Displacement, Asymmetric Information, and Heterogeneous Human Capital

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Gibbons and Katz's asymmetric information model of the labor market predicts that wage losses following displacement should be larger for layoffs than for plant closings. This was borne out in their empirical work. In this article, we examine how the difference in wage losses across plant closing and layoff varies with race and gender. We find that the basic prediction by Gibbons and Katz holds only for white males. We augment their asymmetric information model with heterogeneous human capital and show that this augmented model can match the data.

I. Introduction

The role of asymmetric information in labor market outcomes has long been of interest to labor economists (e.g., Spence 1973; Akerlof 1976; 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 mar-

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ket. 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 plant closing does not provide a negative signal. GK 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. They confirm this prediction in the data, showing that wage penalties are substantially higher for layoffs than for plant closings.

In this study, we take advantage of the fact that we have many more years of displaced workers' data to expand on GK by looking at how the difference in wage losses across plant closing and layoff 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. The basic prediction by GK actually only clearly holds for white males. Both black females and black males actually experience a much greater decline in earnings at plant closings than at layoffs. For white females the losses at plant closing and layoff are very similar. These results arise 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.

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[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. One might expect seniority to be a more important factor for blue-collar than white-collar workers in non-unionized firms as well. Abraham and Medoff (1984) have evidence suggestive of this in that seniority is more important for determining layoffs for nonunionized hourly workers than for nonunionized salary workers. The information content may also differ for these different types of workers. For these reasons we follow GK and focus on white-collar workers, but we present results for blue-collar workers as well.

[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) presents a survey on this topic.

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 an employee has worked for a firm for one period, the current firm knows his or 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 workforce (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 layoff is a substantially stronger signal for white males than for the other groups, this could lead the information hit for layoff to dominate for white males while the human capital aspect dominates for the other groups.

We provide some additional evidence that is 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 inclusion of region, industry, and occupation controls. 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 further 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, layoff should become a relatively more negative signal for blacks after 1991 than prior to it. 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 (although the standard errors are large).

Our evidence on the importance of human capital heterogeneity arises from the distinction 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

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[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 capital.

switching sectors, but they cannot avoid the first-order effect of the latter type shock. Thus if the shocks 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 losses are much larger 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. The distinctions between different types of layoffs are, to our best knowledge, new to the literature on displacement, and we think they are interesting in their own right.

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 layoff to dominate for men while the human capital aspect dominates for women. This allows us to reconcile the result. While we cannot formally prove that one needs asymmetric information and heterogeneous human capital to match the moments, we think that our model provides the most plausible story.

A number of other studies have examined the comparison between layoffs and plant closings using data other than the Displaced Workers Surveys (DWS). Using data from the Panel Study of Income Dynamics (PSID), Stevens (1997) also finds that wage losses following layoffs are larger than those following plant closings. However, she shows that this finding can be explained by the larger wage reductions prior to displacement for plant closings than for layoffs. Her analysis does not condition on race, gender, or blue/white collar, so it is difficult to directly compare to our study, particularly as it is not obvious how respondents answer the retrospective question about previous wages in the DWS. Using data from the National Longitudinal Survey of Youth (NLSY), Krashinsky (2002) also finds that workers displaced by layoffs suffer larger wage losses than those displaced by plant closings. 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 workforce. Therefore laid-off workers tend to lose any wage premium or rents they earned from working at large firms. He shows that when firm size is included in the wage loss regression, the difference between layoffs and plant closings becomes statistically insignificant, although the confidence intervals are wide enough to include substantial differences as well. Song (2007) reexamines the GK 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. We view all of these papers as potentially providing alternative explanations for the main GK finding; however, we do not view them as definitively establishing that GK's explanation is incorrect. The main contribution of our paper is in looking at various interactions (among race, gender, white/blue collar, and types of dismissals) which these other papers do not do. Therefore, we proceed with taking the GK explanation of the data, but it is important for the reader to keep these alternatives in mind.

The remainder of the paper is organized as follows. Section II describes the data. Empirical results are reported in Section III. We present the model in Section IV, discuss the difference between slack work and position abolished in Section V, and then use this information in the simulation in Section VI. Finally, Section VII discusses the results and concludes.

II. Data

We use data from the biennial Displaced Workers Surveys (DWS) Supplement to the Current Population Survey (CPS) between 1984 and 2008. The DWSs were conducted as part of the January CPSs in 1984, 1986, 1988, 1990, 1992, 2002, 2004, 2006, and 2008 and the February CPSs in 1994, 1996, 1998, and 2000. Each of the supplements from 1984 to 1992 asks workers if they lost a job at any time in the previous 5-year period, and each supplement from 1994 to 2008 asks this question for the previous 3-year period.[4] Displacement is defined as involuntary separation based on operating decisions of the employer such as plant closing, employer going out of business, 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 for the job loss: (1) plant closing, (2) slack (insufficient) 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 3-year period due to plant closing, slack

[4] The DWSs 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 or he is asked about information only for the longest job lost.

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

work, or position or shift abolished and who are reemployed in the private sector at the survey date. We focus only 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 1982–84 = 100 consumer price index. As in Gibbons and Katz, we distinguish between blue- and white-collar workers. The white-collar sample consists of workers who were displaced from jobs as managers and administrators, professional and technical workers, clerical workers, and sales workers, while the blue-collar sample consists of workers who were displaced from 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 table 1. We divide the data into 16 different groups, classifying by gender, race, blue/white collar, and layoff/plant closing. Sample means and standard deviations for all of the variables are displayed in the cells. In addition, for each group, we also report the *t*-statistics for testing the equality of sample means between layoffs and plant closings.

III. Empirical Findings

A. 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 the white-collar section of table 1. Note that we have a much longer history of data than Gibbons and Katz, who used data only from 1984–86. Since we can now extend the data until 2008, 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 Gibbons and Katz model holds up. White men lose approximately 6.5% of their wages at plant closings, but this rises to around 9.3% at layoffs. This can be interpreted as evidence that asymmetric information is important. However, for the other three demographic groups the evidence is very different. In particular, for African American males and females the contrast is striking, with substantially larger wage losses associated with plant closings than with layoffs. For white women wage

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[6] We restrict the sample to full-time jobs (at least 35 hours per week) because before 1994 the DWSs only provided information on usual weekly earnings (and not hourly earnings) and the full-/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.

