The Signaling Role of Early Career Job Loss*

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Abstract

I examine the extent to which ability signaling explains long-term wage losses suffered by young workers who experience layoffs. Young workers are of particular interest because employers have limited information about their ability, so signaling theoretically plays a larger role in determining wages. In addition, young workers are unlikely to experience wage losses due to loss of industry-specific human capital or separation from high-quality job matches, which may explain long-term wage decreases among older workers. Using data from the National Longitudinal Survey of Youth 1997, I show that young workers of all ability levels initially experience similar wage losses following layoffs, but high relative ability workers fully recover within five years while low relative ability workers experience persistent wage losses. Consistent with traditional learning models, relative, not actual, ability affects wage trajectories. I illustrate a conceptual model of layoff signaling of ability that varies by pre-layoff experience and can explain divergent wage trajectories across high and low relative ability workers. I test the model empirically and find that low relative ability workers inability to overcome negative layoff signals explains a substantial proportion of long-term wage losses among young workers.

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1 Introduction

The first decade of a young worker's labor market career is an important period of wage growth and job mobility as the worker searches for increasingly better career and job matches, and employers learn about the quality and ability of the worker (Topel and Ward 1992; Farber and Gibbons 1996; Altonji and Pierret 2001).[1] If this period is interrupted by an involuntary job loss, the consequences can be devastating. Workers who experience job losses early in their labor market careers suffer persistent wage and earnings losses for up to a decade or more following the job loss, with some workers never fully recovering.[2] While the effects of early career job loss are well known, the underlying mechanism driving these effects is not clear.[3] One potential explanation comes from the asymmetric employer learning literature built off of the work of Gibbons and Katz (1991). This theory suggests that asymmetric information across employers regarding a worker's ability results in a scenario whereby distressed firms selectively lay off off their lowest ability workers first, which signals prospective employers that a given worker has lower than expected ability. While initially conceived as a method for empirically testing for the presence of asymmetric employer learning, this theory may hold valuable insight into understanding the effects of job loss for young workers, about whom prospective employers have the least amount of information.

This paper focuses on understanding the dynamic nature of layoff signals over a worker's labor market career, and how the changing nature of these signals affects the long-run earnings losses experienced by laid off young workers. The basis of the main analysis of this study builds on the recent empirical work of Pinkston (2009) and Kahn (2013), who find that, while part of the learning that occurs about a worker early in their career is due to asymmetric employer learning, public learning also plays a role, which results in decreasing information asymmetry about a worker's ability the longer the worker remains in the labor market. This suggests that there is room for a layoff signaling explanation for the cost of job loss for young workers, but not necessarily for older workers as employer uncertainty regarding a worker's true ability is decreasing in labor market

[1] See also Keane and Wolpin 1997; Light and McGarry 1998; Neal 1999; Neumark 2002; Liu 2019; Forsythe 2019.

[2] Studies documenting the long-term costs of job loss for young workers include Stevens (1997), Kletzer and Fairlie (2003), von Wachter and Bender (2006), Fuji, Shiraishi, and Takayama (2018), and Barnette, Odongo, and Reynolds (2020). See also a number of studies documenting the scaring effect of early career unemployment, including Mroz and Savage (2006), Kroft, Lange, and Notowidigdo (2013), Schmillen and Umkehrer (2017), and Jarosch and Pilossoph (2019).

[3] Carrington and Fallick (2017) provide a comprehensive review of the theoretical explanations regarding the costs of job loss that have been proposed in the literature.

experience. To my knowledge, this notion that the signaling role of a layoff diminishes over time has not been studied in the literature, and could help explain the mixed evidence of layoff signaling found in previous research (see e.g. Song 2007).

I illustrate an empirically testable layoff signaling model that accounts for the changing nature of information available to employers over a worker's labor market career. The end result is a model that predicts layoffs to be treated as a form of dynamic statistical discrimination wherein workers who are incorrectly assigned a low-ability signal due to being laid off suffer a negative initial signal effect that is decreasing in pre-layoff experience followed by a gradual recovery that is proportional to both the size of the signal and what the return to the worker's ability level would have been in the absence of the layoff. While previous studies on layoff signaling have generally relied on the assumption that firms have discretion over who they lay off, the extent to which firms actually have this discretion is unclear (Kletzer 1998; Oyer and Schaefer 2011). This study seeks to relax this assumption and allow for other possible firm layoff decisions to cloud employers' perceptions of why a worker was laid off. That is, this study treats layoff signaling as a form of statistical discrimination based on the assumption that some, but not all, laid off workers are laid off due to having lower than expected productivity and prospective employers are unable to accurately identify the reason for which a particular worker was laid off.[4] The result is that, for some workers, the layoff signal will be an inaccurate signal of their true ability and will bias employers' beliefs away from the the truth. While these workers will suffer initially from the inaccurate layoff signal, they should see a gradual wage recovery as information about each worker's true ability is revealed to employers.

