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Abstract

In a seminal paper, Gibbons and Katz (1991) develop and empirically test an asymmetric information model of the labor market. The model predicts that wage losses following displacement should be larger for layoffs than for plant closings, which was borne out by data from the Displaced Workers Survey (DWS). In this paper, we take advantage of many more years of DWS data to examine how the difference in wage losses across plant closings and layoffs varies with race and gender. We find that the differences between white males and the other groups are striking and complex. The "lemons effect" of layoffs holds for white males, as in the Gibbons-Katz model, but not for the other three demographic groups (white females, black females, and black males). These three all experience a greater decline in earnings at plant closings than at layoffs. This results from two reinforcing effects. First, plant closings have substantially more negative effects on minorities than on whites. Second, layoffs seem to have more negative consequences for white men than the other groups. These findings suggest that the Gibbons-Katz asymmetric information model is not sufficient to explain all of the data. We augment the model with heterogeneous human capital and show that this model can explain the findings. We also provide some additional evidence suggestive that both asymmetric information and heterogeneous human capital are important. In support of both explanations, we demonstrate that the racial and gender effects are surprisingly robust to region, industry, and occupation controls. To look at the asymmetric information, we make use of the Civil Rights Act of 1991, which induced employers to lay off "protected" workers in mass layoffs rather than fire them for cause. As a result, relative to whites, a layoff would be a more negative signal for blacks after 1991 than before. If information is important, this would in turn imply that blacks experience a relatively larger loss in earnings at layoffs after 1991 than prior; and that's what we find in the data. In addition, as further evidence for heterogeneous human capital, we document for the first time in the literature that the two types of layoffs reported in the DWS data, namely layoffs due to "slack work" and "position abolished," have very different features when compared to plant closings. Finally, we simulate our model and show that it can match the data.

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1 INTRODUCTION

The role of asymmetric information in labor market outcomes has long been of interest to labor economists (e.g., Akerlof 1976; Spence 1973; Greenwald 1986; and Laing 1994). Empirical studies on this topic, however, have been scarce. In a seminal paper, Gibbons and Katz (1991; hereafter GK) construct a model of asymmetric information in the labor market. They use their model to argue that if firms have discretion as to which workers to lay off, a layoff provides a signal to the outside market that a worker is of low quality. By contrast, virtually all workers lose their jobs when their plant closes, so job loss from a plant closing does not provide a negative signal. Gibbons and Katz test for asymmetric information by looking at changes in wages for white-collar workers.[1] Since a layoff provides a negative signal about ability, one would expect wages to fall more following a layoff than for a plant closing. Gibbons and Katz confirm this prediction in the data, showing that wage penalties are substantially higher for layoffs than for plant closings.

In this paper, we take advantage of the fact that we have many more years of displaced worker data to expand on GK by looking at how the difference in wage losses across plant closings and layoffs varies with race and gender. Statistical discrimination against African Americans or women occurs when employers use race and gender as a predictor for productivity.[2] If this is the case, then one would expect the information contained in a layoff to vary across racial and gender groups. Empirically, we find that the differences between white males and the other groups are striking and complex. We find that the basic prediction by GK actually fails for three of our four demographic groups (white females, black females, and black males), as workers actually experience a greater decline in earnings at plant closings than at layoffs. This results from two reinforcing effects. First, plant closings have substantially more negative effects on minorities than on whites. Second, layoffs seem to have more negative consequences for white men than for the other groups.

Does this mean that one should discard the GK model? We think clearly not. However, the simple model is not sufficient to explain all of the data, so we augment it. We propose a new model that extends the asymmetric information model of GK by including heterogeneous human capital.[3] In our model, different types of firms hire different types of workers. Once a worker has worked for a firm for a period, the current firm knows his/her skill level, but outside firms do not. We model layoffs and plant closings as arising when shocks hit firms. Severe shocks lead the firms to cease operation (plant closings), while less severe shocks lead them to reduce the size of their workforces (layoffs). On the one hand, a plant closing may be more devastating than a layoff because it may be associated with a larger negative shock to the human capital of a particular worker. On the other hand, layoffs send a bad signal to the market and thus have additional negative consequences on the worker. If a layoff is a substantially stronger signal for white males than for the other groups, this could lead the information hit for a layoff to dominate for white males while the human capital aspect dominates for the other groups.

We provide some additional evidence that suggests that both asymmetric information and heterogeneous human capital are important. In support of both explanations we demonstrate that the racial and gender effects are surprisingly robust to inclusion of region, industry, and occupation dummies. We argue that this would seem unlikely if the explanation were simply that there is variation in the type of jobs performed by different demographic groups. To look at asymmetric information, we make use of the Civil Rights Act of 1991, which induced employers to lay off "protected" workers in mass layoffs rather than fire them for cause. As a result, a layoff should become a relatively more negative signal for blacks after 1991 than prior. Thus, if asymmetric information is important, one would expect the relative wage losses of blacks following layoffs to increase after 1991, which is precisely what we find.

As further evidence of the importance of human capital heterogeneity, we distinguish between two types of layoffs. In the displaced worker survey, an individual can become laid off either because of "position abolished" or "slack work." In the spirit of our model, a "slack work" layoff can be thought of as arising from a shock to one's firm type (i.e., something like an industry-specific shock). By contrast, a "position abolished" layoff can be thought of as arising from a human capital type specific shock (i.e., something like an occupation-specific shock). An individual can avoid the first order effect of the former type of shock by switching sectors, but they can not avoid the first order effect of the latter type shock. Thus, if they are of similar magnitude, we would expect a substantially larger fall in earnings from the second type of shock than for the first, and that is precisely what we see in the data. Earnings falls are greater when layoff is associated with "position abolished" than when it is associated with "slack work." Furthermore, we find that wage losses from plant closings fall in between these two types of layoffs in terms of their magnitude, which is in contrast to GK prediction. The findings from distinguishing between different types of layoffs are, to the best of our knowledge, new to the literature on displacement, and we think they are interesting in their own right.

Due to the small sample size, we do not formally try to reconcile the stronger negative consequences of plant closing for minority groups. However, we postulate that it could be explained if some firms discriminate against minorities more than others, as in the taste discrimination model of Becker (1971). Minority workers are likely to match with nondiscriminatory firms. As a result, plant closings are likely to have strong negative impacts on these workers. By contrast, if some firms are discriminatory, then minorities who experience layoffs may be more likely to be laid off by a discriminatory firm.

Finally, we simulate our model and show that it can match the data. Due to sample size (and precision) considerations, we focus on the differences across gender. We show in our model that if a layoff is a substantially stronger signal for men than for women, this could lead the information hit for a layoff to dominate for men while the human capital aspect dominates for women. This allows us to reconcile the result. While we can not formally prove that one needs asymmetric information and heterogeneous human capital to match the moments, we think our model provides the most plausible story.

The remainder of the paper is organized as follows. Section 2 describes the data. Empirical results are reported in Section 3. We present the model in Section 4 and then simulate it in Section 5. Finally, Section 6 discusses the results and concludes.

2 DATA

We use data from the biennial Displaced Workers Surveys (DWS) Supplement to the Current Population Survey (CPS) between 1984 and 2002. The DWS were conducted as part of the January CPSs in 1984, 1986, 1988, 1990, 1992, and 2002, and the February CPSs in 1994, 1996, 1998, and 2000. Each of the supplements from 1984–1992 asks workers if they lost a job at any time in the previous five-year period, and each supplement from 1994–2002 asks this question for the previous three-year period.[4] Displacement is defined as involuntary separation based on operating decisions of the employer such as a plant closing, employer going out of business, or a layoff from which the worker was not recalled. Other events, including quits and being fired for cause, were not considered displacement. Thus, the supplement is designed to focus on the loss of jobs that results from business decisions of firms unrelated to the performance of particular workers. If the response to the job loss question is positive, the respondent is then asked about the reason of job loss: 1) plant closing, 2) slack work, 3) position or shift abolished, 4) seasonal jobs ended, 5) self-employment failed, and 6) other. The data have information on workers' demographics, tenure on predisplacement job, occupation, industry and weekly earnings, weeks of joblessness after displacement, and current weekly earnings.[5]

We restrict the sample to workers aged 20–64 who lost a job in the private sector in the preceding three-year period due to plant closing, slack work, or position or shift abolished, and are reemployed in the private sector at the survey date. We only focus on workers who made full-time to full-time job transitions (i.e., lost a full-time job and are reemployed on a full-time job).[6] We exclude workers who have reemployment weekly real earnings under $40. Earnings are deflated by the 1982–1984=100 consumer price index (CPI). As in GK, we distinguish between blue- and white-collar workers. The white-collar sample consists of workers with predisplacement jobs as managers and administrators, professional and technical workers, clerical workers, and sales workers while the blue-collar sample consists of workers with pre-displacement jobs as craft and kindred workers, operatives, laborers, transport operatives, or service workers. We exclude workers in agriculture and construction industries.

Descriptive statistics of the sample are reported in Tables 1A and 1B. We divide the data into 16 different groups, classifying by gender, race, blue- or white-collar, and layoff/plant closing. Sample means and standard deviations for all of the variables are displayed in the cells.