Table 1
Descriptive Statistics of Displaced Workers

	White Collar								Blue Collar							
	Male White		Male Black		Female White		Female Black		Male White		Male Black		Female White		Female Black	
	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff	Plant Closing	Layoff
Log predisplacement real wage	6.095 (.580)	6.149 (.602)	5.773 (.556)	5.895 (.572)	5.688 (.556)	5.736 (.560)	5.577 (.662)	5.584 (.597)	5.734 (.514)	5.690 (.524)	5.565 (.509)	5.468 (.429)	5.300 (.449)	5.341 (.450)	5.234 (.377)	5.259 (.429)
t-statistic	2.94		1.67		2.82		.12		−2.91		−2.13		1.84		.48	
Log postdisplacement real wage	6.012 (.582)	6.033 (.590)	5.651 (.612)	5.827 (.538)	5.623 (.510)	5.674 (.523)	5.474 (.459)	5.520 (.485)	5.650 (.484)	5.615 (.493)	5.468 (.495)	5.390 (.438)	5.237 (.433)	5.257 (.407)	5.104 (.443)	5.120 (.438)
t-statistic	1.21		2.51		3.30		1.01		−2.58		−1.84		.94		.30	
Change in log real wage	−.065 (.427)	−.093 (.463)	−.112 (.445)	−.031 (.444)	−.047 (.457)	−.053 (.426)	−.102 (.591)	−.052 (.545)	−.088 (.456)	−.076 (.492)	−.080 (.450)	−.063 (.398)	−.076 (.431)	−.090 (.413)	−.108 (.393)	−.135 (.398)
t-statistic	−1.98		1.39		−.43		.86		.91		.40		−.61		−.54	
Tenure on previous job	5.428 (6.872)	4.254 (5.847)	5.711 (7.277)	3.865 (5.534)	4.306 (5.673)	3.767 (5.315)	5.420 (6.901)	3.650 (5.252)	5.746 (7.204)	3.429 (5.332)	6.004 (7.772)	3.076 (4.807)	4.971 (6.354)	3.069 (4.791)	7.024 (7.782)	3.600 (4.807)
t-statistic	−6.48		−2.39		−3.36		−3.07		−13.61		−5.04		−6.93		−4.29	
Age	39.223 (10.347)	39.427 (10.321)	37.285 (10.180)	37.350 (9.183)	37.500 (10.669)	38.115 (10.717)	36.469 (10.110)	35.827 (9.584)	37.156 (10.969)	35.145 (10.527)	36.498 (10.517)	34.695 (10.173)	38.781 (11.025)	36.754 (11.103)	38.693 (10.315)	34.955 (10.173)
t-statistic	.69		.06		1.97		−.69		−6.93		−1.96		−3.81		−3.23	
Married	.703 (.457)	.702 (.458)	.593 (.493)	.503 (.502)	.529 (.499)	.484 (.500)	.373 (.485)	.370 (.484)	.700 (.458)	.649 (.477)	.570 (.496)	.434 (.497)	.536 (.499)	.477 (.500)	.331 (.472)	.303 (.497)
t-statistic	−.10		−1.51		−3.15		−.06		−4.00		−3.09		−2.45		−.52	
High school dropout	.032 (.175)	.021 (.144)	.057 (.233)	.025 (.158)	.033 (.179)	.017 (.130)	.038 (.192)	.041 (.199)	.197 (.398)	.165 (.372)	.201 (.401)	.168 (.375)	.264 (.441)	.174 (.379)	.289 (.455)	.205 (.375)
t-statistic	−2.32		−1.34		−3.47		.16		−3.04		−.95		−4.55		−1.67	
High school graduate	.253 (.435)	.195 (.396)	.341 (.476)	.217 (.413)	.386 (.487)	.307 (.461)	.340 (.475)	.239 (.427)	.522 (.500)	.518 (.500)	.534 (.500)	.527 (.500)	.507 (.500)	.559 (.497)	.548 (.499)	.515 (.502)
t-statistic	−4.95		−2.35		−5.76		−2.38		−.33		−.15		2.15		−.57	
Some college	.299 (.458)	.296 (.457)	.341 (.476)	.318 (.467)	.349 (.477)	.365 (.482)	.469 (.500)	.494 (.501)	.235 (.424)	.257 (.437)	.225 (.418)	.270 (.445)	.188 (.391)	.207 (.405)	.163 (.370)	.273 (.447)
t-statistic	−.20		−.41		1.17		.53		1.87		1.16		.95		2.32	
College graduate or above	.417 (.493)	.488 (.500)	.260 (.441)	.439 (.498)	.232 (.422)	.311 (.463)	.153 (.361)	.226 (.419)	.046 (.210)	.060 (.238)	.040 (.197)	.035 (.185)	.041 (.197)	.061 (.240)	.000 (.000)	.008 (.087)
t-statistic	5.03		3.14		6.09		1.97		2.33		−.29		1.96		1.12	
No. observations	2,117	2,882	123	157	2,246	2,488	209	243	2,534	2,981	249	256	913	818	166	132

Source.—Displaced Workers Survey 1984–2008.

Note.—Sample means are presented with standard deviations in parentheses. The *t*-statistics are for testing the null that the differences in sample means between the plant closing and layoff groups are zero. Sample selection: workers aged 20–64; lost job for three reasons: plant closing, position abolished, or slack work; lost a job in previous 3 years; reemployed at survey date; full-time to full-time transition; private sector to private sector; reemployment weekly wage >= $40; not displaced from agriculture and construction.

losses are very similar between plant closing and layoff.[7] In the rest of table 1 we present results for blue-collar workers, and like Gibbons and Katz, we find that wage losses are similar for plant closings as for layoffs. This result holds approximately for all four demographic groups.

A key question is why the relative losses at plant closing and layoff vary so much across the demographic groups in table 1. 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 are presented in table 2. 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 layoff and plant closing. Note that in columns 1–4 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.[8] One can see that the results for white-collar workers 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 2 is quite different. We see only a small difference at plant closing between men and women, particularly after including control variables. However, women experience smaller wage declines following a layoff. In our simulation results below we will explore why this might be true. Estimating the interacted model in column 5 suggests that some additional interactions may exist, but the basic results for white men and women remain.

A particularly striking aspect of the results is the robustness of the results in table 2 to inclusion of control variables. While parameters change some from column 1 to column 2, all of the relevant coefficients change very little between columns 2, 3, and 4. We view it as particularly surprising that region and one-digit industry and occupation controls seem to make little difference in the final result. This strongly suggests that the

[7] In previous versions of our paper this result was different, as we saw larger declines at plant closing than layoff. When we added more recent waves of the DWS the point estimate changed. However, this is not a large deviation from the previous result, as the difference changed from plant closing being slightly larger to plant closing being slightly smaller. One possibility is that over time the labor market treatment of men and women has become more similar. However, in our exploration of this idea we found the data to be too noisy to make strong predictions.

[8] We do this to increase the precision of the results.

Table 2
Wage Losses after Layoffs and Plant Closings, by Race and Gender

	White Collar					Blue Collar				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Layoff × Black	.026 (.025)	.008 (.025)	.008 (.025)	.009 (.025)	.047 (.040)	−.006 (.028)	−.011 (.028)	−.021 (.027)	−.022 (.027)	−.010 (.033)
Layoff × Female	.036 (.013)	.030 (.013)	.027 (.013)	.028 (.013)	.033 (.014)	−.021 (.018)	−.014 (.018)	−.025 (.018)	−.026 (.019)	−.022 (.020)
Layoff	−.027 (.014)	−.038 (.014)	−.035 (.014)	−.037 (.014)	−.039 (.014)	.013 (.013)	−.021 (.013)	−.020 (.013)	−.019 (.013)	−.020 (.014)
Plant closing × Black	−.052 (.029)	−.052 (.028)	−.050 (.028)	−.053 (.028)	−.048 (.028)	−.006 (.026)	−.001 (.026)	−.009 (.026)	−.010 (.026)	−.010 (.033)
Plant closing × Female	.017 (.015)	.004 (.015)	.003 (.015)	.004 (.015)	.004 (.015)	.007 (.018)	.011 (.018)	−.005 (.018)	−.005 (.018)	−.005 (.020)
Layoff × Black × Female	…	…	…	…	.064 (.051)	…	…	…	…	−.036 (.057)
Plant closing × Black × Female	…	…	…	…	.008 (.058)	…	…	…	…	.001 (.053)
Constant	−.065 (.011)	…	…	…	…	−.087 (.010)	…	…	…	…
Married, Age, Age², Education	…	Y	Y	Y	Y	…	Y	Y	Y	Y
Year dummies, Years since displacement, Region	…	Y	Y	Y	Y	…	Y	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)	…	Y	Y	Y	Y	…	Y	Y	Y	Y
Industry	…	…	Y	Y	Y	…	…	Y	Y	Y
Occupation	…	…	…	Y	Y	…	…	…	Y	Y
N	8,750	8,750	8,747	8,747	8,747	6,684	6,684	6,678	6,678	6,678

NOTE.—See table 1 for sample restrictions. The cells present regression coefficients with standard errors in parentheses. The dependent variable in the regression is the difference in log wage between the postdisplacement job and predisplacement job.

racial and gender patterns we document are not simply due to differences in the sector of the economy or jobs in which workers were employed.