As an initial test of my model, I investigate whether their exist divergent post-layoff wage paths for workers who are above versus below average ability, relative to their peers with similar observable characteristics. I use relative ability, as opposed to a worker's actual ability, to account for the fact that employers are likely to be more interested in learning about how productive a worker is relative to someone with identical characteristics, as apposed to the overall population. That is, unless all employers are hiring for generic positions with skill requirements that are unrelated to observable characteristics, such as education, it stands to reason that these characteristics should

[4] Seim (2019) finds evidence that laid off worker's are negatively selected on ability, suggesting that ability plays a role in the layoff decision, while Fredriksson, Hensvik, and Skans (2018) find evidence that idiosyncratic match quality also plays a role in the layoff decision, at least for young workers.

be accounted for when comparing the effects of ability on wage losses suffered by an observationally diverse group of laid off workers.[5] To empirically test for the presence of divergent recovery paths, I follow Farber and Gibbons (1996) in using the residual from a regression of a worker's Armed Forces Qualification Test (AFQT) score on observable characteristics as a proxy for relative ability.[6] Using an event-study framework, I find that workers who have an above average residual AFQT score experience nearly identical initial wage losses as workers with below average scores, but almost fully recover relative to a control group of non-displaced workers within six years. This stands in sharp contrast to workers with below average scores who experience nearly constant wage losses of around 10 percent over this same period.[7]

While the finding of divergent trends provides suggestive support for the layoff signaling hypothesis for young workers, a more robust analysis is required to distinguish these effects from those of similar studies, such as Oreopoulos, von Wachter, and Heisz (2012), who find that, unlike lower ability graduates, high ability graduates are able to slowly recover from the negative effects of entering the labor market during a recession through gradual job mobility to higher wage firms. Furthermore, while event-study models, such as those discussed in this study, are well accepted in the general displaced worker literature, they are likely less suitable for studying the effects of job loss for younger workers. von Wachter and Bender (2006), for example discuss a number of biases that arise when estimating traditional event-study models for young workers due to inherent differences in workers who leave or are let go from firms relative to those who stay.

In order to address issues with identifying layoff signaling using a traditional event-study framework, I develop an empirical framework built off of the empirical employer learning literature that has developed out the work of Farber and Gibbons (1996) and Altonji and Pierret (2001), and focus on the relationship between the interaction of experience and relative ability (as proxied by residual AFQT score). Specifically, using a sample of young workers from the National Longitudinal Survey

[5] Braga (2018) offers a similar discussion when looking at the role of both education and ability in studying the potential signaling effects of job loss.

[6] AFQT scores are derived from components of the Armed Services Vocational Aptitude Battery (ASVAB), a ten-part general skills and aptitude test administered by the United States military to gauge an individual's proficiency along a number of dimensions (mathematical, verbal reasoning, etc.). See e.g. Lange (2007), Altonji, Bharadwaj, and Lange (2012), and Speer (2017) for discussions regarding the use of these variables as proxies for ability.

[7] In a somewhat related study, Seim (2019) finds evidence that the size and persistence of earnings losses for laid off workers do not appear to vary based on a worker's ability. The ability measure used in his study, however, is a worker's ability relative to the population, not relative to worker's with similar characteristics. When I repeat this empirical analysis using a worker's actual AFQT score, the results more closely match those found in the earlier study.

of Youth 1997 (NLSY97), I examine the log wage returns to the interactions of pre- and post-layoff experience with residual AFQT score for laid off workers, relative to the interaction of total experience and residual AFQT score for non-displaced workers. The interaction of total experience and residual AFQT score for non-displaced workers serves as a counterfactual benchmark for assessing what the employer learning profile for a laid off worker would have been expected to be if they had not been laid off.

In line with the predictions of the conceptual framework, I find that, when a worker is laid off, (1) the coefficient on residual AFQT score decreases discontinuously at the time of the layoff; (2) this discontinuous effect decreases in magnitude with pre-layoff experience; (3) the coefficient on the residual AFQT score variable grows at a faster rate with post-layoff experience than it would have in the absence of the layoff, relative to non-displaced workers; and (4) the rate at which the coefficient grows following the layoff decreases with pre-layoff experience. Simply put, (1) and (3) indicate that high relative ability laid off workers are hurt disproportionately relative to their non-displaced peers, but recover rapidly with post-layoff experience as employers update and correct their beliefs. Likewise, (2) and (4) imply that both the initial signal effect and the rate of recovery from the signal are decreasing in pre-layoff experience, suggesting that employers gradually reduce the weight they place on the initial layoff signal as a worker's pre-layoff experience grows and the uncertainty about the worker's true ability decreases. I then provide a number of robustness checks and alternate sample specifications to ensure that these results are truly capturing a layoff signaling effect, as apposed to some inherent difference in how workers recover from job loss based on their relative ability level.

The rest of this paper is organized as follows. Section 2 provides a brief discussion of some of the related literature. Section 3 discusses the conceptual framework that will guide the empirical analysis of the paper. Section 4 discusses the data used in the primary analysis and provides sample statistics of key variables. Section 5 informally reviews the methods used in the general worker displacement literature and presents evidence of the divergent recovery paths for laid off workers by relative ability. Section 6 presents and estimates the empirical framework for estimating and identifying layoff signaling based on the conceptual framework. Section 7 concludes.