3 EMPIRICAL FINDINGS

3.1 Basic Results

The main focus of our empirical work is on the wage losses associated with plant closings and layoffs for various demographic groups. To a large extent our main results can be seen from our summary statistics in Table 1A. Note that we have a much longer history of data than GK, who only use 1984–1986. Since we can now extend the data until 2002, our sample size is large enough to condition on specific demographic groups. The key variable is the change in the logarithm of the real wage, which is shown in the third row. First, focusing on white males, one can see that the main prediction of the GK model holds up. White men lose approximately 6 percent of their wages at plant closings, but this rises to around 10 pecent at layoffs. This can be interpreted as evidence that asymmetric information is important.[7] However, for the other three demographic groups the point estimates actually go in the opposite direction. In particular, for African American males and females the contrast is striking, with substantially larger wage losses associated with plant closings than with layoffs. Both of these differences are statistically significant.[8] In Table 1B we present results for blue-collar workers, and like GK, we find that wage losses are similar for plant closing as for layoffs. This result holds approximately for all four demographic groups.

A key question is why the relative losses at plant closing and layoffs vary so much across the demographic groups in Table 1A. Is it because the losses at plant closing are larger, or is it that the losses at layoffs are smaller? To add control variables and formally test for differences, we set up the model in a regression framework. The main results for white-collar workers are presented in Table 2A. The key dependent variable is the change in log wages (i.e., log of postdisplacement wage minus log of predisplacement wage). We regress that variable on black and female dummy variables interacted with layoffs and plant closing. Note that this specification is not completely free in that we do not interact race with gender so that the gender effect is constrained to be the same for the two different races.[9] One can see that the results described above depend on differences at both layoff and plant closing. In particular, blacks experience both smaller wage losses at layoff and larger losses at plant closing than do whites. However, the plant closing effect seems to be the larger of the two and the layoff effect is not statistically significant at conventional levels.

For women the story portrayed in Table 2A is quite different. We see only a small difference at plant closing between men and women, but women experience much smaller wage declines following a layoff. In our simulation results below we will explore why this might be true.

A particularly striking aspect of the results is the robustness of the results in Table 2A to inclusion of control variables. While parameters change some from column (1) to (2), all of the relevant coefficients change very little between columns (2), (3), and (4). We view it as particularly surprising that occupation, industry, and region controls seem to make little difference in the final result. This strongly suggests that the racial and gender patterns we document are not simply due to differences in the sector of the economy in which workers were employed.

In Table 2B we present results for blue-collar workers. The interactions are virtually all smaller in absolute value than those in Table 2A, and none of the interactions are statistically significant at conventional levels.

3.2 Employment Discrimination Legislation

The GK model assumes that firms maximize profits and rationally decide whom to dismiss. It also assumes that the only way for an employer to dismiss low-quality workers is through a layoff. In reality, firms can also dismiss workers by firing them for cause. It is plausible that firms can fire the lowest quality workers in the initial period, and when facing a shock, lay off the next lowest quality workers in a later period. Noneconomic factors, such as concerns about discrimination lawsuits, can lead employers to alter their methods of dismissal. For example, if workers are more likely to sue for wrongful termination when fired than when dismissed as a part of a layoff (see for example, Donohue and Siegelman [1993]), then increases in the expected costs to firms should induce substitution toward layoffs and away from individual firings (i.e., lowering cutoff in the initial screen for those who are more likely to sue).

Oyer and Schaefer (2000) test the hypothesis by exploring the passage of the Civil Rights Act of 1991 (CRA91), which increases the expected costs to firms of displacing “protected” employees (such as blacks and females).[10] Using data from the 1987–1993 SIPP, they find that, relative to whites, rates of overall involuntary job loss (including both layoff and firing) of black men were unaffected by CRA91.[11] However, while black men were significantly more likely to be fired than white men in the pre-CRA91 period, this difference disappeared in the post-CRA91 period. Following the logic of the GK model, a layoff (as opposed to a firing) should be a more negative signal for black workers after 1991 than before. Since we are examining layoffs rather than firings, the GK model and the Oyer and Shaefer (2000) results imply that the lemon effect for black workers should be larger after the CRA91 than before. Thus, we would expect wages to fall more dramatically at layoffs for blacks relative to whites after 1991 than before.[12]

The DWS data contain information about the year in which workers lost their jobs, by which we divide the sample into two subperiods: 1981–1991 and 1992–2001. In Table 3 we repeat the specification of Table 2A except that we interact all of the main coefficients with a dummy variable for post 1991. The point estimates tell a strong story that conforms with our prediction if signaling is important. Relative to whites, the wage hit for blacks associated with a layoff is substantially larger after 1991. To put it more literally, prior to 1991 whites had much larger wage declines at layoff than blacks, but that difference essentially disappeared after the CRA91. Further evidence that this is not just sporadic comes from examining the other coefficients. None substantially differ before and after the Civil Rights Act. We take this as evidence that asymmetric information plays an important role in the labor market. However, one should keep in mind that the confidence interval for the key interaction found in the first row of Table 3 is wide. It is significant at the 10 percent level (or 5 percent one-sided level) with a large point estimate. At the very least, we find these results highly suggestive that layoff appears to be a relatively more negative signal of quality for African American workers after the CRA91.

3.3 Length of Unemployment

Our results to this point have focused only on wages. However, an obvious selection problem arises since we focus only on workers who have been subsequently hired. We are also interested in the overall well being of these individuals, which depends not only on the wage impact of displacement, but also the length of the subsequent unemployment spell.

To examine this, we follow GK by using a Weibull proportional hazard model to analyze a sample of first spells of joblessness.[13] The hazard can be specified as

$$\gamma^{t^{\gamma-1}e^{X_i'\beta}},$$

where X_i is observable covariates, t is duration and (γ, β) are parameters. The nice aspect of the Weibull model is that the expected value of the log duration is linear, so that if T_i represents the duration of unemployment for individual i,

$$\frac{\partial E\left(\log\left(T_i\right)\right)}{\partial X_i} = -\frac{\beta}{\gamma}.$$

In Table 4 we report estimates of our model using a specification analogous to Table 2. We report the results in terms of change in average log duration ($-\beta/\gamma$). For clarity, a positive number means that the average unemployment spell would be longer.

The main results in Table 4 are similar to those found in Table 2. First, one can see that for white-collar workers, plant closing is relatively worse than layoff for women and blacks in comparison to white males. We also see that for white males, layoff is associated with significantly longer unemployment spells than plant closing. The result for blue-collar workers is similar although with smaller magnitude. We also again see that plant closing has a much more negative impact on African Americans (and women) than on white males.

Other results are somewhat different than for wage differences in that we find that layoffs are associated with longer unemployment spells for women and blacks than for white males. However, this should not be viewed as surprising. Our results in Table 2 were on wage differences so that we implicitly allow for a fixed effect. The length of unemployment is not analogous because there is nothing like a fixed effect. Thus, the comparisons of the level of unemployment by race and gender in Table 4 do not contradict the results in Table 2, which compare wage differences by race and gender.[14] It is straightforward to show in a search model (see, for example Mortensen [1987]) that one would expect workers with higher wage options to experience shorter unemployment spells. Thus we do not view this result as at all surprising.

Another result that does tell a somewhat different story than before is that in Table 2A we found that white males are the only group for which layoff is worse than plant closing. In terms of unemployment spells, the other three demographic groups seem to look similar to white men in the sense that unemployment spells are longer following a layoff. One explanation for this result is that workers have advanced warning before a plant closing and may begin the search process at an earlier stage so that they are better prepared when it actually happens.

Overall, we view these results as telling a story similar to those in Table 2. Relative to layoffs, plant closings are associated with longer spells of unemployment for blacks and women than for white men. Note further that these results suggest that selection bias is not the main driving force behind the wage loss results. To see why, consider a simple reservation wage model in which workers accept a job when the offered wage exceeds the reservation wage. When the reservation wage increases, one would expect the average reemployment wage to go up and the length of the unemployment spell to increase. However, this does not seem to be the driving force behind our estimates. We find that in cases in which reemployment wages fall, relative unemployment spells tend to lengthen. For example, the reemployment wage between layoff and plant closing is relatively worse for men than women, and the unemployment spell is relatively longer. This suggests that the results are not driven by different behavior in the reservation wages, but rather by changes in the demand for workers. In the example the relative demand for workers who lost their jobs from a layoff versus plant closing is worse for men than women.

3.4 Discussion

To summarize our basic results, we find that plant closings have substantially more negative effects on minorities than on whites. By contrast we find that layoffs seem to have more negative consequences for white men than the other groups. For three of our four demographic groups (black men, black women, and white women) we find the opposite of the GK prediction; plant closings lead to more negative consequences than do layoffs. The question arises as to which models can explain these results.

Perhaps the simplest explanation is that individuals from different demographic groups perform different types of jobs and thus have different displacement experiences. We find this difficult to reconcile with Table 2A, which shows that these effects are remarkably robust to inclusion of industry and occupation controls.

The strongest evidence in favor of asymmetric information can be found in Table 3. As described above, if asymmetric information were important, one would expect the relative wage losses of blacks following layoffs to increase after 1991, which is precisely what we find.

An intriguing aspect of our empirical results is that the negative consequences of plant closings are much worse for African American white-collar workers. One explanation for this result is that some firms discriminate against minorities more than others (Becker 1971). Minority workers should be more likely to match with nondiscriminatory firms. In that case, the consequences of these nondiscriminatory plants closings is likely to have strong negative consequences for these workers. By contrast, the same argument would not hold for layoffs. If discriminatory firms hire minorities, they may be more likely to be lay them off. If this is the case, one would not expect to see such an effect in layoffs.[15] Formal development of this model would be relatively difficult if one wants to avoid the unrealistic prediction of perfect segregation across firms. Incorporating labor market frictions such as search frictions could be used to obtain more realistic predictions. For example, one could augment a Burdett and Mortensen (1998) type model by allowing firms to have heterogeneity in tastes for workers by race. However, given the small sample size of blacks in our sample and the added complication of search frictions (in addition to asymmetric information and heterogeneous human capital), we do not address the race gap in the model. Rather, we focus in the rest of the paper on the gender gap. The basic result is that the wage loss is similar for men and women at plant closing, but larger for men at layoff. In the next few sections we will show that an asymmetric model modified to include heterogeneous human capital can reconcile these results.