One interesting question is whether these results could be explained by Stevens's (1997) finding that the difference between layoff and plant closing occurs because much of the wage losses accompanying plant closing occur prior to the displacement. For this to explain our findings, one would need to see that, relative to the other groups, white males would experience larger losses at plant closing prior to displacement. This may seem unintuitive, as one might expect white males to be more mobile and thus better able to avoid these losses. We do not have a panel of wages prior to displacement, so we cannot look at this directly. However, our best evidence is to look at wage differences prior to displacement. One can see in table 1 that for whites, the layoff/plant closing gap in predisplacement wages between men and women is virtually identical.[9] Furthermore, we know from table 2 that the main difference across gender occurs at layoff and not at plant closing. For blacks, in table 1 one can see that the values for black men go in one direction (i.e., the predisplacement gap is larger than for white males) while for black women they go in the other (i.e., smaller than for white males). In appendix table A1 we rerun the specifications in table 2 but use predisplacement wages as the dependent variable. No clear evidence in support of this hypothesis arises.

In the rest of table 2 we present results for blue-collar workers. The interactions are virtually all smaller in absolute value than those for white-collar workers, and none of the interactions are statistically significant at conventional levels. However, note that many of the signs are quite similar. Even though we cannot reject that the coefficients are zero,[10] typically we can also not reject that they are different than the coefficients for white-collar workers.[11]

As mentioned in note 1, the reason we follow GK and focus our main analysis on white-collar workers is because layoff decisions for blue-collar workers are often determined by seniority. But if this is the case, within a plant's blue-collar workforce, any high seniority blue-collar worker who is laid off must on average be particularly unproductive. This implies that we should see a large lemon effect for this group.[12] We verify this by

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[9] That is, for both white men and white women the difference in predisplacement wages for layoff versus plant closing is roughly 0.05, as can be seen in the first row of table 1.

[10] The only exception to this in column 3 is the interaction between layoff and female.

[11] We also rerun the specifications in table 2 for blue-collar workers using predisplacement wage as dependent variable. The results are reported in table A1 in the appendix. Overall the basic pattern is similar to that of white collar workers.

[12] We thank Charlie Brown for suggesting this idea to us.

rerunning the regressions of table 2 but using a restricted sample of blue-collar workers, including only those who had tenure on the predisplacement job for at least 3 years (which is about 44% of the full sample). In the specification corresponding to column 9 of table 2, the coefficient on layoff is −0.041 with a standard error of 0.020. So, as predicted, there is a lemon effect for white male high seniority blue-collar workers who are laid off. All other coefficients on the interactions remain statistically insignificant.

B. 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. Non-economic 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, e.g., 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 the 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). While previous federal employment discrimination legislation typically limited plaintiff recovery to lost wages, CRA91 allows employees to sue for intentional gender and race discrimination for up to $300,000 in punitive damages; furthermore, CRA91 allows employees claiming unlawful termination on the basis of race to sue for unlimited punitive damages. (See Oyer and Schaefer [2000] for more details of the law.) Using data from the 1987–93 Survey of Income and Program Participation (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.[13] 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.

We use CRA91 to look at the implications of asymmetric information for blacks. We do not expect the same argument to work well for women

[13] The data used in Oyer and Schaefer (2000) cannot separately identify job losses due to plant closing from the other forms of layoffs (selective downsizings such as abolished positions).

for two reasons. First, the changes in the law affect blacks to a larger extent than they do women (and thus represent a larger increase in the expected costs of displacing the "protected" workers). While punitive damages (up to $300,000) apply to employment discrimination for both race and gender, the CRA91 explicitly extends the Civil Rights Act of 1866, which allows plaintiffs alleging racial discrimination to sue for unlimited damages, to cover both on-the-job activities and termination of employment. In other words, the CRA91 essentially removed all limits on damage awards in cases of racial discrimination in termination. So blacks could have the most to gain from the passage of the CRA91. Second, empirical evidence from Oyer and Schaefer (2000) suggests that firms responded to the CRA91 by lowering firing rates for blacks more than whites, but the change in the difference between men and women was statistically insignificant. For both reasons, we would expect the law to have a smaller wage effect for women than for blacks.

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 Schaefer (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.[14]

The DWS data contain information about the year in which workers lost their jobs, by which we divide the sample into two subperiods: 1981–91 and 1992–2008. In table 3 we repeat the specification of table 2 except that we interact all of the main coefficients of interest with a dummy variable for post-1991. For white-collar workers, the 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

[14] There might be other reasons for worrying about changes over time in general. It is widely believed that there was 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 and 2003) lend 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 positions abolished. If mass layoffs occur increasingly frequently, then the event layoff might become less informative about an individual worker's productivity. Therefore, we would expect the difference in wage losses between layoffs and plant closings to become smaller over time.

Table 3
Effects of the CRA91 on Relative Wage Changes

	White Collar		Blue Collar	
	(1)	(2)	(3)	(4)
Post91 × Layoff × Black	-.130	-.117	-.032	−.025
	(.058)	(.057)	(.055)	(.054)
Post91 × Layoff × Female	-.019	-.005	-.046	−.033
	(.027)	(.027)	(.037)	(.036)
Post91 × Layoff	.004	.014	.085	.073
	(.029)	(.028)	(.027)	(.026)
Post91 × Plant closing × Black	.013	.001	.008	.004
	(.059)	(.058)	(.052)	(.051)
Post91 × Plant closing × Female	-.014	-.003	-.012	−.014
	(.029)	(.029)	(.036)	(.035)
Post91	.027	.000	.025	−.001
	(.022)	(.044)	(.020)	(.048)
Layoff × Black	.121	.096	.008	−.009
	(.050)	(.049)	(.041)	.041
Layoff × Female	.047	.031	.004	−.009
	(.022)	(.022)	(.027)	(.027)
Layoff	-.032	-.046	-.034	−.057
	(.022)	(.022)	(.019)	(.019)
Plant closing × Black	-.061	-.053	-.010	−.012
	(.046)	(.045)	(.035)	(.035)
Plant closing × Female	.024	.005	.013	.002
	(.022)	(.022)	(.025)	(.025)
Constant	-.079	Y	-.099	Y
	(.016)		(.013)	
Married, Age, Age², Education	. . .	Y	. . .	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)	. . .	Y	. . .	Y
Years since displacement, Year dummies, Regions	. . .	Y	. . .	Y
Industry, Occupation	. . .	Y	. . .	Y
N	8,750	8,747	6,684	6,678

NOTE.—See table 1 for sample restrictions. The cells present regression coefficients with standard errors in parentheses. The dependent variable in the regression is the difference in log wage between the postdisplacement job and predisplacement job.

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 very wide. It is significant at the 5% level but also is a very high 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.[15]

C. 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

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[15] We also ran the regressions for the blue-collar sample. The coefficient is of the expected sign but is smaller than for the white-collar workers and statistically insignificant from both zero and the white-collar coefficient.

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 on 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.[16] 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 that in 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. We also again see that plant closing has a much more negative impact on African Americans (and women) than on white males. The results for blue-collar workers are quite similar in this case.