2 Background Information and Related Literature

[Probably should work in a reference to Aryal, Bhuller, and Lange (2020) (R& R at AER) and Kahn and Lange (2014) (for a discussion on how employers actually learn about worker ability)... also probably worth relating to the (growing?) literature on signaling due to the frequency of job changes, specifically Fan and DeVaro (2020) and Cohn et al. (2020)]

This paper contributes to the literatures on identifying the causes of the long-term earnings losses associated with involuntary job loss and the role that asymmetric employer learning plays in determining those effects. More specifically, I expand on research that seeks to empirically identify asymmetric employer learning based on stigma effects of being laid off. In a seminal paper, Gibbons and Katz (1991) (hereafter GK) show that, under asymmetric information, distressed firms selectively lay off their lowest ability workers first, which sends negative ability signals about those workers to prospective employers. GK attempt to identify these layoff signals by comparing outcomes across laid off workers and workers who lost their jobs due to plant closure, where plant closures are assumed to be exogenous. While some researchers following GK's empirical approach find strong evidence of layoff signaling (Nakamura 2008; Kosovich 2010; Michaud 2018), others find minimal evidence supporting the theory (Grund 1999; Krashinsky 2002; Song 2007) or find evidence of layoff signaling only within specific populations (Gibbons and Katz 1991; Doiron 1995; Hu and Taber 2011) (summarized in Table ???). Stevens (1997) and Krashinsky (2002), however, provide evidence that differences in pre-job loss characteristics between workers who lost their jobs due to layoff versus plant closure, such as earnings trends and establishment size, may explain the effects found based on GK's approach. Further, there is evidence that relatively high ability workers leave distressed firms before those firms shut down (Lengermann and Vilhuber 2002; Schwerdt 2011). Hence, the workers who remain at the firm until it closes may be negatively selected. My empirical approach avoids these issues associated with using workers who lost their jobs due to plant closer as a comparison group for laid off workers because I identify layoff signaling by comparing how employers learn about laid off workers relative to non-laid off workers with the same levels of ability.

My paper also expands the literature on the stigma effects of layoffs by allowing for layoff signals that change with experience and are imperfect in revealing information about the ability of laid off workers. That is, while GK's theoretical analysis, which is based on a two-period lemons model, is informative, it is limited in the sense that it does not take a stand on how layoff signals evolve with experience after a layoff, or how the interpretation of these signals change if some workers are laid off for non-productivity related purposes, such as due to seniority rules.[8] While there are numerous empirical studies on the signaling role of layoffs (discussed previously), they all generally follow the same theory motivating GK and do not take a stand on the evolution of these signals with experience, or the idea that layoff signals are a form of statistical discrimination more generally. A notable exception to this is the recent work of Michaud (2018), who analyzes a model that allows for employers to both inaccurately believe that some high ability workers are in fact low ability workers due to a layoff signal, and correct their beliefs over time as they learn the worker's true type. Like GK, Michaud (2018) empirically tests her model by comparing long-run effects of job lose for workers who lose their jobs due to layoff versus plant closure, but does so in an event-study framework so as to pick up the dynamics of the effects with post-job loss experience. This current study goes a step beyond Michaud (2018)'s work by specifically assessing the dynamics of the employer learning processes regarding laid off workers ability by analyzing the changing returns to a worker's relative ability with post-layoff experience, which allows for a more precise treatment of the learning process than an event-study model allows. Additionally, unlike this current study, data limitations inherent to the PSID force Michaud (2018) to treat layoffs and terminations with cause (firings) as indistinguishable events, which may lead to an overstated signaling effect of layoffs.[9]

I also contributes to the growing literature on empirically identifying employer learning that has grown out of the seminal symmetric learning models of Farber and Gibbons (1996) (hereafter FG) and Altonji and Pierret (2001) (hereafter AP). These models are based on the idea that employers form initial beliefs about each workers ability on a set of time-invariant, easily observe characteristics (education). As the worker's labor market experience increases, employers update their beliefs based on the noisy output signals the worker sends each period. This implies that ability correlates, such

[8]GK do acknowledge that alternative layoff reasons, specifically seniority based layoff rules, likely affect their empirical analysis. They attempt to get around this issue by focusing on white-collar workers who are less likely to be laid off due to seniority rules.