4 MODEL

We develop an equilibrium model with asymmetric information and heterogeneous worker and firm types. We allow for an infinite number of periods, although only the first few periods are of interest. We do this to avoid the results in the model being driven by the fact that we are getting close to the terminal period of the model rather than the economic factors that we model.

We have J sectors and L different types of workers. We label the sectors by j for $j = \{1, \ldots, J\}$ and label labor types by ℓ for $\ell = \{1; \ldots, L\}$. Let $H_{t\ell sj}$ be the aggregate human capital of type ℓ working in sector j in state of the world s at time t and let $H_{tjs} = (H_{t1js}, \ldots, H_{tLjs})$ be the vector of inputs for a firm. The production function for sector j at time t in state s takes the form

$$G_{tjs}\left(H_{tjs}\right).$$

We assume further that each firm within the sector is large enough so that the law of large numbers holds (so that average productivity is all that matters) and that *G* has constant returns to scale.[16]

Before providing the details of the model, we begin by describing the timing of the model:

Period 1: Workers are hired by firms, but the firms have only limited information about worker quality.

Period 2 Firms learn about worker quality and only retain workers above a minimum threshold.

Period 3 The economy is hit by a shock that leads firms to either close or lay off workers. These workers are then rehired by other firms.

Period 4 and beyond Nothing additional happens as workers continue to work for firms.

Displacement as defined in the DWS occurs not from screening by ability as would occur in period 2, but rather by some shock to the firm (plant closing, slack work, or position abolished). Thus the focus of this model is on workers who are displaced in period 3. The changes in earnings depends on the type of shock that hits the economy, which effects overall demand for worker types and how employers infer worker quality from the layoff.

Both of these are equilibrium phenomena, so it is essential to model the interaction between types of firms in the economy. The first piece of the equilibrium concept is that once a worker has started working for a firm, the firm has all of the bargaining power and can take all of the surplus. Specifically, firms can make "take it or leave it" offers. However, the second piece is that the labor market is perfectly competitive. As a result, competition will bid the rent that firms make from workers to zero (on average). Thus, firms will tend to make profit on workers beyond the first period but will pay for this future profit in terms of higher first period wages. Thus, the outside wage is determined competitively and the current employer will always offer the outside wage (that is for workers who are retained). We now present the details of the model.

In terms of more specifics about the timing, the production function remains the same in periods 1 and 2, in which case the index s is degenerate. However, we assume that in period 3 the production process is potentially hit by a shock that may or may not affect different sectors. In particular, there is a finite set of states of the world $s = 1, \ldots, S$ with μ_s representing the probability of state s (so that $\sum_{s=1}^{S} \mu_s = 1$). After period 3, G_{tjs} remain fixed at those values forever. Thus, the production function only changes between periods 2 and 3. Abusing notation somewhat, we do not explicitly express the state subscript s for periods 1 and 2 across different variables in the model.

We essentially follow a single cohort, so that t represents both time and age, which are collinear. We use Y_ℓ to denote the amount of human capital that an individual of type ℓ possesses. A key aspect of the model is asymmetric information. When firms make offers to workers, they do not know their productivity. However, after employing the worker for a period, they learn their productivity. At that point the firm may choose to fire or layoff workers. Also during the first period that a worker works for a firm, his productivity is Y_ℓ. For the second period and beyond, his productivity at that firm is τY_ℓ where $\tau > 1$. This parameter τ plays an important role in the analysis. If $\tau = 1$, no workers would be retained in the equilibrium we examine (unless there is an upper bound to the support of productivity that has a positive probability of occurring).[17] We have modeled τ as if it is specific human capital. Alternatively, we could interpret $(\tau - 1)Y_\ell$ as a training cost (or other type of hiring cost) that results in lower productivity during the first period.[18]

At the beginning of each period in which a worker's productivity is known, each firm can decide whether to lay off the workers. Since firms are indifferent between laying off a worker and retaining them with a wage that is lower than the market wage, there will be multiple equilibria in the model. Gibbons and Katz describe this class of equilibria. We focus only on the equilibria in which firms never pay a worker lower than their outside option.[19]

Within human capital types, firms strictly prefer higher ability workers so they can construct a cutoff value for each type of labor. They then only retain workers whose ability is above this cutoff value. For workers in the second period, we write the cutoff as $y^*_{2\ell j}$. In the third, the cutoff depends on the shock to the economy s so we will write the cutoff as $y^*_{3\ell js}$.

In our model, firms dismiss workers at the beginning of period 2 and then again at the beginning of period 3. It is important to point out that we view these as distinct phenomena. During period 1, firms learn about the quality of a worker. They choose not to retain the worker because they have fallen below the screening value of the firm. Thus, in period 2 the event that leads to the separation is the firm learning about the quality of the worker.

The retention decision at the beginning of period 3 is quite different. These workers have already made it beyond the initial screen, so the event that leads to workers being laid off is an adverse effect to the firm.[20] Given the wording of the questions in the DWS, we assume that the data correspond to the latter type of dismissal rather than the former. Since they are not of primary concern, workers who are below the cutoff value in period 2 leave this part of the economy (which may seem reasonable given that we are focusing on the white-collar sector). However, since our main goal is to focus on the displaced workers, we allow those who are not retained in period 3 to be rehired within this part of the economy.

We assume that outside firms know the cutoff levels of other firms in the economy but do not know the level of productivity of individual workers. Thus, workers who are above the cutoff may be potentially poached by other firms. However, all that the potential poachers know about the ability of the worker is that their productivity is higher than the cutoff. Some sectors will not fire anyone during the third period, so for notational purposes we denote this by assuming that cutoff remains the same $\left(y^*_{3\ell js} = y^*_{2\ell j}\right)$.

Let $f_{\ell j}$ denote the fraction of workers of type ℓ who work in sector j at time 1 and $\varphi_{\ell hjs}$ the fraction of ℓ-type workers who worked for an h type firm in periods 1 and 2, but were not retained by h in period 3 and were hired into sector j in state of the world s. In principle, firms can "poach" retained workers from other firms. This will not happen in equilibrium, so to economize on notation, we do not explicitly account for it when describing sectorwide human capital. However, this potential "poaching" plays a role in the analysis as it determines the outside wage.

During the first period, Y_ℓ is not revealed so there will be no sorting among workers into sectors. Thus the aggregate human capital takes the value

$$H_{1\ell j} = f_{\ell j} E\left(Y_\ell\right). \tag{1}$$

During the second period, some workers can be laid off. The ones who remain will be more productive by the factor τ so that

$$H_{2\ell j} = f_{\ell j} E\left(\tau Y_\ell 1\left(Y_\ell \geq y^*_{2\ell j}\right)\right), \tag{2}$$

where 1(•) is the indicator function. In the third period, some additional new workers can be hired from other sectors.

$$H_{3\ell js} = f_{\ell j} E\left(\tau Y_\ell 1\left(Y_\ell \geq y^*_{3\ell js}\right)\right) + \sum_{h=1}^{J} \phi_{\ell hjs} E\left(Y_\ell \middle| y^*_{2\ell h} < Y_\ell \leq y^*_{3\ell hs}\right)$$

We allow firms to both dismiss workers $\left(\text{if } y^*_{3\ell js} > y^*_{2\ell j}\right)$ and hire new workers (if $\varphi_{\ell hjs} > 0$). In our simulations below we did not have firms simultaneously doing both.

Note that, in principle, a firm could fire a worker in period 4 that it hired in period 3 after learning about his ability. However, in practice this should happen only very rarely. The worker's ability Y_ℓ was large enough so that in period 3 the worker was retained, and now we are cutting off the right-hand tail so the wage premium to them is even smaller. Thus, for computational reasons, we ignore this possibility and just assume that workers hired during period 3 will remain forever. Thus, for $t > 3$, all that changes is that the productivity of the new hires improves,

$$H_{t\ell js} = f_{\ell j} E\left(\tau Y_\ell 1\left(Y_\ell \geq y^*_{3\ell js}\right)\right) + \sum_{h=1}^{J} \phi_{\ell hjs} E\left(\tau Y_\ell \middle| y^*_{2\ell h} < Y_\ell \leq y^*_{3\ell hs}\right). \qquad (3)$$

Once a worker is hired, she may be more productive than her market wage because $\tau > 1$. We allow the firm to reap all of the benefits of this surplus by making a "take it or leave it" offer. However, we also assume that the labor market is competitive, with free entry into the market, so that the outside wage that a worker can receive is set so that the marginal profit on that worker is zero (in expectation). Inside wages are set by the firm to the worker's reservation value.

Thus, equilibrium can be characterized by the following four criteria:

1) Outside wages are determined so that firms earn zero profit on average for a worker.

2) Inside wages (after the first period a worker has worked for a firm) are chosen by the firm to make a worker indifferent between staying or leaving.

3) Firms retain workers for whom it is profitable to do so.[21]

4) Workers make employment choices to maximize their expected present discounted value of earnings.