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

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[16] 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 a job is found, that is, 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 the previous 3 years from full-time, private-sector jobs not in agriculture and construction industries and had weekly wage no less than $40. Note that the subsequent duration analysis is applied to the sample using all years data between 1986 and 2008, but the results are robust when 1988 and 1994 data were removed.

Table 4
Duration of Joblessness after Layoffs and Plant Closings, by Race and Gender

	White Collar			Blue Collar		
	(1)	(2)	(3)	(4)	(5)	(6)
Layoff × Black	−.028	.035	.050	.176	.113	.104
	(.055)	(.052)	(.055)	(.062)	(.057)	(.061)
Layoff × Female	.047	.109	.098	.221	.130	.119
	(.030)	(.029)	(.031)	(.045)	(.041)	(.044)
Layoff	.104	.171	.192	−.008	.134	.119
	(.034)	(.032)	(.034)	(.035)	(.032)	(.034)
Plant closing × Black	.129	.134	.118	.227	.166	.148
	(.063)	(.059)	(.063)	(.061)	(.057)	(.060)
Plant closing × Female	.057	.118	.137	.235	.204	.214
	(.035)	(.034)	(.037)	(.044)	(.041)	(.044)
Married, Age, Age^2	…	…	Y	…	Y	Y
Education	…	…	Y	…	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)	…	…	Y	…	Y	Y
Years since displacement, Year dummies, Regions	…	…	Y	…	Y	Y
Industry, Occupation	…	…	Y	…	Y	Y
Log predisplacement wage	…	…	.020	…	…	.020
			(.024)			(.032)
Weibull scale parameter	1.127	1.046	1.037	1.201	1.079	1.076
	(.009)	(.008)	(.009)	(.011)	(.010)	(.010)
Percentage who lost job due to plant closing			42.09			46.60
Percentage who lost job due to position abolished			31.83			12.62
Percentage who lost job due to slack work			26.08			40.79
N	10,277	10,244	9,095	7,914	7,887	7,125

Note.—The results are based on ML estimates of a Weibull proportional hazard model in which duration is the number of weeks on the first spell of joblessness since displacement. Cells present the marginal effects of covariates on the expected log durations. Standard errors are in parentheses. Sample selection: workers aged 20–64; lost job for three reasons: plant closing, position abolished, or slack work; lost a job in previous 3 years; displaced from private-sector jobs; predisplacement weekly wage >= $40; not displaced from agriculture and construction.

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.[17] It is straightforward to show in a search model (see, e.g., 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 2 we found that white males are the only white-collar group for which layoff is substantially 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 versus 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 job from a layoff versus plant closing is worse for men than women.

D. Discussion

To summarize our basic results, we find that among white-collar workers, 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 for the other groups. The only

[17] 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.

group for which wages clearly decline more at layoff than plant closing is white males. The question arises as to what 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 2, which shows that these effects are remarkably robust to inclusion of industry and occupation controls.

The cleanest 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 (although with large point estimates and standard errors).

An intriguing aspect of our empirical results is that the negative consequences of plant closing are much worse for African American white-collar workers. One explanation for this result is that some firms discriminate against minorities more than others, as shown in Becker (1971). Minority workers should be more likely to match with nondiscriminatory firms. In that case, the consequences of these nondiscriminatory plant 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 lay them off. If this is the case, one would not expect to see such an effect in layoffs.[18] 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 below.

Rather, we dedicate the rest of this article to 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.

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[18] The fact that we do not 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.

IV. Model

We develop an equilibrium model with asymmetric information as well as heterogeneous worker and firm types. We present the model in pieces. We first present an overview of the model and then discuss the agents and technology. Next we discuss the behavior of the firms and workers and then describe the equilibrium. We finish this section with a discussion of the specific parameterization we take of the model for the simulations. Derivation of the equilibrium conditions is presented in the appendix.

A. Overview of Model

Our model is characterized by the following key features:

Heterogeneous human capital: There are a finite number (L) of worker types. The key feature of a worker type is that workers are perfectly substitutable with other workers of the same type but not perfectly substitutable with workers of a different type.

Heterogeneity in sectors: There are a finite number (J) of sectors in the economy. Firms within each sector are identical, but firms across different sectors have different production functions. In general, firms from all sectors hire all human capital types, but some sectors will hire certain types at higher rates than others. As an example, both law firms and construction firms hire both blue- and white-collar workers, but presumably law firms hire relatively more white-collar workers.

Asymmetric information: Within each worker type, workers are heterogeneous in ability. A firm can observe the ability of its current workers but not the ability of other potential hires.

Job separations: There are two distinct sources of job separation. The first, as in the model of GK, is that when the firm learns the ability of its workers, it lays off the lowest ability workers. The second source is that the firm may be hit by a negative productivity shock and choose to lay off some workers or to close its plants.

Displacement as defined in the DWS occurs not from screening by ability 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 due to a productivity shock. If the shock is not severe enough to lead to a plant closing, the firm chooses to lay off the least productive workers, so there will be a lemon effect. At the same time, the nature of the technology shock will influence the wage change since it leads not only to a job separation but to a decline in the outside opportunity for the worker as well. Thus changes in earnings depend on both the nature and magnitude of the shock that hits the economy. They affect wages through equilibrium effects as well as through an employer's inference of worker quality from the layoff.

B. Agents and Technology

As mentioned in the previous section, 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 $\ell = \{1, \ldots, L\}$.

We use Y_ℓ to denote the ability of an individual of type ℓ. A key aspect of the model is asymmetric information. When firms make offers to workers, they do not know their ability. However, after employing the worker for a period, they learn it. At that point the firm may choose to lay off unproductive workers. As in GK, we need to give the incumbent firm some comparative advantage in keeping the worker. We assume that 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). The reason is because the worker's outside wage is essentially the expected productivity of all retained workers. With a smooth cumulative distribution function (cdf), the worst retained worker must be lower than the productivity of the average retained worker, so one cannot find an equilibrium. With $\tau > 1$, workers have more value in the current firm than in outside firms so that some workers will be retained. In general, the larger is τ, the larger the fraction of workers who will be retained.

We have modeled τ as if it is firm-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.[19]

Let $H_{t\ell j}$ be the aggregate human capital of type ℓ working in sector j at time t. We formally define this in the appendix. It is basically the sum of the productivity across all workers of type ℓ who work in sector j at time t. Let $H_{tj} = (H_{t1j}, \ldots, H_{tLj})$ be the vector of inputs for a sector. The production function for sector j at time t takes the form

$$G_{tj}(H_{tj}).$$

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.[20] There are a large

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[19] 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.

[20] 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.

number of firms within each sector, free entry, and no search frictions, so the labor market for new hires will be competitive.

C. Timing

Two different aspects of the timing are important. The first is the definition of the different periods, and the second is the timing within a period. We discuss these in order.

Finite period versions of our model can have implications on wage changes that are driven by the fact that a worker is close to retirement. To avoid this problem, we allow for an infinite number of periods, although only the first few periods are of interest. We essentially follow a cohort of workers and firms across time. The timing is defined as

Period 1: Workers are hired by firms, but the firms have only limited information about worker quality.
Period 2: After learning about worker quality from the first period, during the second the firms only retain workers above a minimum threshold.
Period 3: The economy is potentially 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.

In terms of more specifics about the timing, the production function remains the same in periods 1 and 2. However, we assume that in period 3 the production process is potentially hit by a shock which may or may not affect different sectors. After period 3, the parameters of G_{tj} remain fixed at those values forever. Thus the production function changes only between periods 2 and 3.

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 the worker has fallen below the screening value of the firm. The event that leads to the separation in this case 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 shock to the firm.[21] 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.

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[21] Of course it is still true that firms typically do not lay off all workers but choose the ones of lower ability. Thus one sees a lemon effect for both types of dismissals.