[9]Generally speaking, workers who are fired from their jobs tend to be avoided in the job loss literature due to endogeneity concerns regarding the type of worker who gets fired from a job (an activity that generally has higher fixed costs for firms (Oyer and Schaefer 2000)). See also Postel-Vinay and Turon (2013), Acharya, Baghai, and Subramanian (2013), Davis and Haltiwanger (2014), Haltiwanger, Scarpetta, and Schweiger (2014), and Mukoyama and Osotimehin (2019) for additional discussions on firing decisions/costs.

as test scores, that are available to the researcher but not prospective employers, should not affect a worker's early career wages. As a worker's labor market experience increases, however, employers learn about the worker's true ability, which increases the role of ability correlates in determining the worker's wage. AP's employer learning and statistical discrimination (EL-SD) model also shows that as employers learn about a worker's true ability, the less employers rely on on observable characteristics in determining the worker's wage. FG and AP test their models using data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). They examine returns to observable characteristics, as well as each worker's Armed Forces Qualifying Test (AFQT) score, a measure of their general aptitude that it not observed by a worker's employer, and find support for their theoretical predictions.[10] To the best of my knowledge, this study is the first to merge aspects from the FG and AP models into a dynamic framework that allows for an imperfect layoff signal to be identified as a form of dynamic statistical discrimination that changes with both pre- and post-layoff experience.

In bridging the gap between the empirical employer learning literature and the layoff signaling literature, I also contribute to the broader work on empirically identifying asymmetric employer learning. While the theoretical foundation of asymmetric employer learning has been well established for some time (see Waldman (2012) for a review), tractable empirical tests of asymmetric employer learning, outside of the layoff signaling literature, are a relatively new development and have reached mixed conclusions. Schönberg (2007), for instance, develops a two-period theoretical model of asymmetric employer learning and derives predictions related to the return to ability with current tenure, relative to overall experience, that she tests using an employer learning model based on AP. She finds little evidence of asymmetric employer learning, except possibly for college graduates.[11] On the other hand, Pinkston (2009) develops an empirical asymmetric employer learning model in which asymmetric information is passed between employers in a worker's current employment spell, as opposed to being specific to a unique employer. He finds evidence that asym-

[10] Other authors have expanded the general employer learning model in a number of ways. Lange (2007) modifies AP's EL-SD model to allow for the speed of employer learning to be structurally identified. Mansour (2012) expands on the AP model to test for differences in employer learning across initial occupation. Arcidiacono, Bayer, and Hizmo (2010) and Light and McGee (2015a) break AP's NLSY79 sample into two separate samples based on highest education level attained (high school and college). Light and McGee (2015b) and Petre (2018) adjust these models to test the importance of different skill dimensions (ASVAB component test scores) and ability types (cognitive versus non-cognitive).

[11] Zhang (2007) extends Schönberg (2007)'s theoretical model to three periods and finds evidence in support of asymmetric employer learning based on the predictions of his model.

metric learning has at least as large of an effect on wages as public learning during an employment spell.[12] While these earlier models allow for the identification of asymmetric employer learning in general, they do not specifically provide a means of addressing certain specific predictions from the literature, such as the signaling role of layoffs. This current paper, then, can be seen as complimentary to these earlier asymmetric employer learning studies by providing a general empirical framework for assessing predictions from the theory that are not easily identified using these earlier models. Further, while the main empirical specification analyzed in this study is based solely off of the FG and AP models, it can be augmented to match the empirical specifications used in these earlier studies, thus allowing different predictions of the theory to be tested simultaneously, so that researchers may better understand the manner in which the predictions interact.

My work also contributes to the large body of work focused on understanding the causes of the long-term earnings losses associated with involuntary job loss. While the overall effects of involuntary job loss have been well established (see e.g. Jacobson, LaLonde, and Sullivan 1993; Couch and Placzek 2010; Lachowska, Mas, and Woodbury 2020), the underlying mechanism leading to these effects is not as well understood (Carrington and Fallick 2017). A number of theories attempting to understand this mechanism have been proposed related to, among other things, lost industry/occupation specific capital (Topel 1990; Fallick 1993; Neal 1995); forgone human capital while unemployed (Burdett, Carillo-Tudela, and Coles 2020); skill mismatches upon reemployment (Nedelkoska, Neffke, and Wiederhold 2015; Kostol 2017); loss of position on career/occupation job ladders (Krolikowski 2017; Forsythe 2020); and costly post-job loss search (Jarosch 2015), to name a few. While each of these theories has some empirical support, distinguishing between each theory, in practice, is difficult due to how the theories overlap for many workers (e.g. more experienced workers are likely to suffer due to being separated from good quality job matches as well as due to being kicked down the job ladder). By focusing on younger workers who are likely to be less affected by these alternate theoretical explanations for the costs of job loss, this study is able to specifically assess the contribution that the revelation of negative information about a worker's productive ability to future employers has in determining the long-run costs of job loss. As a result, my

[12] Additional empirical tests for asymmetric employer learning include Devaro and Waldman (2012), Kahn (2013), Michaud (2018), Bates (2019), Fan and DeVaro (2020), and Cohn et al. (2020) all of which find evidence in support of asymmetric employer learning, but do so outside of the FG and AP framework. Additionally, while not specifically focused on asymmetric learning, the results of Mansour (2012) suggest that asymmetric employer learning exists at least between employers across occupations.