It is easiest to solve this model by working backwards from period $t > 4$. Since nothing changes after period 4, all of these periods will look identical. Consider a firm j trying to poach an ℓ type worker from another firm. Let $\tilde{y}_{\ell \mathrm{H}}$ be the conditional expectation of the productivity of a worker of type ℓ who has experienced labor market history H. During the second period, a worker who worked in sector j during period 1 and was retained will have history H = j and $\tilde{y}_{\ell j} = E\left(Y_\ell \middle| Y_\ell \geq y^*_{2\ell j}\right)$. During period 3 and beyond, after being hit by shock s, a worker who worked in sector j will have history H = jsr where r is a dummy variable indicating whether the worker was retained. For example, one history H may be that a worker started at firm j and were retained throughout; then, H = $js1$ and $\tilde{y}_{\ell js1} = E\left(Y_\ell \middle| Y_\ell \geq y^*_{3\ell js}\right)$. Another potential history H is that an individual was retained by a firm in sector j in period 2 but then laid off by that firm in period 3. In that case, H = $js0$ and $\tilde{y}_{\ell js0} = E\left(Y_\ell \middle| y^*_{2\ell j} < Y_\ell \leq y^*_{3\ell js}\right)$. Then for any history H, the expected marginal value of these types of workers to the new firm is

$$
\begin{aligned}
&\tilde{y}_{\ell \mathrm{H}} \frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}} + \sum_{t=5}^{\infty} \beta^{t-4} \tau \tilde{y}_{\ell \mathrm{H}} \frac{\partial G_{tjs}\left(H_{tjs}\right)}{\partial H_{t\ell js}} \\
&= \tilde{y}_{\ell \mathrm{H}} \frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}} \left(\frac{1-\beta+\beta\tau}{1-\beta}\right) \qquad ,
\end{aligned} \tag{4}
$$

where β is the discount rate since $G_j(H_{tj}; s)$ doesn't vary over time (after period 4). Since wages will be constant across time and since the wage will be the best outside opportunity, this yields that the outside wage during period 4 for an individual of type ℓ with labor market history H is

$$
w_{t\ell \mathrm{E}} = \max_{j=\{1,\ldots,J\}} \tilde{y}_{\ell \mathrm{H}} \frac{\partial G_{tjs}\left(H_{4js}\right)}{\partial H_{t\ell js}} \left(\frac{1-\beta+\beta\tau}{1-\beta}\right) \tag{5}
$$

for t ≥ 4. Since employers must keep the workers indifferent between leaving and staying, and because the outside wage does not change after period 4, employers will pay the constant outside wage $w_{t\ell H}$ in all periods after period 4.

Now consider period 3, in which there will be some turnover. We first consider the market for workers of type ℓ from a firm in sector h who are retained $\left(Y_\ell > y^*_{3\ell hs}\right)$. If a firm in sector j considers hiring them, it will make expected profit

$$\frac{\partial G_{3js}\left(H_{3js}\right)}{\partial H_{3\ell js}}\tilde{y}_{\ell hs1} - w_{3\ell hs1} + \frac{\beta}{1-\beta}\left(\frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}}\tau\tilde{y}_{\ell hs1} - w_{4\ell hs1}\right), \tag{6}$$

where $w_{3\ell hs1}$ is the outside wage for such a retained worker. Since the market is competitive between firms both within and between sectors,

$$w_{3\ell hs1} = \max_{j=\{1,\ldots,J\}}\left[\frac{\partial G_{3js}\left(H_{3js}\right)}{\partial H_{3\ell js}}\tilde{y}_{\ell hs1} + \frac{\beta}{1-\beta}\left(\frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}}\tau\tilde{y}_{\ell hs1} - w_{4\ell hs1}\right)\right].$$

In determining the cutoff $y^*_{3\ell js}$, the firm has to be indifferent between releasing and retaining a worker with $Y_\ell = y^*_{3\ell js}$. This yields that

$$y^*_{3\ell js} = \max\left\{\frac{w_{3\ell js1} + \frac{\beta}{1-\beta}w_{4\ell js1}}{\frac{\partial G_{3js}\left(H_{3js}\right)}{\partial H_{3\ell js}}\tau + \frac{\beta}{1-\beta}\frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}}\tau}, y^*_{j\ell 2}\right\}.$$

Finally, consider a worker of type ℓ who was displaced $\left(Y_\ell \le y^*_{3\ell hs}\right)$ from firm h. He will be paid his best opportunity in the competitive market:

$$w_{3\ell hs0} = \max_{j=1\{1,\ldots,J\}}\left\{\frac{\partial G_{3js}\left(H_{3js}\right)}{\partial H_{3\ell js}}\tilde{y}_{\ell hs0} + \frac{\beta}{1-\beta}\left(\frac{\partial G_{4js(H_{4js})}}{\partial H_{4\ell js}}\tau\tilde{y}_{\ell hs0} - w_{4\ell hs0}\right)\right\}, \tag{7}$$

where the expression on the right hand-side comes from the zero profit constraint for each firm.

For workers who are above the cutoffs during period 3, the firms that retain them will receive rents. Since these rents will be bid away by firms when hiring workers in earlier periods we will need to keep track of them. We define the expected rent as a function of a worker's ability y as

$$\pi_{\ell j}(y)=\sum_s \mu_s 1\left(y \geq y^*_{3\ell js}\right)\left[\frac{\partial G_{3js}\left(H_{3js}\right)}{\partial H_{3\ell js}}\tau y - w_{3\ell hs1}+\frac{\beta}{1-\beta}\left(\frac{\partial G_{4js}\left(H_{4js}\right)}{\partial H_{4\ell js}}\tau y - w_{4\ell hs1}\right)\right] \ .$$

Next consider period 2. In this case workers who are not retained leave this sector of the market. We write the production function in sector j for periods 1 and 2 as F_j. Using notation analogous to above, we let $w_{2\ell h}$ be the outside wage for workers who are retained in sector h. The equilibrium outside wage is defined so that expected marginal profit is zero

$$w_{2\ell h}=\max_{j=\{1,\ldots,J\}}\frac{\partial G_{2j}\left(H_{2j}\right)}{\partial H_{2\ell j}}\tilde{y}_{\ell h}+\beta E\left(\pi_{\ell j}\left(Y_\ell\right)\middle| Y_\ell \geq y^*_{2\ell h}\right)$$

A firm chooses the cutoff value $y^*_{2\ell h}$ so that it is just indifferent about retaining the worker.

$$\frac{\partial G_{2j}\left(H_{2j}\right)}{\partial H_{2\ell j}}\tau y^*_{2\ell h}-w_{2\ell h}+\beta E\left(\pi_{\ell j}\left(y^*_{2\ell h}\right)\right)=0$$

Finally, during the first period, in equilibrium firms will offer wages so that the marginal profit is zero.

$$w_{1\ell j}=E\left(Y_\ell\right)\frac{\partial G_{1j}\left(H_{1j}\right)}{\partial H_{1\ell j}}+\beta \Pr\left(Y_\ell > y^*_{2\ell h}\right)\left[\frac{\partial G_{2j}\left(H_{2j}\right)}{\partial H_{2\ell j}}\tau \tilde{y}_{\ell j}-w_{2\ell j}+\beta E\left(\pi_{\ell j}\left(Y_\ell\right)\middle| Y_\ell \geq y^*_{2\ell h}\right)\right] \quad (8)$$

Workers choose firms to maximize their expected present value of earnings. We assume that workers have no more information about their ability than do the firms. We do not explicitly give the form for the present value of earnings, but all of the components of the wages have been defined.

The equilibrium of the model is characterized by equations (1) – (8).

5 RECONCILING MODEL WITH DATA

Our goal in this section is to simulate the model and show that it can reconcile the data. Given the limited sample size of black workers in white-collar jobs, in this section we only attempt to explain the gender differences.

We use a CES production function

$$G_{tjs}\left(H_{tjs}\right)=\left(\sum_{\ell=1}^{L}\alpha_{t\ell js}H_{t\ell js}^{\rho}\right)^{\frac{1}{\rho}}$$

with the number of firm types (J) equal to five. We assume that individuals of different genders are different worker types, so we allow for 10 worker types—5 for each gender. In our model we allow for shocks to $\alpha_{t\ell js}$ to occur between periods two and three. We will essentially model two different types of shocks to this economy. One type is a "sector-specific shock" in which $\alpha_{t\ell js}$ falls for all values of ℓ in a given sector j. This can be thought of as a sector specific productivity shock, but could also be viewed as a demand shock to the sector. If the shock is large enough, the sector will disappear, which we view as analogous to a plant closing. We also consider a "human capital type shock" in which $\alpha_{t\ell js}$ falls for all values of j for a given human capital type ℓ. We view this as "skill-biased" technological shock that affects the productivity of a particular skill type. An example of this type of shock is a technological discovery that is substitutable with type ℓ workers (such as the improvement of word processing software for typists).

Our data allow us to distinguish between these two types of shocks. To be in our layoff sample, an individual reported that the reason of job loss was either "slack work" or "position abolished." We view these as mapping into our model well with the human capital type shock corresponding to position abolished while the firm shock relates to slack work. Intuitively in the model, if the shocks are of similar magnitude, a worker who is laid off through a human capital type shock will likely experience a much larger wage loss. The reason is simply that if the shocks occur at the sector level, a worker can move into a different sector that did not experience the shock. The worker's wage still falls because her outside wage has fallen as a result of the shock. By contrast, a worker laid off because of a shock to her human capital can do no such thing. Her productivity, and analogously her wage, has fallen at all firms.