Since they are not of primary concern, workers who are below the cutoff value in period 2 leave this part of the economy permanently (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.

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 was high enough so that in period 2 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 and no worker mobility takes place.[22]

The timing within a period is the following:

1. The firm observes the ability levels for all of its workers from the previous period.
2. It chooses whether to lay workers off or to offer them a wage to continue. We do not allow the firm to make an offer that it knows will be turned down.
3. Outside firms make offers to both the laid off and retained workers.
4. Workers decide which offer to take.
5. Workers participate in the production process.

Note that in part 2 we are not allowing firms to make lowball offers to workers they do not want but are forcing them to lay these workers off. Since firms are indifferent between laying off a worker and retaining him with a wage that is lower than the market wage, there will be multiple equilibria in the model. GK describe this class of equilibria. We focus only on the equilibria in which firms never pay a worker lower than their outside option.[23]

D. Behavior of Workers and Firms

Worker behavior is not particularly interesting in this model. Workers are risk neutral and simply make wage choices to maximize their present discounted value of income. We implicitly assume that workers do not

[22] By assuming that all workers who are laid off in period 2 disappear from the market, we have imposed that these workers cannot be rehired either.

[23] 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.

know any more about their own ability than an outside firm as we are not allowing outside firms to construct contracts that might induce the worker to reveal their own ability.

Firms are much more interesting as they have essentially three things to decide: (*a*) which workers to lay off at the beginning of the period, (*b*) the wage to offer the workers that are retained, and (*c*) the wage to offer to outside workers.

First consider the layoff decision. Firms strictly prefer higher ability workers to lower ability workers. Thus, for each human capital type in each sector there exists a cutoff value such that firms retain only those workers whose productivity is above this cutoff value. Denote these cutoff values by $y_{t\ell j}^*$ so that workers are laid off if $Y_\ell < y_{t\ell j}^*$.

Next consider the offers that firms make to outside workers. 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, they make offers based on the expected present value of revenue from the worker conditional on $Y_\ell < y_{t\ell j}^*$ for workers who were laid off and conditional on $Y_\ell \geq y_{t\ell j}^*$ for workers who were retained. In theory workers who are above the cutoff may be potentially poached by other firms. While this will not happen in equilibrium, this potential "poaching" plays a key role in the analysis as it determines the outside wage.

Finally we consider the retention offer. Given the timing of the model, the current firm has no incentive to pay more than a tiny bit over the outside wage. Note that this means that the firm is going to receive rents on many workers in these periods due to the training costs τ. However, since the hiring market is competitive, the expected value of these rents was essentially competed away in the form of higher wages given to the worker during the first period.

E. Equilibrium

Equilibrium is characterized by the following four criteria:

- Outside wages are determined so that firms earn zero profit on average for a worker.
- 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.
- Firms retain workers for whom it is profitable to do so.[24]
- Workers make employment choices to maximize their expected present discounted value of earnings.

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[24] 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.

The details and derivation of the equilibrium conditions are provided in the appendix.

F. Parameterization in Simulation

We use a constant elasticity of substitution (CES) production function

$$G_{tj}(H_{tj}) = \left(\sum_{\ell=1}^{L} \alpha_{t\ell j} H_{t\ell j}^{\rho} \right)^{1/\rho}$$

with the number of sectors (J) equal to five. We assume that individuals of different genders are different worker types and allow for 10 worker types—five for 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 $\alpha_{1\ell j}$ takes on each of the five values for some sector.[25]

We simulate shocks to $\alpha_{t\ell j}$ to occur between periods 2 and 3. We model three different types of shocks to this economy.

1. Modest proportional change in $\alpha_{t\ell j}$ by j (sector shock),
2. Large change in $\alpha_{t\ell j}$ by j causing sector to disappear (sector shock-plant closing),
3. Proportional change in $\alpha_{t\ell j}$ by ℓ (human capital type shock).

The first type is a "sector-specific shock" in which $\alpha_{t\ell j}$ 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 $\alpha_{t\ell j}$ 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).

V. Slack Work and Position Abolished

A very nice thing about our data is that they contain something akin to the difference between sector shocks and human capital shocks. To be in our layoff sample, an individual reported that the reason for 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

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[25] 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.

to position abolished while the firm shock relates to slack work. Intuitively in the model, if the shocks are of similar magnitude, workers who are 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, workers can move into a different sector that did not experience the shock. Due to the equilibrium effect, their wage will still fall but by switching sectors they avoid the first-order effect of the shock. By contrast, workers laid off because of a shock to their human capital can do no such thing. Their productivity and, analogously, their wage have fallen at all firms.[26]

The model does not formally imply that the wage losses associated with a human capital shock will be larger than those from a sector shock. However, intuitively one might expect this to be the case, and we consistently find it for reasonable parameter values. In particular, if the magnitudes of the shocks are similar, we consistently find larger wage losses for the human capital shock. In fact, in the simulation below, the sector shock is considerably larger than the human capital shock, but the wage losses are almost twice as large for the human capital shock. Thus our intuition from the model is that we would expect to see substantially larger wage losses for those who lose their jobs by position abolished as opposed to slack work.

We first informally look at this issue in the data by presenting analyses analogous to table 2 but distinguishing a layoff between slack work and position abolished. These results are shown in table 5. Looking first at white-collar workers, 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. At the bottom of the table 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 in every specification. Once again, one also sees the striking result that neither industry nor occupation is important in explaining these results. We believe that 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 longer unemployment spells, although the effect is not statistically significant.

Gibbons and Katz argue against using blue-collar workers because their

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[26] As previously mentioned in n. 3, in their paper GK discuss the fact that a plant closing could be associated with poor local labor markets and thus be associated with worse outcomes. This is related to our model if one interprets sectors *j* as local labor markets.

Table 5
Wage Losses after Displacement: Slack Work, Position Abolished, and Plant Closing

	White Collar				Blue Collar			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black × Slack work	.097 (.047)	.074 (.046)	.076 (.046)	...	.006 (.041)	-.003 (.040)	-.006 (.040)	...
Black × Position abolished	.057 (.045)	.044 (.044)	.046 (.044)	...	-.021 (.064)	-.033 (.063)	-.035 (.062)	...
Female × Slack work	.013 (.024)	.016 (.024)	.017 (.024)	...	-.043 (.028)	-.041 (.027)	-.034 (.027)	...
Female × Position abolished	.028 (.023)	.035 (.022)	.033 (.022)	...	.025 (.041)	.027 (.041)	.024 (.041)	...
Slack work	.010 (.017)	-.010 (.017)	-.012 (.017)	.002 (.012)	.027 (.014)	-.010 (.014)	-.007 (.014)	-.016 (.012)
Position abolished	-.058 (.016)	-.062 (.016)	-.059 (.016)	-.038 (.011)	-.035 (.021)	-.056 (.021)	-.058 (.021)	-.056 (.018)
Black	-.052 (.028)	-.052 (.028)	-.053 (.028)	-.019 (.019)	-.006 (.026)	-.002 (.026)	-.010 (.026)	-.016 (.019)
Female	.017 (.015)	.005 (.015)	.004 (.015)	.019 (.010)	.007 (.018)	.011 (.018)	-.005 (.018)	-.015 (.013)
Constant	-.065 (.011)				-.087 (.010)			
Married, Age, Age², Education			Y	Y			Y	Y
Year dummies, Years since displacement, Region		Y	Y	Y		Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)		Y	Y	Y		Y	Y	Y
Industry			Y	Y			Y	Y
Occupation				Y				Y
P-value for the F-test (null hypothesis: the coefficient on slack work and position abolished are jointly equal)	.0000	.0056	.0162	.0020	.0240	.1167	.0836	.0305
Percentage who lost job due to plant closing				44.14				47.89
Percentage who lost job due to position abolished				30.95				12.19
Percentage who lost job due to slack work				24.91				39.92
N	8,750	8,750	8,747	8,747	6,684	6,684	6,678	6,678