work also contributes to understanding the long-run effects of job loss for young workers. Previous studies on the effects of job loss for young workers have generally found that earnings losses for young workers are dramatic in the period following job loss (though generally of smaller magnitude than for older workers), and tend persist for at least five years following displacement, though these losses tend to taper out far faster than for older workers (Kletzer and Fairlie 2003; Barnette et al. 2020). Having a better understanding of the impact events that occur early in a career have on young workers long-term is especially important given the vast literature on the long-run effects of early labor market conditions (Mroz and Savage 2006; von Wachter and Bender 2006).[13]

3 Conceptual Framework

In order to motivate the empirical methodology used to analyze the signaling role of layoffs, this section discusses the intuition and basic predictions of a stylized dynamic extension of the original Gibbons and Katz (1991) model that allows for the layoff signal to change over time. The underlying intuition of this model is fairly straightforward and can be seen as a cross between repeated GK-type layoff "games" that vary based on the amount of information available about workers' abilities in each period and a dynamic version of Altonji and Pierret (2001)'s EL-SD model, where layoffs serve as a form of statistical discrimination.

3.1 Basic Structure

Workers enter the labor market with some level of unobserved productive ability and a vector of observed production related characteristics, such as schooling, which employers use to infer a worker's unobserved ability. In line with the empirical approach, employers learn over time about how far a worker's true productive ability is from what they expect it to be, given the worker's characteristics at labor market entry. That is, employers learn about the expectation error in their beliefs about the worker's ability, given the worker's characteristics. This is analogous to saying that employers learn about each worker's relative ability, which is simply the difference between a worker's actual ability and the average ability of the worker's peers with the same observable characteristics. In the remainder of this section, when referring to a worker's ability, it will be in

[13]Additional examples of studies examining the long-run effects of initial labor market conditions include Kahn (2010), Hershbein (2012), Altonji, Kahn, and Speer (2016), Liu, Salvanes, and Sørensen (2016) and Schwandt and von Wachter (2019). See also Rothstein (2020) who studies the effects of labor market entry after the Great Recession.

regard to this relative ability term.

Employers observe workers over time and gain information about their true ability, which is then used by the employers to update their initial beliefs. The amount of information an employer has about a worker's ability is based on both publicly available information and any private information that the employer may have gained through private observation of the worker. While employers with more private information learn faster about a worker's ability early in the worker's career than those with only public information, I assume that both private and public information converge to full information as a worker's experience in the labor market increases. Thus, while there is assumed to exist some degree of information asymmetry about a worker's ability early in the worker's career, this asymmetry gradually decreases the longer a worker remains in the labor market. This decreasing information asymmetry has a direct effect on the extent to which public information is altered based on the observed actions of a privately informed employer, specifically their decision to selectively lay off a worker.

The decision of a privately informed employer to lay off a particular worker is a function of an exogenous firm level productivity shock and the employer's expected profit for that worker, which is a function of how much more information the employer has about the worker's ability relative to outside employers. Workers are laid off if the the size of the exogenous shock is such that it is not profitable for the firm to retain the worker given the employer's expected profit from the worker. It is assumed that these firm-level productivity shocks are such that the probability that a worker is laid off is never zero, so even the highest ability workers face some non-zero chance of being laid off. As in GK, the nature of any involuntary job losses that have previously occurred in a worker's labor market career, and the layoff rule used by a previously laid-off worker's prior employer, are publicly known. Additionally, while the distribution of the firm-level shocks is publicly known, the size of the exogenous shock leading to a particular worker's layoff is not. Thus, after observing that a worker has been laid off, public information about the worker's ability is updated to account for this new "layoff signal," which is based on the relationship between the publicly known layoff rule and the expected size of the productivity shock that resulted in the worker being laid off; weighted relative to the degree of information asymmetry regarding the worker's ability at the time of the layoff. Since employers are unable to distinguish between workers who are laid off due a large productivity shock from those laid off due to low productivity, the layoff signal attributes to each worker the average amount of negative information expected to be conveyed based on the distribution of the ability of the laid off workers.

At the start of each period, the wage of a continually employed worker is determined based on a bidding process between the worker's current employer and at least one prospective employer. Each employers bid accounts for all information, both public and private, that they currently have about the worker's ability, including any information contained in the worker's previous job loss history. Wages for an unemployed worker, however, are determined by dueling take-it-or-leave-it offers from at least two potential employers for whom the worker has not previously worked. Since these employers have not previously employed the worker, only public information is accounted for in determining the wage offers that the worker receives. Due to the gradual convergence of public information to full information, the wage offers to both employed and unemployed workers gradually converge to each workers true productivity as experience grows.

The general idea behind this setup is that, as employers gradually learn about a worker's ability over time, the changing nature of asymmetric information across employers about the worker's ability, after controlling for the amount of public information available through that experience level, allows for repeated GK-type layoff signaling "games" to occur at each level of a worker's experience. That is, at the end of each period a worker is in the labor market, any new public information available about the worker's ability is captured in an updated public expectation of the worker's ability, which in turn results in a new public expectation error for each worker. This new expectation error can be thought of as a worker's updated relative ability, which is simply the new difference between the worker's actual ability and the average ability of his or her peers with the same observable characteristics and the same amount of public information. Then, at the start of each new period the worker is in the labor market, employers without access to private information are unable to distinguish between workers based on their updated relative ability levels, just as they were unable to do so based on workers' initial relative ability levels during the first period the workers were in the labor market. Thus, in each period, the underlying mechanism driving layoff signaling essentially resets based on any new public information gained the prior period, and is analogous to the general mechanism described in GK, except that, in this setup, the information asymmetry regards a worker's updated relative ability, rather than the worker's initial relative ability at labor market entry.