In their paper, GK discuss the fact that a plant closing could be associated with poor local labor markets and thus could be associated with worse outcomes. This is related to our model if one interprets sectors j as local labor markets.

We first informally look at this issue in the data by presenting tables analogous to Tables 2A and 2B, but distinguishing a layoff between "slack work" and "position abolished." These results are shown in Tables 5A and 5B. One can see that in every specification, the point estimates indicate that every group experiences a larger fall in wages for position abolished than for slack work. In the second to last row we present the p-value of a joint test as to whether the coefficients on slack work and position abolished are jointly the same. One can see that this hypothesis is strongly rejected for white-collar workers and is rejected in the specification of column (4) for blue-collar workers.[22] Once again, one also sees the striking result that neither industry nor occupation is important in explaining these results. We believe these results in Table 5 are of interest in their own right as (to our knowledge) they have not been previously discussed in the literature on displaced worker effects. Although we do not show them explicitly, we also looked at slack work versus position abolished using the Weibull proportional hazard model. We find that for white-collar workers, position abolished leads to both economically and statistically significantly longer unemployment spells.[23]

We now turn toward reconciling the model with the data. With this in mind we chose six moments in the data that we hope to match. By gender, we constructed the change in wages at displacement for three different types of displacement: plant closing, position abolished, and slack work. Since the model does not explicitly allow for an experience effect (although it would be very easy to add since it is presumably observable by everyone) we want to focus on the change that occurred between the last predisplacement wage and the first wage after displacement. Specifically we control for potential experience by including a proxy, which is defined as the number of years since displacement minus the total number of weeks unemployed during this period divided by 52, in the regression of change in log wage. We then obtain the predicted values for each of the 6 groups by fixing the potential experience at 0 years.

The 6 moments we try to fit are presented in Table 6. One can see three key features of the data that we will show can be explained by the model. The difference in wage loss by gender for a plant closing is very small, and is in fact not statistically distinguishable. By contrast, for the two types of layoffs we see substantially larger losses for men than for women. The second key feature of the data that we plan to match is the difference between slack work and position abolished. We show that with heterogeneous human capital in the model it is straightforward to match this feature of the data. The third feature is that for both genders, the plant closing result is in between the other two.

There are essentially 10 different labor types—five basic types of each gender. A key aspect of the model is that different types of human capital are used differently in different firms. In particular we will assume that originally $\alpha_{1\ell j} \in \{1, 2, 3, 4, 5\}$. For each firm and for each gender, α will take on each of these five numbers. Furthermore, the model is completely symmetric so for each labor type ℓ, the share parameter α takes on each of the 5 values for some firm type.[24]

A key piece of this thought exercise is that we restrict the model in another important way by assuming that the gender productivity does not interact with sector at all because the results in Table 2A suggest that industry and occupation differences between men and women do not play a crucial role in explaining the results. For this reason we restrict the model so the "industry/occupation" composition is the same for men and women. Formally, let $\ell = \{1, \ldots, 5\}$ denote men and $\ell = 16, \ldots, 10\}$ denote women. We impose that for all states of the world s,

$$\alpha_{t\ell js} = \alpha_{t(\ell-5)js} \text{ for } \ell > 5 .$$

Thus, shocks hit men and women in exactly the same way. So, for example, a human capital type shock that hits skill group $\ell = 3$ for men will also hit group $\ell = 8$ for women. This means that in the end we have three data moments that differ by gender, but in the simulation we only have either a 2 or 1 parameter that differs by gender. Thus even though there are many parameters in the model, we are certainly not guaranteed to be able to fit the data.

We simulate three different changes in α between periods 2 and 3:

1) modest proportional change in $\alpha_{j\ell}$ by j (slack work),

2) large change in $\alpha_{j\ell}$ by j causing sector to disappear (plant closing), and

3) proportional change in $\alpha_{j\ell}$ by ℓ (position abolished).

In particular, we will assume that there are 16 states of the world in period 3 (S = 16). With probability 0.85, no shock is experienced. Then we put 1 percent probability on each of the other 15. These other 15 correspond to 5 of each type of the shock above. That is because we have 5 sectors, each sector has a 1 percent probability of getting hit by a modest proportional change in $\alpha_{j\ell}$ and also a 1 percent probability of getting hit by a large change in $\alpha_{j\ell}$ which causes it to shut down. For each gender, we also have 5 labor types and each has a 1 percent probability of getting hit by a proportional change in $\alpha_{j\ell}$.

The model has many different margins to complicate it. To ease the computational burden, we restrict turnover in a few ways. First, as mentioned above in Section 4, we do not allow firms to fire workers after period 3. Second, for the sector-specific shock we only allow for layoffs in the sectors which experienced the shocks. In principle, since the outside option has changed, there could be some layoffs for other firms as well. However, this should be small, not of primary interest in this analysis, and incorporating it would make the model substantially more difficult to solve.

We assume that the ability of a worker i of type ℓ can be written as

$$\log\left(Y_{\ell i}\right) = \theta_{\ell i} + \upsilon_{\ell i} \quad ,$$

where $\theta_{\ell i}$ is observable to an outside firm and $\nu_{\ell i}$ is orthogonal to information about the quality of a worker. Further, we assume that $\nu_{\ell i} \sim N\left(0, \sigma^2_{\vartheta_i}\right)$, where ϑ_i is the gender of individual i. Allowing the information to vary by gender is important in fitting the data. While we have no clear explanation as to why σ^2_{ϑ} would vary across gender, we discuss it more below. Since wages will be proportional to observable ability, heterogeneity in $\theta_{\ell i}$ across individuals plays no crucial role in the model so we just fix $\theta_{\ell i} = 0$ for everyone. Modifying this assumption would make no difference to any of the results we show.[25]

This leaves us with essentially four types of parameters: 1) the elasticity of substitution (ρ), 2) the training cost (τ), 3) the standard deviation of the unknown component of ability (σ_g), and 4) the size of the shocks. As a practical matter, we found that when a plant closes, the only parameter that matters substantially for the simulated results is the elasticity of substitution. Furthermore, in practice, the wage loss with plant closing in the simulations will be very close across gender, and the difference in the data is not statistically significant. Thus, we do not try to match this difference exactly, but rather choose a value of ρ that matches approximately.[26] This process led to the value $\rho = 0.85$. We then numerically solved for values of the other parameters to match the four data points. While we have a number of different parameters, only τ and σ_g vary by gender. Thus, again we should highlight that our goal is to show that the model can reconcile with the data (which it is certainly not guaranteed to). Another value of this exercise is that the reader can see the types of parameter values that are needed to fit the results and can judge whether they seem "plausible" or not.

The results of this simulation are presented in Table 6. One can see that we do fit the four moments that we are trying to fit. The parameters that lead to this fit are shown in the bottom panel of Table 6. As one can see, one result is that the standard deviation of unobserved ability is substantially higher for men than it is for women. In the simulation, this leads the "lemon effect" to be larger for men than for women. It essentially embodies the idea that a layoff is a stronger signal for men than it is for women. It is important that the reader not take this parameter too literally. Another interpretation of the phenomena is that the decision to lay off an individual is more complicated than in the model and involves other factors beyond just pure ability such as the value of home production which could change the threshold.[27] If it were the case that the decision to lay off a man was based purely on his market ability, but the decision to lay off a woman depended on both market ability and the value of nonmarket time, then the signal for a man would be stronger than the signal for a woman. We don't view this as a fundamentally different model than the one we have written down, but rather as a potential reason why layoff is a more informative signal for men than it is for women (which is the essence of the higher value of σ_g in the results).

A second feature of the results is that the value of τ is quite high. Note that in the model, this will not reflect into a higher measured return to tenure in a log wage regression because the firm pays the outside wage. The fact that τ is quite high is essentially necessary if asymmetric information is important. Since a firm pays workers with identical observable characteristics the same as their outside market, the firm has a strong incentive to fire the workers with the worst unobservable attributes. If a majority of workers are retained, it must be that these worst workers are relatively more productive for the current firm than for the outside labor market. Thus, it must be the case that some combination of hiring costs, training costs, or specific human capital are important. Any of these can be interpreted as τ. One may feel uncomfortable about why τ should vary with gender. We relax that restriction below. Even given the current parameters in which τ is larger for men, one can see that the retention probability in the second period is much higher for women than for men. This is due to the differences in τ_g.

We simulate the effects of three types of shocks. With a plant closing, one sector disappears and all workers leave for another sector. For the sector shock, sector j^* is hit by a shock of 0.948. Formally this means that

$$\alpha_{3\ell j} = \begin{cases} 0.948\alpha_{2\ell j} & j = j^* \\ \alpha_{2\ell j} & \text{otherwise} \end{cases}.$$

We see that this leads 20 percent of men (and 16 percent of women) who were employed in this sector to be laid off.

Similarly, for the human capital type shock the effect is 0.943. If type $\ell^* \leq 5$ is hit by the shock this means that

$$\alpha_{3\ell j} = \begin{cases} 0.943\alpha_{2\ell j} & \ell = \ell^* \text{ or } \ell^*+5 \\ \alpha_{2\ell j} & \text{otherwise} \end{cases}.$$

Since this is a negative shock to all sectors, the layoff probabilities are much lower—less than 1 percent for both men and women. Also note that while the size of the shocks is virtually identical between the two cases, the wage penalty is substantially larger for position abolished than for slack work. This is a more general feature that comes out of the model rather than being an artifact of the particular normalization. When a sector is hit by a shock, other sectors are not. Therefore, a worker can move to a sector that was not hit. However, this is not possible for a human capital shock as the worker's productivity has declined everywhere.