Note.—See table 1 for sample restrictions. The cells present regression coefficients with standard errors in parentheses. The dependent variable in the regression is the difference in log wage between the postdisplacement job and predisplacement job.

layoff decisions are determined in large part by collective bargaining decisions. This is an argument as to why one might not expect the lemon effect to arise for blue-collar workers but has little to do with the distinction between slack work and position abolished. Our argument for slack work versus position abolished should hold for blue-collar workers as well. We verify this in the blue-collar part of table 5. One can see that we find similar orders of magnitude in the results. The standard errors for blue-collar workers are somewhat bigger, leading to larger p-values.[27] In fact the similarity between blue- and white-collar workers in table 5 is remarkable. The simplest summary statistic is the difference between the coefficients on slack work and position abolished in columns 4 and 8. This is 0.040 in both cases (with a somewhat larger standard error for blue-collar workers). Looking at the comparison with plant closing, one sees that the results are again qualitatively similar. Workers experience larger wage losses at position abolished than either plant closing or slack work. The difference between plant closing and slack work is not statistically significant for either group.[28]

Following the logic of our argument, if the magnitudes of the two types of shocks were similar, we would expect to see workers who are laid off due to position abolished to be more likely to switch occupations than workers displaced for other reasons. To verify this, we looked at the probability of changing one-digit occupation after displacement by job loss reason. The results, which are reported in table 6, confirm this prediction. For both blue- and white-collar workers, those who lost their jobs due to position abolished are more likely to switch occupations than those who lost their jobs due to plant closing or slack work.

VI. Reconciling Model with Data

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 based on

[27] Note that we strongly reject the null hypothesis in column 4 but do so only at the 10% level for column 3. There are two major differences between the two columns. First the null hypothesis is different since column 3 allows for more interactions. Second, the test is different since the test in column 4 is one-dimensional while the test in column 3 is a joint null about three sets of coefficients. Given that we essentially have a one-sided alternative and that the results for the different groups basically all point in the same direction (with white women being weaker than the other groups), one might expect this test to be particularly weak. To see whether the smaller p-value comes from the more flexible null or the more powerful test, we reestimated the model with the same null as in column 3 but a one-dimensional test for the difference between slack work and position abolished and we obtain a p-value of 0.0313, suggesting that it is the difference in the test that leads to the difference in p-values.
[28] When we look at the duration model, we find that the point estimate goes in the opposite direction but is not statistically significant.

Table 6
Propensity of Changing Occupation after Displacement

	White Collar		Blue Collar	
	(1)	(2)	(3)	(4)
Slack work	.017	.028	.066	.048
	(.012)	(.011)	(.011)	(.011)
Position abolished	.038	.063	.081	.089
	(.011)	(.011)	(.016)	(.016)
Constant	.654	Y	.657	Y
	(.007)		(.008)	
Married, Age, Age², Education	. . .	Y	. . .	Y
Year dummies, Years since displacement, Region	. . .	Y	. . .	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)	. . .	Y		Y
Industry	. . .	Y	. . .	Y
Occupation	. . .	Y		
P-value for the F-test (null hypothesis: the coefficient on slack work and position abolished are jointly equal)	.085	.006	.334	.012
Mean of the dependent variable	.670	.670	.693	.694
N	10,465	10,421	8,049	8,006

Note.—See table 1 for sample restrictions. Cells present estimates from a linear probability model in which the dependent variable equals one if a worker changed one-digit occupation after displacement. Robust standard errors are in parentheses.

column 3 of table 5. As mentioned above, we focus on nonblack workers only. By gender, we construct the change in wages at displacement for three different types of displacement: plant closing, position abolished, and slack work. Specifically we calculate the sample average for the other control variables in the model and give this sample average to all groups.

The six moments we try to fit are presented in the data columns of table 7. 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 plant closing is very small and is in fact not statistically distinguishable. By contrast, for the two types of layoff we see substantially larger losses for men than for women.[29] 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 slack work is worse than plant closing for men, but this result goes the other way for women. We should point out that this final feature for men is not statistically significant nor robust across columns in table 5. We will discuss this issue more below in interpreting the results.

[29] While this cannot be seen directly from either table 5 or from table 7, the gender difference for position abolished is statistically significant with a *p*-value of .033, and the gender differences for position abolished and slack work are jointly significant with a *p*-value of .06.

Table 7
Simulation Results for the Augumented Model

| | A. Simulated Log Wage Differentials | | | |
| | Male | | Female | |
	Data	Simulation	Data	Simulation
Slack work	-.066	-.067	-.045	-.046
	(.013)		(.015)	
Position abolished	-.112	-.112	-.075	-.082
	(.012)		(.013)	
Plant closing	-.054	-.053	-.049	-.053
	(.011)		(.010)	

| | B. Parameters of Simulated Model | |
	Male	Female
ρ		.15
τ		1.49
σ	.06	.02
Initial retention probability	.776	.999
Sector shock:		
Shock		.985
Layoff probability	.051	.031
Human capital type shock:		
Shock		.997
Layoff probability	.015	.011

NOTE.—The six moments in the data are based on the regression in col. 3 of table 5. Standard errors are in parentheses.

In the simulation we assume that $\log(Y_\ell)$ is normal with standard deviation σ_g, where g denotes gender. Allowing the information to vary by gender is important in fitting the data. We discuss below why σ_g^2 might vary across gender. Thus the difference in wage losses across groups is identical to what the gender × dismissal reason would suggest.

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 tables 2 and 5 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 $\ell = \{6, \ldots, 10\}$ denote women. We impose that for all states of the world,

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

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 one 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 assume that there are 16 states of the world in period 3. With probability 0.97 no shock is experienced. Then we put 0.2% probability on each of the other 15. These other 15 correspond to five of each type of the shock above. That is because we have five sectors, and each sector has a 0.2% probability of getting hit by a modest proportional change in $\alpha_{j\ell}$ and also a 0.2% probability of getting hit by a large change in $\alpha_{j\ell}$ which causes it to shut down. For each gender, we also have five labor types, and each has a 0.2% 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 IV, we restrict the amount of multiple layoffs in two ways: (*a*) workers who do not make the initial cut in period 2 disappear from this part of the labor market and (*b*) we do not allow for additional layoffs after period 3. Additionally, for the sector-specific shock we only allow for layoffs in the sectors that 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 and not of primary interest in this analysis; incorporating it would make the model substantially more difficult to solve.

This leaves us with essentially four types of parameters: the elasticity of substitution (ρ), the training cost (τ), the standard deviation of the unknown component of ability (σ_g), and the magnitudes of the shocks. Despite the simplifications described in the previous paragraph, we found the model to be very difficult to solve. We need to solve for the firing, hiring, and wage decisions for different sectors in different states of the world for different times. Thus this is a high dimensional problem and is nonsmooth as every sector turns out to be at a corner solution either in terms of layoffs or hiring or both at every point in time. We do not know which constraints will bind ex ante. While ideally we would simultaneously solve for the parameters of the model to fit the data and solve for the equilibrium of the model, this did not work well. While we were able to find a set of parameters that fit our data perfectly, the equilibrium had some odd features. We would, of course, be happy to provide those details to any interested readers. The strange features primarily arose from the fact that we found $\tau = 1.011$ for men but 1.16 for women and $\sigma_g = 0.005$ for men but 0.0001 for women. This made the behavior of men and women look very different. We see no reason for τ to differ by gender and prefer results where we fix it to be the same by gender.[30] Instead we chose a more adaptive approach to find solutions for the model. As a practical matter, we found that when a plant closes, the only para-

[30] We never replicated the data exactly when τ was fixed across gender, but this does not mean that such a case does not exist.

meter 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. This process led to the value $\rho = 0.15$. We then searched over other parameters for a version of the model that was close to the data. While we have a number of different parameters, only σ_g varies by gender. Thus again we should highlight that our goal is to show that the model can reconcile the data (which it is certainly not guaranteed to) and to give a sense of the parameter values that do that.