In addition to allowing for GK-type layoff signaling to occur in each period based on a worker's updated relative ability, controlling for all of the public information about a worker's initial relative ability prior to a layoff allows for an analysis of how employers learn about the accuracy of the layoff signal for a given worker over time. More specifically, since all laid workers are assigned the average amount of negative information contained in a layoff signal, even those for whom the layoff was the result of a large productivity shock, this signal can thought of as a form of statistical discrimination, about which employers learn the accuracy of over time as more information becomes available. Further, since public information about a worker's ability would have converged to full information over time in the absence of a layoff, the longer a worker is in the labor market post-layoff, the more employers reduce the weight placed on the negative information conveyed by a layoff signal in favor of the additional public information revealed about each workers' ability since the layoff. Ultimately, this setup will allow statistical discrimination in the form of layoff signals to be analyzed in a similar manner to the EL-SD model developed by Altonji and Pierret (2001).

3.2 Implications For Post-Layoff Wage Dynamics

In order to better understand the implications of this conceptual framework regarding post-layoff wage dynamics, and to identify some specific predictions that can be taken to the data, Figure 1 provides a graphical illustration based on the setup described previously. This figure illustrates the signaling effect of a layoff at experience level t_0, after accounting for public information prior to the layoff, for two "types" of workers with mirror-opposite levels of t_0-relative ability, one with a positive amount (denote by P), the other with a negative amount (denoted by N). Following the layoff, both types of workers suffer an initial layoff signal effect of x_{t_0}, which is a function of the amount of information asymmetry across employers about the workers at t_0. Since public information prior to the layoff is accounted for by employers, both types of workers look the same at t_0, and thus both types of workers receive a post-layoff wage given by w_{t_0}. For simplicity, the difference between w_{t_0} and the counterfactual wage that the workers' would have received had they not been laid off ($w^0_{t_0}$), is equal to the layoff signal. While both types of workers experience the same wage effect relative to their counterfactual wage at t_0, relative to the wages that the workers would receive under full information, denoted $w^{i*}_{t_0}$ for $i = P, N$, the type-P worker suffers a more severe negative effect due to the signal being inaccurate for this type of worker. More specifically, the magnitude of the difference between a type-P worker's initial post-layoff wage and their full information wage, given by $I_{t_0}^{P}$, is larger than the analogous term for the type-N worker, $I_{t_0}^{N}$, as the signal is more accurate for the type-N worker. Additionally, while $I_{t_0}^{P}$ is always weakly greater than the magnitude of the difference between a type-P worker's full information wage and their initial counterfactual wage, denoted by $I_{t_0}^{P0}$, the same is not true for type-N workers. As is illustrated in Figure 1, for a type-N worker, $I_{t_0}^{N}$ is less than $I_{t_0}^{N0}$ so long as the layoff signal does not result in a post layoff wage that is further from the worker's full information wage than their counterfactual wage would have been. More specifically, $I_{t_0}^{N} \leq I_{t_0}^{N0}$ if $x_{t_0} \leq 2 \times I_{t_0}^{N0}$, else $I_{t_0}^{N}$ is larger than $I_{t_0}^{N0}$.

Figure 1 also shows how the layoff signaling effect changes with post-layoff experience. Following the layoff at t_0, wage growth paths at experience levels $t > t_0$ for type-P and type-N workers are colored blue and red, respectively. Dropping the t_0 subscript, solid line segments $\overline{BD}_P$ and $\overline{BD}_N$ show the post-layoff wage growth paths for type-P and type-N workers, respectively, while transparent dashed line segments $\overline{AD}_P$ and $\overline{AD}_N$ show the counterfactual wage growth paths had the workers not been laid off. As all wages are assumed to converge to full information wages with experience, at all experience levels $t > t_0$, the slopes of $\overline{BD}_P$ and $\overline{BD}_N$, denoted by y_{t,t_0}^{P} and y_{t,t_0}^{N}, respectively, are weakly greater (more positive) than the corresponding slopes of $\overline{AD}_P$ and $\overline{AD}_N$, denoted by y_{t,t_0}^{P0} and y_{t,t_0}^{N0}. However, if $I_{t_0}^{N} < I_{t_0}^{N0}$, then $|y_{t,t_0}^{N}| \leq |y_{t,t_0}^{N0}|$, which means that the post-layoff wage growth path for a type-N worker is flatter than their counterfactual wage growth path. This occurs when $I_{t_0}^{N} < I_{t_0}^{N0}$ because the type-N worker's wage is closer to their full information wage than it would have been if they had not been laid off, resulting in a post-layoff wage is less responsive to new information than their counterfactual wage. That is, while employers still receive new information about this type of worker, a portion of this information simply confirms and replaces the information from the layoff signal, as opposed to revealing something "new" about the worker, as would happen in the counterfactual case, thus resulting in a smaller wage change as a result of the new information. For type-P workers, on the other hand, any non-zero layoff signal is necessarily inaccurate and thus $I_{t_0}^{P} > I_{t_0}^{P0}$. As such, a type-$P$ worker's post-layoff wage is always at least weakly more responsive to new information than their counterfactual wage. This occurs because any new information gained about a type-P worker is used to correct some of the information from the layoff signal, while also adding additional new information about the worker. As a result, post layoff wages for type-P workers increase as a result of both the new information and the decreased weight placed on the information from the layoff signal.[14]