We were uncomfortable with the result that the value of τ would differ by gender. We were not able to perfectly match all of the moments when we imposed the condition that τ does not vary across gender. Instead we performed the following exercise. We took all of the parameters from the previous simulation as given. However, we restricted τ = 1:5 for each gender that was in between the estimates in the previous model. We then simulate the model again and present it in Table 7. One can see that the numbers between the data and the simulation are no longer identical but are quite close. Most importantly, we tested whether these simulated moments could be rejected in the data and did not reject. One thing that changes is that the initial retention probability for men falls substantially as one would expect. However, the wage losses change little.

We have shown in this section that our model is consistent with the data. Since the model is highly parameterized there might be a question of whether the fact that we can reconcile the data is particularly surprising or interesting. On this point we make three main comments. First, an important finding in the empirical section is that occupation and industry play little roles in explaining the gender difference in plant closings and layoffs. Thus we do not allow this to reconcile the difference. Second, asymmetric information plays the key role in explaining the gender gap. Specifically, in Table 7 it is only σ_g that can explain the difference between men and women. The result in the model is reconciled by the fact that wage losses at both types of layoff (but not plant closing) differ substantially by gender. The basic idea is that for some reason being laid off is a relatively more important signal for a man than for a woman. We do not have a strong ex-ante reason to explain why this would be the case. The point estimates of the model would suggest that the standard deviation of unobserved ability (to the outside firm) is larger for men than for women. Of course, one does not necessarily want to take this literally. The difference could be standing in for some other feature of the data; for example, the layoff decision is more complicated for women than for men, so that unobserved ability is a relatively more important factor. Third, heterogeneous human capital is crucial to explain the results. For both genders we see the largest wage losses at position abolished, second at plant closing, and third at slack work. Heterogeneous human capital is crucial for reconciling this result. Without it, one would expect, as in GK, that the wage loss at layoff (of both types) would be larger than the wage loss at plant closing.

6 CONCLUSIONS

In a seminal paper, Gibbons and Katz (1991) develop and empirically test a model of asymmetric information in the labor market. They derive an implication of their model that if asymmetric information is important, one should expect a larger fall in earnings at layoff than at plant closing. Using the Displaced Worker Survey, they show this implication to be true for men. We revisit this question, making use of the many more years of data that are available now. We test the hypothesis on four different demographic groups. For three of our four groups (black men, black women, and white women) we find the opposite of the Gibbons and Katz prediction; plant closings lead to more negative consequences than do layoffs. We show that this difference occurs for two reasons. First, white men experience larger earnings declines at layoff than the other groups. Second, black workers experience substantially larger decreases in their earnings at plant closing than do whites.

We document four other aspects of the data. First, the basic results are remarkably robust to occupation and industry controls. Second, following Oyer and Schaefer (2000), we make use of the passage of the Civil Rights Act of 1991 (CRA91) to test an implication of the model. We show that black workers experience a relatively larger loss in earnings at layoffs after 1991 than before, which is consistent with asymmetric information. We think this is the strongest evidence in favor of asymmetric information. Third, we demonstrate similar patterns when we look at the length of unemployment spells following displacement. Fourth, we document for the first time in the literature that the two types of layoffs reported in the DWS data have very different features in terms of earnings losses. In particular, we find that earnings falls are greater when layoff is associated with "position abolished" then when it is associated with "slack work." Furthermore, wage losses from plant closings fall between these two types of layoffs in terms of their magnitude.

We develop a model that incorporates heterogeneous human capital into an asymmetric information framework based on GK. The model includes different types of firms and different types of workers. In the model, once a worker has worked for a firm for a period, the current firm knows his/her skill level but outside firms do not. We model layoffs and plant closings as resulting when shocks hit firms in which the workers work. We then numerically simulate the model and show that one can find parameters of the model to make it consistent with the data.

We simulate the model and show that it captures the key features of the data. In particular, asymmetric information plays the key role in explaining the gender gap in the model—this result is reconciled with the fact that in the data wage losses at both types of layoff (but not plant closing) differ substantially by gender. The basic idea is that for some reason being laid off is a relatively more important signal for a man than for a woman. The point estimates of the model would suggest that the standard deviation of unobserved ability (to the outside firm) is larger for men than for women. As we cautioned earlier, however, one does not necessarily want to take this literally. It could be standing in for some other feature of the data such as the layoff decision is more complicated for women than for men so that unobserved ability is a relatively more important factor. One interesting extension can be to extend the model to allow for layoff decisions to depend on both market ability and the value of nonmarket time, which in general can differ by gender, and then investigate the mechanisms directly.

Another extension of the analysis would be to incorporate heterogeneity of taste discrimination across firms in the model to explain the fact that blacks suffer greater wage penalties from plant closings than whites.

Both of these extensions are very interesting and important. More generally, our model is overly simple in many dimensions. However, sorting out these alternatives requires more data than we get in the DWS, where we essentially just have the six numbers in Tables 6 and 7. Other useful data sets are available and we leave this work for future research.

Gibbons and Katz acknowledge at the end of their paper that, "Unfortunately, the nature of asymmetric information seems to imply that direct empirical tests of its importance are not possible, so indirect tests of the kind presented here may be all that is possible." We share the sentiment and agree that our data are not rich enough to precisely distinguish between all potential explanations. However, we think we have provided additional evidence to bear on these issues, and our results suggest that explanations of asymmetric information and heterogeneous human capital are important. We hope that alternative data sources can be found that will shed more light on these important issues in the future research.

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Table 1A: Displaced Worker Surveys 1984–2002
(White Collar)
Descriptive Statistics: Sample Means with Standard Deviations in Parentheses

	Male white		Male black		Female white		Female black	
	Plant closing	Layoff	Plant closing	Layoff	Plant closing	Layoff	Plant closing	Layoff
Log predisplacement real wage	6.059 (0.565)	6.126 (0.573)	5.713 (0.467)	5.811 (0.544)	5.664 (0.525)	5.694 (0.544)	5.593 (0.449)	5.526 (0.490)
Log postdisplacement real wage	5.981 (0.565)	6.015 (0.572)	5.610 (0.588)	5.810 (0.464)	5.601 (0.496)	5.650 (0.502)	5.462 (0.458)	5.495 (0.444)
Change in log real wage	-0.063 (0.431)	-0.099 (0.448)	-0.108 (0.439)	0.022 (0.420)	-0.049 (0.416)	-0.033 (0.420)	-0.143 (0.385)	-0.023 (0.445)
Tenure on previous job	5.407 (6.948)	4.300 (5.953)	5.747 (7.678)	3.711 (4.858)	4.122 (5.504)	3.571 (5.009)	4.913 (6.152)	3.337 (4.907)
Age	38.69 (10.36)	38.71 (10.32)	36.52 (9.908)	34.69 (8.12)	36.50 (10.52)	37.04 (10.24)	35.42 (9.613)	34.50 (9.63)
Married	0.706 (0.456)	0.701 (0.458)	0.576 (0.497)	0.484 (0.502)	0.522 (0.500)	0.496 (0.500)	0.395 (0.490)	0.388 (0.489)
High school dropout	0.034 (0.182)	0.023 (0.149)	0.065 (0.248)	0.033 (0.180)	0.037 (0.188)	0.019 (0.137)	0.043 (0.204)	0.036 (0.188)
High school graduate	0.268 (0.443)	0.210 (0.407)	0.348 (0.479)	0.231 (0.424)	0.400 (0.490)	0.326 (0.469)	0.333 (0.473)	0.248 (0.433)
Some college	0.302 (0.459)	0.295 (0.456)	0.348 (0.479)	0.341 (0.477)	0.353 (0.478)	0.362 (0.481)	0.500 (0.502)	0.521 (0.501)
College graduate or above	0.396 (0.489)	0.473 (0.499)	0.239 (0.429)	0.396 (0.492)	0.210 (0.408)	0.293 (0.455)	0.123 (0.330)	0.194 (0.397)
No. obs.	1,670	2,17092		91	1,741	1,841	162	165

Sample selections: (1) White-collar workers aged 20–64; (2) lost job for three reasons: plant closing, position abolished, or slack work; (3) lost a job in previous three years; (4) reemployed at survey date; (5) full-time to full-time transition; (6) private sector to private sector; (7) delete if reemployment weekly wage < $40; (8) delete agriculture and construction.