The results of this simulation are presented in table 7. These simulation results are very close to the four moments that we are trying to fit. The parameters that lead to this fit are shown in the bottom panel of table 7. 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.[31] 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, view it 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).[32]

A second feature of the results is that the value of τ is quite large. Note that in the model, this does not lead to a higher measured return to tenure in a log wage regression because the firm pays the outside wage. High values of τ cannot be avoided when asymmetric information is important and retention rates are reasonably high. Since a firm pays workers with identical observable characteristics the same—and the same as their outside market—they have a strong incentive to fire the workers with the worst

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

[32] Note that one thing that cannot be directly compared to table 5 is the difference in the relative layoff rates. In table 7 we present the layoff rates conditional on a shock occuring. Table 5 presents these results unconditionally. Thus by changing the relative frequency of the shocks we could fit this feature of the data.

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 is important. Any of these can be interpreted as τ.

We simulate the effects of three types of shocks. With plant closing, one sector disappears and all workers leave for another sector. For the sector shock, sector j^* is hit by a shock that leads to a 1.5% decline in the factor loading parameter. Formally this means that

$$\alpha_{3\ell j} = \begin{cases} 0.985\alpha_{2\ell j} & j = j^* \\ \alpha_{2\ell j} & \text{otherwise} \end{cases}.$$

We see in panel B of table 7 that this leads 5.1% of men and 3.1% of women who were employed in this sector to be laid off. Note that this is a somewhat larger shock than it might initially appear to be. Part of the CES production function can be written as $\alpha H^\rho = (\alpha^{1/\rho}H)^\rho$. So multiplying α by 0.985 is analogous to multiplying worker productivity by $0.985^{1/\rho} = 0.904$.

For the human capital type shock we consider a decline of 0.3% in the factor loading parameter. That is, if type $\ell^* \leq 5$ is hit by the shock this means that

$$\alpha_{3\ell j} = \begin{cases} 0.997\alpha_{2\ell j} & \ell = \ell^* \text{ or } \ell = \ell^* + 5 \\ \alpha_{2\ell j} & \text{otherwise} \end{cases}.$$

Since this is a negative shock to all sectors, the layoff probabilities are lower: 1.5% for men and 1.1% for women. This multiple is analogous to a $0.997^{1/\rho} = 0.980$ multiple on human capital. Note that while the decline in productivity of the shocks is substantially smaller in this case, the wage penalty is much 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. As mentioned above, 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 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 role in explaining the gender difference in plant closing and layoff. Thus we do not allow this to reconcile the difference. Second, heterogeneous human capital is crucial to explain the results. For both genders we see larger wage losses at position abolished than for slack work.

The third and most nuanced is understanding the role that asymmetric

information plays in the model. Given our parameterization, asymmetric information is important for two reasons. First, it is only σ_g that can explain the difference between men and women. Second, it is necessary to explain the fact that the loss for slack work is larger than the loss at plant closing for men. However, both of these might be regarded as weak support. We do not have a good theory as to why the standard deviation of unobserved ability varies by gender but other parameters do not. We could presumably allow all of the parameters to vary by gender and still be able to reconcile the results. The second reason is that in the model, the only way to explain the fact that men experience larger wage losses for slack work than for plant closings is because of the lemon effect. However, as noted above, the difference here is not statistically significant nor robust across specifications. A better view of the data is that the wage loss for slack work and plant closing is roughly the same. However, note that this is not what the model would predict in the absence of asymmetric information. Since a plant closing represents a much larger shock to the sector, it would lead to a larger wage loss. Thus the fact that slack work is similar to plant closing can be taken as evidence of asymmetric information. The strength of this evidence depends on one's priors of how large this difference might be. At the very least, we take the simulations as evidence that asymmetric information could be important and that the results for women should not be taken as evidence against this idea.

VII. 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. The GK prediction stands for white men. However, for two of the four groups (black men and black women), we find the opposite of the Gibbons and Katz prediction; plant closings lead to more negative consequences than do layoffs. For white women, the losses at plant closings and layoff are very similar. We show that these differences occur 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 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 losses in earnings are greater when layoff is associated with position abolished than when it is associated with slack work.

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 or 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 a key role in explaining the gender gap in the model, and 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 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 that the layoff decision is more complicated for women than for men so that unobserved ability is a relatively more important factor. One interesting extension would 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 table 7. Other useful data sets are available, and we leave this work for future research.

Gibbons and Katz (1991, 377–78) 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 have provided additional evidence to bear on these issues, and our results strongly suggest that heterogeneous human capital is important. While the evidence in support of asymmetric information is weaker, in our simulations it does play an important role. We hope that alternative data sources can be found that will shed more light on these important issues in future research.

Appendix

Derivation of Equilibrium Conditions

We start by defining the aggregate human capital inputs. Let $f_{\ell j}$ denote the fraction of workers of type ℓ who work in sector j at time 1 and $\phi_{\ell h j}$ the fraction of ℓ-type workers who worked for an h sector firm in periods 1 and 2, were not retained by h in period 3, and were hired into sector j. In principle, firms can "poach" retained workers from other firms and we should include notation to account for this. Since this does not happen in equilibrium we do not explicitly account for it.

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

$$H_{1\ell j} = f_{\ell j} E(Y_\ell). \tag{A1}$$

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

$$H_{2\ell j} = f_{\ell j} E(\tau Y_\ell 1(Y_\ell \geq y^*_{2\ell j})), \tag{A2}$$

where $1(\cdot)$ is the indicator function. In the third period in addition some new workers can be hired from other sectors:

$$H_{3\ell j} = f_{\ell j} E(\tau Y_\ell 1(Y_\ell \geq y^*_{3\ell j})) + \sum_{h=1}^{J} \phi_{\ell h j} E(Y_\ell | y^*_{2\ell h} < Y_\ell \leq y^*_{3\ell h}). \tag{A3}$$

We allow firms to both dismiss workers (if $y^*_{3\ell j} > y^*_{2\ell j}$) and hire new workers (if $\phi_{\ell h j} > 0$). In our simulations we allow firms to do both but never found a case in which they do. Finally for all periods after period 3,

$$H_{t\ell j} = f_{\ell j} E(\tau Y_\ell 1(Y_\ell \geq y^*_{3\ell j})) + \sum_{h=1}^{J} \phi_{\ell h j} E(\tau Y_\ell | y^*_{2\ell h} < Y_\ell \leq y^*_{3\ell h}). \tag{A4}$$

We define some additional notation. Let $\tilde{y}_{\ell \mathcal{H}}$ be the conditional expectation of the productivity of a worker of type ℓ who has experienced labor market history $\mathcal{H}$. During the second period, a worker who worked in sector j during period 1 and was retained will have history $\mathcal{H} = j$ and $\tilde{y}_{\ell j} = E(Y_\ell | Y_\ell \geq y^*_{2\ell j})$. During period 3 and beyond, a worker who worked

in sector j will have history $\mathcal{H} = jr$, where r is a dummy variable indicating whether the worker was retained. For example, one history $\mathcal{H}$ may be that a worker started at firm j and was retained throughout; then $\mathcal{H} = j1$ and $\tilde{y}_{\ell j1} = E(Y_\ell | Y_\ell \geq y^*_{3\ell j})$. Another potential history $\mathcal{H}$ 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, $\mathcal{H} = j0$ and $\tilde{y}_{\ell j0} = E(Y_\ell | y^*_{2\ell j} < Y_\ell \leq y^*_{3\ell j})$.