While the wage paths illustrated in Figure 1 provide some insight into the key implications of this conceptual framework when public information at the time of the layoff is held constant, of equal interest to this study is understanding how these implications change as public information prior to a layoff evolves. To better understand these dynamics, it is helpful to describe the relationship between public information and the layoff signal in the context of the notation previously used. Specifically, denote the amount of public information available about a worker at experience level t by P_t. Then, as information asymmetry across employers about a worker's ability decreases as public information increases, the layoff signal decreases as well, and thus $\partial x_{t_0}/\partial P_{t_0} < 0$. As x_{t_0} decreases, so does the difference between a type-i worker's wage and their counterfactual wage, which means that, as pre-layoff public information increases, the overall difference between a worker's post-layoff wage path and their counterfactual wage path becomes less pronounced, indicating that changes in pre-layoff information directly effect the wage dynamics described in Figure 1.

3.3 Empirical Predictions

The wages dynamics discussed in this section yield a number of predictions based off of the conceptual framework motivating Figure 1 that I will take to the data. These predictions are driven by the size of the disparity between public and private information about a worker's ability and how this disparity evolves as a worker's experience increases. If this disparity is large, then prospective employers are expected to believe that a layoff contains informative negative information about a worker's ability. Conversely, if this disparity is small, then prospective employers are expected to believe that a layoff conveys little information about the worker's ability, and thus it should be thought of as more of an exogenous event than an ability signal. The empirical predictions based on this framework as summarized as follows.

(i) **The initial signal effect disproportionately affects workers with positive relative ability -** Since the layoff signal is assumed to contain negative information about a worker, it will always move a type-P worker's wages further from their full information wage than it will for a type-N worker, as at least some of the negative information from the layoff signal will be accurate for the latter worker. Thus, when $I^{P0}_{t_0}{=}I^{N0}_{t_0}$ and $x_{t_0} \neq 0$, we have that $I^{P}_{t_0}{>}I^{N}_{t_0}$.

[14] This is also true for type-N workers for whom the layoff signal significantly overshot their true ability such that $I^{N}_{t_0} > I^{N0}_{t_0}$. That said, when comparing type-P and type-N workers, while the counterfactual wages of both types of workers are equally responsive to new information ($|y^{P0}_{t,t_0}| = |y^{N0}_{t,t_0}|$), the post-layoff wages of type-P workers are strictly more responsive to new information than the post-layoff wages of type-N workers ($|y^{P}_{t,t_0}| > |y^{N}_{t,t_0}|$). This is due to the fact that, for any non-zero layoff signal, while $I^{P0}_{t_0}{=}I^{N0}_{t_0}$ by construction, $I^{P}_{t_0}$ is always larger than $I^{N}_{t_0}$.

(ii) **The initial signal effect is weakly decreasing in pre-layoff experience -** Under the assumption that, in the absence of a layoff, public information is weakly improving with experience, then $\partial P_{t_0}/\partial t_0 \geq 0$ and $\partial x_{t_0}/\partial P_{t_0} < 0$ implies that $\partial x_{t_0}/\partial t_0 \leq 0$. Also, since P_{t_0} converges on full information as t_0 grows, there exist some t_0 such that $\partial x_{t_0}/\partial t_0$ is strictly decreasing. Hence, $x_0 \geq x_1 \geq \cdots \geq x_{t_0} \geq x_\infty = 0$ and $x_0 > x_\infty = 0$.

(iii) **Following a layoff signal, the wage return to ability for laid off workers increases at a more positive rate with experience than for similar non-laid off workers -** The change in a laid off worker's wage given some amount of new information can be expressed as the change in that worker's counterfactual wage minus the change in the layoff signal given the same amount of new information. Since for any non-zero layoff signal, $\partial x_{t_0}/\partial P_t < 0$ then the change in a type-i laid off worker's wage at experience level t can be expressed as $y^i_{t,t_0} = y^{i0}_{t,t_0} - \partial x_{t_0}/\partial t > y^{i0}_{t,t_0}$.