Table 1B: Displaced Worker Surveys 1984–2002
(Blue Collar)
Descriptive Statistics: Sample Means with Standard Deviations in Parentheses

	Male white		Male black		Female white		Female black	
	Plant closing	Layoff	Plant closing	Layoff	Plant closing	Layoff	Plant closing	Layoff
Log predisplacement real wage	5.727 (0.517)	5.679 (0.525)	5.560 (0.506)	5.486 (0.433)	5.288 (0.443)	5.323 (0.447)	5.215 (0.373)	5.252 (0.467)
Log postdisplacement real wage	5.646 (0.480)	5.603 (0.486)	5.470 (0.482)	5.416 (0.424)	5.231 (0.428)	5.255 (0.396)	5.107 (0.418)	5.120 (0.450)
Change in log real wage	-0.089 (0.457)	-0.082 (0.478)	-0.072 (0.450)	-0.067 (0.416)	-0.068 (0.427)	-0.075 (0.412)	-0.099 (0.359)	-0.143 (0.406)
Tenure on previous job	5.500 (6.997)	3.375 (5.180)	5.916 (7.563)	3.212 (5.011)	4.744 (6.023)	2.905 (4.591)	6.629 (7.380)	3.037 (4.567)
Age	36.32 (10.73)	34.55 (10.25)	35.70 (9.89)	33.76 (9.82)	38.18 (10.94)	35.95 (10.91)	38.01 (10.07)	34.03 (8.81)
Married	0.705 (0.456)	0.659 (0.474)	0.573 (0.496)	0.438 (0.497)	0.536 (0.499)	0.485 (0.500)	0.331 (0.472)	0.309 (0.464)
High school dropout	0.207 (0.405)	0.176 (0.381)	0.228 (0.421)	0.179 (0.384)	0.273 (0.446)	0.174 (0.380)	0.296 (0.458)	0.236 (0.427)
High school graduate	0.520 (0.500)	0.529 (0.499)	0.515 (0.501)	0.502 (0.501)	0.515 (0.500)	0.563 (0.496)	0.542 (0.500)	0.482 (0.502)
Some college	0.229 (0.420)	0.236 (0.425)	0.218 (0.414)	0.279 (0.449)	0.172 (0.377)	0.205 (0.404)	0.162 (0.370)	0.273 (0.447)
College graduate or above	0.044 (0.205)	0.058 (0.235)	0.038 (0.194)	0.040 (0.196)	0.041 (0.198)	0.057 (0.232)	0.000 (0.000)	0.009 (0.095)
No. obs.	2,108	2,515	206	201	763	682	142	110

Sample selections: (1) Blue-collar workers aged 20–64; (2) lost job for three reasons: plant closing, position abolished, or slack work; (3) lost a job in previous three years; (4) reemployed at survey date; (5) full-time to full-time transition; (6) private sector to private sector; (7) delete if reemployment weekly wage < $40; (8) delete agriculture and construction.

Table 2A: Displaced Worker Surveys 1984–2002
(White Collar)
Dependent variable: Change in log wage

	(1)	(2)	(3)	(4)
Layoff*Black	0.052	0.029	0.028	0.031
	(0.030)	(0.029)	(0.029)	(0.029)
Layoff*Female	0.059	0.053	0.050	0.054
	(0.014)	(0.014)	(0.014)	(0.014)
Layoff	-0.034	-0.049	-0.046	-0.050
	(0.015)	(0.015)	(0.015)	(0.015)
Plant closing*Black	-0.075	-0.080	-0.077	-0.080
	(0.031)	(0.030)	(0.030)	(0.030)
Plant closing *Female	0.011	-0.002	-0.003	-0.001
	(0.015)	(0.015)	(0.015)	(0.016)
Constant	-0.062	Y	Y	Y
	(0.011)			
Married, Age, Age2, Education	--	Y	Y	Y
Yr. dummies, Yrs. since disp, Region	--	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y	Y	Y
Industry	--	--	Y	Y
Occupation	--	--	--	Y
N	6,981	6,981	6,978	6,978

Sample selections: See Table 1A.

Table 2B: Displaced Worker Surveys 1984–2002
(Blue Collar)
Dependent variable: Change in log wage

	(1)	(2)	(3)	(4)
Layoff*Black	-0.015	-0.025	-0.035	-0.035
	(0.030)	(0.030)	(0.030)	(0.030)
Layoff*Female	-0.002	-0.002	-0.018	-0.020
	(0.019)	(0.019)	(0.019)	(0.020)
Layoff	0.007	-0.021	-0.020	-0.019
	(0.014)	(0.014)	(0.014)	(0.014)
Plant closing*Black	-0.002	0.003	-0.012	-0.012
	(0.028)	(0.028)	(0.028)	(0.028)
Plant closing *Female	0.015	0.019	0.000	-0.001
	(0.019)	(0.019)	(0.019)	(0.019)
Constant	-0.087	Y	Y	Y
	(0.010)			
Married, Age, Age2, Education	--	Y	Y	Y
Yr. dummies, Yrs. since disp, Region	--	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y	Y	Y
Industry	--	--	Y	Y
Occupation	--	--	--	Y
N	5,926	5,926	5,885	5,875

Sample selections: See Table 1B.

Table 3: Displaced Worker Surveys 1984–2002
(White Collar Only)
Dependent variable: Change in log wage

	(1)	(2)
Post91* Layoff*Black	-0.097	-0.102
	(0.060)	(0.059)
Post91* Layoff*Female	0.003	0.015
	(0.028)	(0.028)
Post91* Layoff	0.004	0.020
	(0.030)	(0.029)
Post91* Plant closing* Black	-0.012	-0.044
	(0.061)	(0.060)
Post91* Plant closing* Female	-0.016	-0.005
	(0.031)	(0.030)
Post91	0.035	0.028
	(0.023)	(0.039)
Layoff*Black	0.107	0.090
	(0.046)	(0.045)
Layoff*Female	0.055	0.044
	(0.021)	(0.020)
Layoff	-0.039	-0.059
	(0.020)	(0.020)
Plant closing* Black	-0.070	-0.057
	(0.043)	(0.042)
Plant closing* Female	0.017	0.002
	(0.020)	(0.020)
Constant	-0.076	Y
	(0.015)	
Married, Age, Age2, Education	--	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y
Yrs. since disp., Yr. dummies, Regions	--	Y
Industry, Occupation	--	Y
N	6,981	6,978

Sample selections: See Table 1A.

Table 4: Displaced Worker Surveys 1986–2002
Effects on Duration of the First Spell of Joblessness since Displacement
Dependent Variable: Log (Weeks of Joblessness)
MLE Estimates from Weibull Duration Model

	White			Blue Collar		
	(1)	(2)	(3)	(1')	(2')	(3')
Layoff*Black	0.031	0.068	0.073	0.228	0.165	0.156
	(0.070)	(0.066)	(0.069)	(0.072)	(0.067)	(0.071)
Layoff*Female	0.013	0.105	0.077	0.217	0.117	0.114
	(0.037)	(0.036)	(0.039)	(0.051)	(0.047)	(0.050)
Layoff	0.141	0.210	0.221	0.007	0.144	0.125
	(0.041)	(0.039)	(0.041)	(0.040)	(0.037)	(0.039)
Plant Closing*Black	0.189	0.184	0.161	0.236	0.170	0.149
	(0.077)	(0.072)	(0.075)	(0.070)	(0.064)	(0.067)
Plant Closing*Female	0.106	0.153	0.141	0.264	0.236	0.234
	(0.042)	(0.040)	(0.043)	(0.049)	(0.046)	(0.050)
Married, Age, Age2	--	Y	Y	--	Y	Y
Education	--	Y	Y	--	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y	Y	--	Y	Y
Yr. dummies, Yrs. since disp, Regions	--	Y	Y	--	Y	Y
Industry, Occupation	--	Y	Y	--	Y	Y
Log Predisplacement wage	--	--	-0.018	--	--	-0.014
			(0.029)			(0.037)
Weibull scale parameter	1.145	1.054	1.046	1.210	1.077	1.074
	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)	(0.012)
N	7,325	7,306	6,539	6,314	6,193	5,656

Sample selections: (1) workers aged 20–64; (2) lost job for three reasons: plant closing, position abolished, or slack work; (3) lost a job in previous three years; (4) displaced from full-time jobs; (5) displaced from private sector jobs; (6) delete if predisplacement weekly wage < $40; (7) not displaced from agriculture and construction.
Note: Standard errors are in parentheses.

Table 5A: Displaced Worker Surveys 1984–2002
(White Collar)
Dependent variable: Change in log wage

	(1)	(2)	(3)	(4)
Black*Slack work	0.164	0.150	0.152	--
	(0.052)	(0.051)	(0.051)	
Black*Position abolished	0.086	0.066	0.069	--
	(0.052)	(0.051)	(0.051)	
Female*Slack work	0.053	0.057	0.060	--
	(0.025)	(0.025)	(0.025)	
Female*Position abolished	0.050	0.055	0.051	--
	(0.025)	(0.024)	(0.024)	
Slack work	-0.005	-0.027	-0.032	0.008
	(0.018)	(0.018)	(0.018)	(0.013)
Position abolished	-0.063	-0.070	-0.067	-0.036
	(0.018)	(0.017)	(0.017)	(0.012)
Black	-0.075	-0.080	-0.080	-0.023
	(0.030)	(0.030)	(0.030)	(0.021)
Female	0.011	-0.001	0.000	0.031
	(0.015)	(0.015)	(0.015)	(0.011)
Constant	-0.062	Y	Y	Y
	(0.011)			
Married, Age, Age2, Education	--	Y	Y	Y
Yr. dummies, Yrs. since disp, Region	--	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y	Y	Y
Industry	--	--	Y	Y
Occupation	--	--	Y	Y
P-value for the F-test (null hypothesis: the coefficients on slack work and position abolished are jointly equal)	0.0000	0.0027	0.0062	0.0016
N	6,981	6,981	6,978	6,978

Sample selections: See Table 1A.