It is easiest to solve this model by working backwards from period $t \geq 4$. 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. Then for any history $\mathcal{H}$, the expected marginal value of workers who are hired in period 4 is

$$\tilde{y}_{\ell\mathcal{H}}\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}} + \sum_{t=5}^{\infty} \beta^{t-4}\tau\tilde{y}_{\ell\mathcal{H}}\frac{\partial G_{tj}(H_{tj})}{\partial H_{t\ell j}} = \tilde{y}_{\ell\mathcal{H}}\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}}\left(\frac{1-\beta+\beta\tau}{1-\beta}\right),$$

where β is the discount rate since G_{tj} and H_{tj} do not vary over time (after period 4). Wages will be constant across time, and the wage will be determined by the best outside opportunity. This yields that the outside wage during period 4 for an individual of type ℓ with labor market history $\mathcal{H}$ is

$$w_{t\ell\mathcal{H}} = \max_{j=\{1,\dots,J\}} \tilde{y}_{\ell\mathcal{H}}\frac{\partial G_{tj}(H_{4j})}{\partial H_{t\ell j}}\left(\frac{1-\beta+\beta\tau}{1-\beta}\right) \tag{A5}$$

for $t \geq 4$. Employers must keep the workers indifferent between leaving and staying and the outside wage does not change after period 4, so employers will pay the constant outside wage $w_{t\ell\mathcal{H}}$ 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 ($Y_\ell > y^*_{3\ell h}$). If a firm in sector j considers hiring them, it will make expected profit

$$\frac{\partial G_{3j}(H_{3j})}{\partial H_{3\ell j}}\tilde{y}_{\ell h1} - w_{3\ell h1} + \frac{\beta}{1-\beta}\left(\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}}\tau\tilde{y}_{\ell h1} - w_{4\ell h1}\right),$$

where $w_{3\ell h1}$ is the outside wage for such a retained worker. Since the market is competitive between firms both within and between sectors,

$$w_{3\ell h1} = \max_{j=\{1,\dots,J\}}\left[\frac{\partial G_{3j}(H_{3j})}{\partial H_{3\ell j}}\tilde{y}_{\ell h1} + \frac{\beta}{1-\beta}\left(\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}}\tau\tilde{y}_{\ell h1} - w_{4\ell h1}\right)\right]. \tag{A6}$$

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

$$y^*_{3\ell j} = \max\left\{\frac{w_{3\ell j1} + [\beta/(1-\beta)]w_{4\ell j1}}{\{[\partial G_{3j}(H_{3j})]/\partial H_{3\ell j}\}\tau + [\beta/(1-\beta)]\{[\partial G_{4j}(H_{4j})]/\partial H_{4\ell j}\}\tau}, y^*_{j\ell 2}\right\}. \tag{A7}$$

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

$$w_{3\ell h0} = \max_{j=\{1,\ldots,J\}} \left\{ \frac{\partial G_{3j}(H_{3j})}{\partial H_{3\ell j}} \tilde{y}_{\ell h0} + \frac{\beta}{1-\beta} \left(\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}} \tau \tilde{y}_{\ell h0} - w_{4\ell h0} \right) \right\}, \quad (A8)$$

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

$$\pi_{\ell j}(y) = E\left\{ 1(y \geq y^{*}_{3\ell j}) \right.$$
$$\left. \times \left[\frac{\partial G_{3j}(H_{3j})}{\partial H_{3\ell j}} \tau y - w_{3\ell h1} + \frac{\beta}{1-\beta} \left(\frac{\partial G_{4j}(H_{4j})}{\partial H_{4\ell j}} \tau y - w_{4\ell h1} \right) \right] \right\}.$$

Next consider period 2. In this case workers who are not retained leave this labor market (and presumably go to the blue-collar sector). 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:

$$w_{2\ell h} = \max_{j=\{1,\ldots,J\}} \frac{\partial G_{2j}(H_{2j})}{\partial H_{2\ell j}} \tilde{y}_{\ell h} + \beta E(\pi_{\ell j}(Y_\ell)|Y_\ell \geq y^{*}_{2\ell h}). \quad (A9)$$

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

$$\frac{\partial G_{2j}(H_{2j})}{\partial H_{2\ell j}} \tau y^{*}_{2\ell h} - w_{2\ell h} + \beta E(\pi_{\ell j}(y^{*}_{2\ell h})) = 0. \quad (A10)$$

Note that from equations (A9) and (A10) one can see the importance of $\tau > 1$. The final part of equation (A10) involves future profits for the average worker while the expression (A10) involves future rents from the marginal worker which must be lower. One needs $\tau > 1$ to find a non-degenerate value of $y^{*}_{2\ell h}$ to solve these equations.

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

$$w_{1\ell j} = E(Y_\ell) \frac{\partial G_{1j}(H_{1j})}{\partial H_{1\ell j}} + \beta \Pr(Y_\ell > y^{*}_{2\ell h})$$
$$\times \left[\frac{\partial G_{2j}(H_{2j})}{\partial H_{2\ell j}} \tau \tilde{y}_{\ell j} - w_{2\ell j} + \beta E(\pi_{\ell j}(Y_\ell)|Y_\ell \geq y^{*}_{2\ell h}) \right]. \quad (A11)$$

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 (A1)–(A11).

Table A1
Wages Prior to Layoffs and Plant Closings, by Race and Gender

	White Collar				Blue Collar			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Layoff × Black	-.192	-.149	-.155	-.139	-.177	-.124	-.106	-.100
	(.032)	(.028)	(.028)	(.027)	(.029)	(.027)	(.026)	(.026)
Layoff × Female	-.406	-.298	-.307	-.283	-.334	-.315	-.277	-.257
	(.016)	(.014)	(.014)	(.014)	(.019)	(.018)	(.017)	(.017)
Layoff	.058	.042	.028	.028	-.043	.015	.013	.007
	(.018)	(.015)	(.015)	(.015)	(.014)	(.013)	(.013)	(.013)
Plant closing × Black	-.194	-.139	-.144	-.122	-.130	-.097	-.080	-.078
	(.036)	(.031)	(.031)	(.030)	(.028)	(.026)	(.025)	(.025)
Plant closing × Female	-.394	-.264	-.275	-.255	-.421	-.385	-.339	-.318
	(.018)	(.016)	(.016)	(.016)	(.019)	(.018)	(.017)	(.017)
Constant	6.088				5.730			
	(.013)				(.010)			
Married, Age, Age², Education	...	Y	Y	Y	...	Y	Y	Y
Year dummies, Years since displacement, Region	...	Y	Y	Y	...	Y	Y	Y
Predisplacement tenure (1–3, 3–5, 5–10, 10+, omitted <1)	...	Y	Y	Y	...	Y	Y	Y
Industry	...	...	Y	Y	...	...	Y	Y
Occupation	...	...	Y	Y	...	...	Y	Y
N	9,120	9,120	9,117	9,117	7,066	7,066	7,059	7,059

Note.—See table 1 for sample restrictions. Cells present regression coefficients with standard errors in parentheses. The dependent variable in the regression is the log predisplacement wage.

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