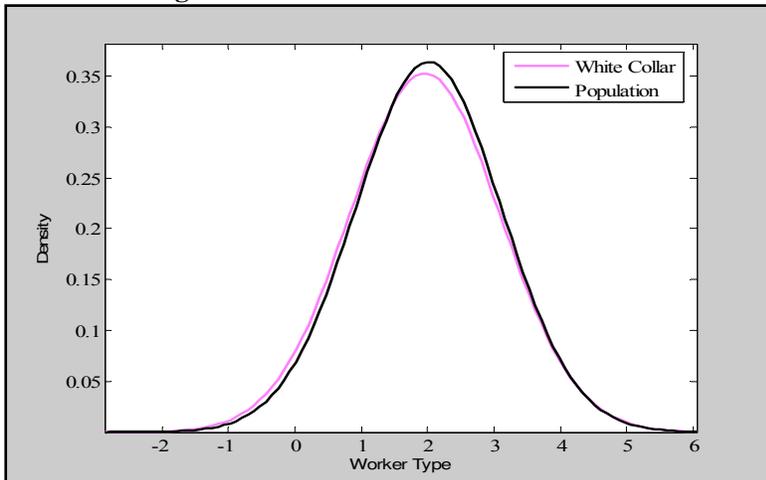
Figure 7: Marginal Distributions of ξ7 in the Population and Among Blue Collar Workers
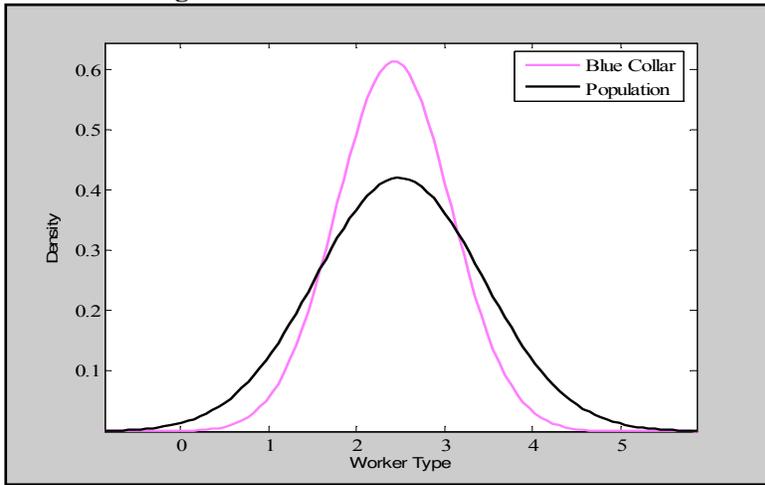
Figure 8: Dismissal Rates in White Collar Occupation
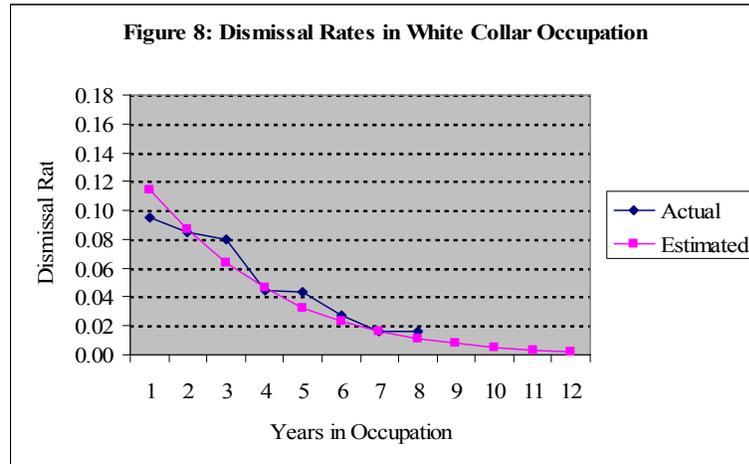
Figure 9: Dismissal Rates in Blue Collar Occupation
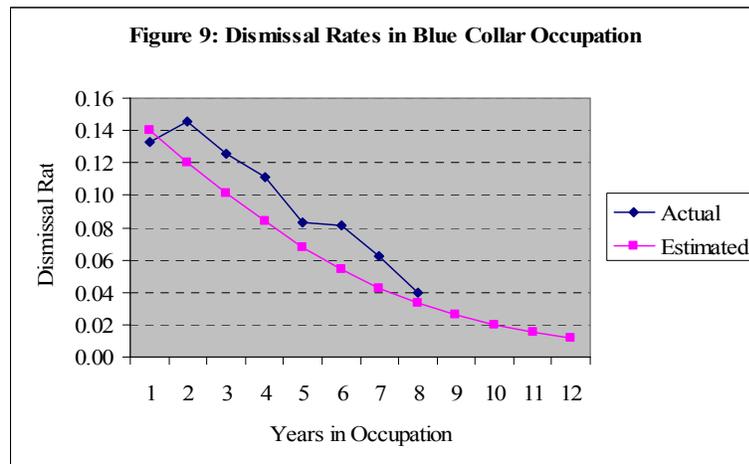
Figure 10: Ratio of Actual to Estimated Dismissal Rates
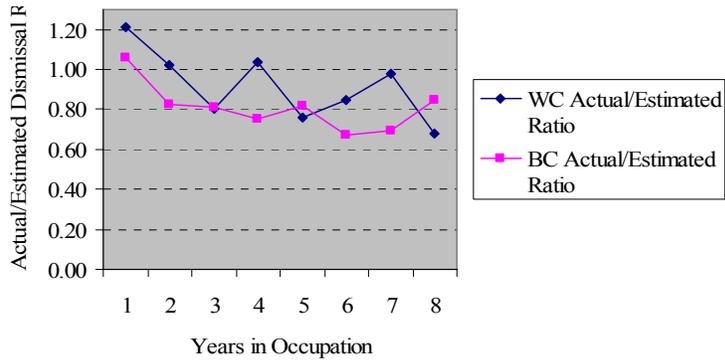