Table 5B: Displaced Worker Surveys 1984–2002
(Blue Collar)
Dependent variable: Change in log wage

	(1)	(2)	(3)	(4)
Black*Slack work	-0.014	-0.025	-0.020	--
	(0.044)	(0.043)	(0.043)	
Black*Position abolished	-0.014	-0.039	-0.034	--
	(0.069)	(0.068)	(0.069)	
Female*Slack work	-0.032	-0.033	-0.028	--
	(0.029	(0.029)	(0.029)	
Female*Position abolished	0.037	0.024	0.019	--
	(0.045	(0.044)	(0.044)	
Slack work	0.019	-0.013	-0.008	-0.017
	(0.015	(0.015)	(0.015)	(0.013)
Position abolished	-0.034	-0.050	-0.058	-0.057
	(0.023)	(0.022)	(0.023)	(0.019)
Black	-0.002	0.003	-0.012	-0.023
	(0.028	(0.028)	(0.028)	(0.021)
Female	0.015	0.018	-0.002	-0.011
	(0.019)	(0.019)	(0.019)	(0.014)
Constant	-0.087	Y	Y	Y
	(0.010)			
Married, Age, Age2, Education	--	Y	Y	Y
Yr. dummies, Yrs. since disp, Region	--	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted < 1)	--	Y	Y	Y
Industry	--	--	Y	Y
Occupation	--	--	Y	Y
P-value for the F-test (null hypothesis: the coefficients on slack work and position)	0.1266	0.3632	0.1623	0.0436
N	5,926	5,926	5,875	5,875

Sample selections: See Table 1B.

Table 6
Results for Model 1

Simulated Log Wage Differentials

	Male		Female	
	Data	Simulation	Data	Simulation
Slack work	-0.107	-0.107	-0.042	-0.042
	(0.020)		(0.020)	
Position abolished	-0.162	-0.162	-0.107	-0.107
	(0.019)		(0.019)	
Plant closing	-0.119	-0.102	-0.099	-0.114
	(0.018)		(0.017)	

Parameters of Simulated Model

	Male	Female
ρ	0.85	
τ	1.990	1.372
σ	0.097	0.018
Initial retention probability	0.710	0.999
Sector Shock		
Shock	0.948	
Layoff probability	0.202	0.161
Human Capital Type Shock		
Shock	0.943	
Layoff probability	0.008	0.002

Table 7
Results for Model 2

Simulated Log Wage Differentials

	Male		Female	
	Data	Simulation	Data	Simulation
Slack work	-0.107	-0.084	-0.042	-0.037
	(0.020)		(0.020)	
Position abolished	-0.162	-0.130	-0.107	-0.119
	(0.019)		(0.019)	
Plant closing	-0.119	-0.113	-0.099	-0.111
	(0.018)		(0.017)	

Parameters of Simulated Model

	Male	Female
ρ	0.85	
τ	1.500	1.500
σ	0.097	0.018
Initial retention probability	0.366	0.999
Sector Shock		
Shock	0.948	
Layoff probability	0.076	0.119
Human Capital Type Shock		
Shock	0.943	
Layoff probability	0.009	0.000

NOTES

1. They use white-collar workers because they argue that blue-collar jobs are much more likely to be covered by collective bargaining agreements. In that case seniority is typically the main determinant of the layoff decisions so that a layoff will not necessarily convey negative information.

2. The theory of statistical discrimination was introduced by Phelps (1972) and Arrow (1973) and subsequently developed by, among others, Aigner and Cain (1977), Lundberg and Startz (1983), and Coate and Loury (1993). Empirical studies of statistical discrimination are still scarce. A notable exception is Altonji and Pierret (2001). Altonji and Blank (1999) present a survey on this topic.

3. Gibbons and Katz also informally make the point that if plant closing occurs in worse labor markets then we might see bigger drops in wages. This is related to our concept of heterogeneous human capita.

4. The DWS ask and collect information on, at most, one job loss for each individual. If the respondent lost more than one job in the reference period, she/he is asked about information only for the longest job lost.

5. In 1994 and later DWS, individuals who report a job loss for the reasons other than the first three are not asked follow-up questions about the lost job.

6. We restrict to the sample to full-time jobs (at least 35 hours per week) because the DWS only provided information on usual weekly earnings (and not hourly earnings) and the full- or part-time status of the worker's old job. By limiting our sample to full-time workers we attempt to control for hours of work on the old job.

7. Using data from the NLSY, Krashinsky (2002) also finds that workers displaced by layoffs suffer larger wage losses than those displaced by plant clostings. However, he provides an alternative explanation attributing the effect to differences in firm size of predisplacement employers. He argues that small firms are more likely to close down when facing adverse economic shocks, while larger firms are more likely to reduce their workforces. Therefore, laid-off workers tend to lose any wage premium or rents they earned from working at large firms. Using data from the PSID, Stevens (1997) also finds that wage losses following layoffs are larger than those following plant closings, but she argues that that can be explained by the larger wage reductions prior to displacement for plant closings than for layoffs. Song (2007) reexamines the Gibbons-Katz study and argues that their findings can be partly attributed to differential recall bias for layoffs versus plant closings in the 1984 and 1986 DWS and, in later years, mostly by higher wage-tenure profile prior to displacement for layoffs than for plant closings.

8. The t-stat for black men is 1.93, which falls barely below the 5 percent convention but is well above the 10 percent level. For black women, the t-stat is well above 1.96.

9. We do this to increase the precision of the results.

10. While previous federal employment discrimination legislation typically limited plaintiff recovery to lost wages, CRA91 allows employees to sue for intentional gender and race discrimination up to $300,000 in punitive damages; furthermore, CRA91 allows employees to claim unlawful termination on the basis of *race* to sue for unlimited punitive damages. (See Oyer and Schaefer [2000] for more details of the law.)

11. The data used in Oyer and Shaefer (2000) can not separately identify job losses due to plant closing from the other forms of layoffs (selective downsizings such as abolished positions).

12. There might be other reasons for worrying about changes over time in general. It is widely believed that there has been an increase in the number of layoffs, especially from white-collar jobs in some large corporations, in the early to mid-1990s. Findings in Farber (1997, 2003) lead support to this belief. He finds that although the overall involuntary job loss rate did not change substantially from the 1980s to 1990s, there was a decade-long increase in the rate of job loss due to position abolished. If mass layoffs occur increasingly frequently, then the event layoff might become less informative about individual worker's productivity. Therefore we would expect the difference in wage losses between layoffs and plant closings to become smaller over time.

13. Each DWS has a question about weeks unemployed since job loss. In 1984 and 1986, it is total weeks of joblessness since displacement. In 1986, there was also information on the number of jobs held since displacement. These two variables allow us to determine the length of the initial spell of joblessness for those employed in their first job at the survey date. Since 1988, the question directly asks about weeks unemployed until found a job, i.e., the initial spell length. (Due to a survey error, this variable was missing for most observations in 1994.) Workers who had not worked since displacement are always included in the sample just with censored length of the initial spell. We then construct a sample of first spells of joblessness from various years subject to the following additional restrictions: workers aged 20–64 who were displaced in previous three years from full-time, private sector jobs not in agriculture and construction industries and had weekly wage no less than $40.

14. While including the wage at displacement is similar, one still finds lower labor supply by race and gender conditional on wages. So while this might help, it does not completely account for the differences.

15. The fact that we don't see much of a plant closing effect for black workers in the blue-collar data adds to the puzzle. Of course, this can be consistent with the taste discrimination theory if there is much greater prejudice against minorities in white-collar jobs than in blue-collar jobs.

16. We model each sector as being composed of a large number of smaller firms. With constant returns to scale, we can focus on the aggregate human capital production function, and each of

the smaller firms will look identical. It is also easier to think about what an entering firm would do. With increasing or decreasing returns, this would be much more complicated.

17. The reason is that all workers have the same outside market, firms would have an incentive to fire the worst worker and thus eventually fire all workers. With $\tau > 1$, workers have more value in the current firm than in outside firms so that some workers will be retained.

18. Gibbons and Katz (1991) argue similarly that their analogue could represent firm specific human capital, mobility costs of the worker, hiring cost of the new employer, or a firing cost from the old employer.

19. One could make some assumptions to guarantee that this condition holds. Alternatively, one could analyze all of the equilibria. However, our goal is to show that the model is consistent with the data, rather than to try to distinguish between equilibria. We strongly suspect that more than one equilibrium can reconcile the data.

20. Of course, it is still true that firms typically do not lay off all workers—they choose the ones of lower ability. Thus one sees a lemon effect for both types of layoffs.

21. Given the assumptions we have made, one will only lay off the worst workers because the outside market is identical for all workers. Thus there will always be a "lemon" effect.

22. When both heterogeneous human capital and asymmetric information are at work, we would see differences between white collars and blue collars in the relative wage losses for layoffs and plant closings. The fact that we see similar patterns between white collars and blue collars in the relative wage losses for position abolished and slack work suggests that the human capital story applies to both in the similar way. Thus, for the human capital story we think the blue-collar data is supportive (although somewhat weaker).

23. The point estimate for blue-collar workers actually goes the other direction, but the difference is not close to statistically significant. The p-value for the test that the coefficients on slack work and position abolished are the same in the specification similar to column (4) of Table 5 is 0.0082 for white-collar workers and 0.5733 for blue-collar workers.

24. Making it symmetric substantially lowers the computational cost because of similarities in behavior across groups. Without this the model would be much harder to estimate.

25. The only place where this is somewhat relevant is in determining the outside wage for individuals who are laid off after the first period. Here we assume that the outside wage is 0.5. This only matters in determining the first period wage which plays no role in our analysis.

26. Here we just iterated trying alternative values of ρ until we found a value that gave simulated values of wage loss in between the gender specific values (i.e., simulated values in the interval $[-0.119, -0.099]$).

27. This would involve a more complicated model in which home production was the relevant outside option for some. Individuals with higher value of home production could require more compensation and be laid off earlier.