Figure 11: Wages in White Collar Occupation
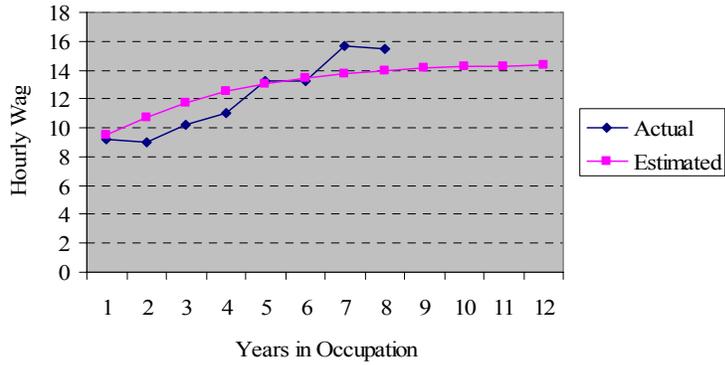
Figure 12: Wages in Blue Collar Occupation

Figure 13: Ratio of Actual to Estimated Hourly Wages
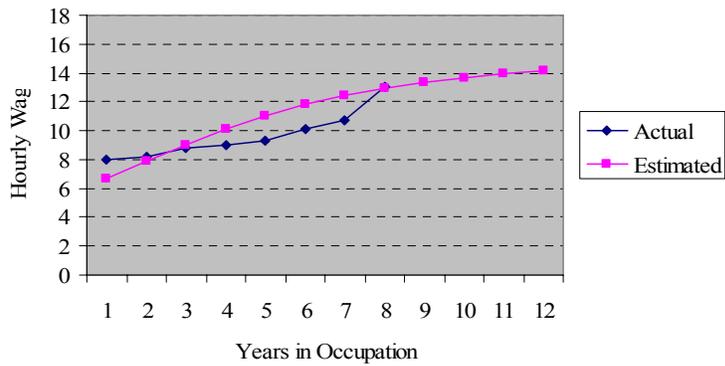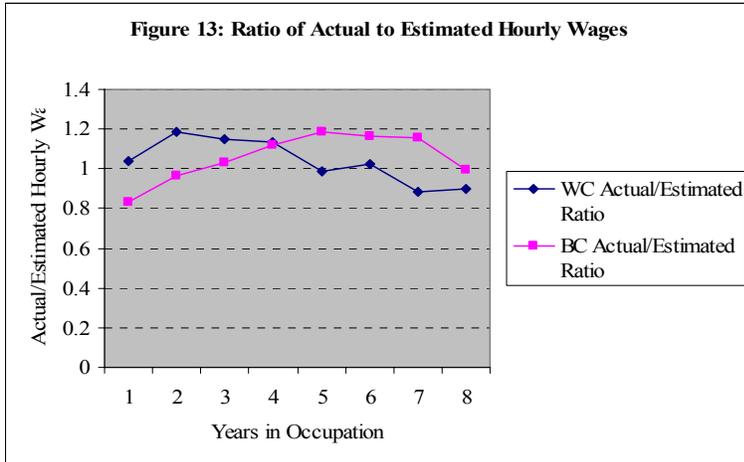
Figure 14: Marginal Distributions of ξ1 in the Population and among White Collar Workers When There is No Moral Hazard
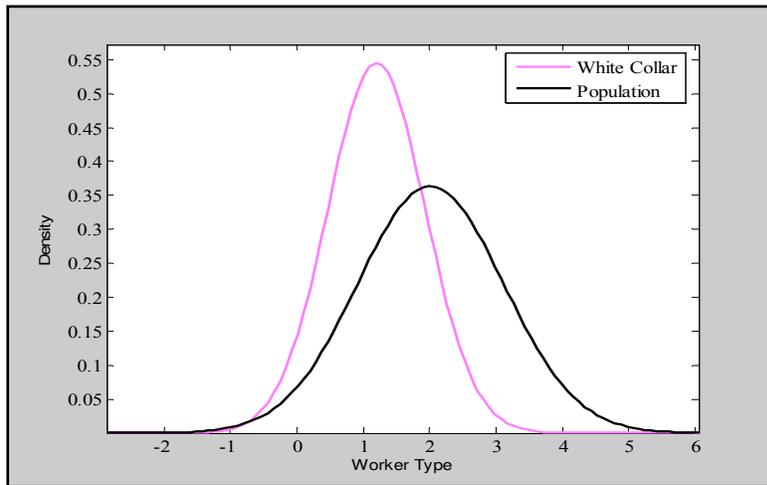

Figure 15: Marginal Distributions of ξ2 in the Population and among Blue Collar Workers When There is No Moral Hazard