(iv) **The extent to which the wage return to ability for laid off workers increase at a more positive rate than for similar non-laid off workers is weakly decreasing in pre-layoff experience. -** From (iii), the amount to which the wage of a type-i laid off worker increases more positively with experience compared to a similar non-laid off worker is given by $y^i_{t,t_0} - y^{i0}_{t,t_0} = -\partial x_{t_0}/\partial t > 0$. Observing that $\partial x_{t_0}/\partial t_0 \leq 0$, we have that,

$$-\frac{\partial(y^i_{t,t_0} - y^{i0}_{t,t_0})}{\partial t_0} = \frac{\partial \frac{\partial x_{t_0}}{\partial t}}{\partial t_0} = \frac{\partial^2 x_{t_0}}{\partial t \partial t_0} = \frac{\partial x_{t_0}}{\partial t}\frac{\partial x_{t_0}}{\partial t_0} > 0.$$

This implies that the extent to which laid off workers experience more positive wage returns to their ability compared to their non-laid off peers, decreases as experience, and public information about the worker's ability, increases prior to the layoff. Thus, $y^i_{t,0} - y^{i0}_{t,0} \geq y^i_{t,1} - y^{i0}_{t,1} \geq \cdots \geq 0$, and since $x_0 > x_\infty = 0$, $y^i_{t,0} - y^{i0}_{t,0} > 0$.

(v) **Following a layoff signal, the wage return to ability for laid off workers with positive relative ability increases faster with experience than for laid off workers with negative relative ability -** The extent to which a given amount of new public information will affect a worker's wage depends on how far the worker's current wage is from the full information wage. Since the type-P worker's wage is always further away from their full information wage than a type-N worker's wage, the type-P worker's wage is always more responsive to new information than the type-N worker's wage. This is true even though the workers' counterfactual wages are assumed to be equally responsive to new information, albeit in opposite directions. In other words, when $x_{t_0} \neq 0$ and $I^{P0}_{t_0} = I^{N0}_{t_0}$, we have that $|y^{P0}_{t,t_0}| = |y^{N0}_{t,t_0}|$, but $|y^{P}_{t,t_0}| > |y^{N}_{t,t_0}|$.

To examine these predictions, I need an empirical strategy that allows for the return to a measure of a worker's relative ability to vary across pre- and post-layoff experience. I discuss such a strategy in Section 6.

Before examining each of these specific predictions in a dynamic empirical setting, however, I first investigate a more general prediction of this framework related to prediction (v). Specifically, since both the P and N type workers experience identical initial layoff signal effects (conditional on pre-layoff public information), but the type-P worker experiences a steeper learning recovery than the type-N worker's relatively flat learning "recovery", the wage recovery paths following layoffs should diverge for these different types of workers. That is, in an empirical setting, we should expect to see that both types of workers experience similar initial layoff effects, but over time, we should expect to see that workers with positive relative ability gradually recover from these effects, while workers with negative relative ability do not. These divergent trends in the layoff recovery paths for workers with positive versus negative relative ability provide a simple initial test of the predictions of this model, and can be estimated using the same empirical frameworks commonly used in the job displacement literature. I discuss this initial estimation approach in Section 5.

4 Data

The data used to study the empirical predictions discussed in the previous section come from the 2017 release of the National Longitudinal Survey of Youth 1997 cohort (NLSY97), a nationally representative survey of 8,984 men and women who were between the ages of 12 and 16 on December 31st, 1996. This survey, which was designed to capture the evolution of employment career paths of individuals from the time they leave school through adulthood, was administered annually between 1997 and 2011 before switching to its current biennial format following the completion of the 2011 interview round. During these interviews, extensive events histories are collected from the respondents related to a variety of topics covering employment, program participation, and education, as well as other important life events such as marital status and parental cohabitation. The event history data available in the NLSY97, as well as the detailed employer roster, make this an ideal source from which to study the effects of early career job loss.[15]

There are two additional features of the NLSY97 data that make it ideal for this type of study. The first of these features is the detailed respondent report regarding the reason for job loss. That is, the data allow me to identify whether a worker loses his or her job due to layoff, plant closure, or termination with cause. This stands in contrast to other data sources which do not allow for termination with cause to be separately identified from layoffs (PSID), or which do not offer detailed

[15]The employer roster provides information on a variety of employment characteristics for each job an individual works ranging from the industry/occupation to whether the worker enjoys his/her job. Additionally, each employer on the roster is assigned a unique identifier which can be matched with the employer identifiers used in the event history data.

information about such terminations at all (DWS). The second key feature of the NLSY97 is the information available on pre-market skills, aptitude and cognition tests (such as the ASVAB), as well detailed histories on a variety of topics such as incarceration or drug use, which can be used as proxies for ability/quality in empirical work. For this study, I will be using the age adjusted AFQT scores created by Altonji et al. (2012) that are directly comparable to the AFQT measures used in FG and AP. AFQT scores, which are derived from the math and reading portions of the ASVAB test, have been a standard measure of a worker's productive ability used in the literature dating back to Neal and Johnson (1996). For ease of interpretation, I normalize the AFQT scores to be mean zero with unit variance in the sample.

To study these effects, I match the employer identification numbers in the NLSY97's weekly employment array with information form the employer roster to construct an aggregated quarterly employment panel for each individual which details the total earnings and hours worked across up to five reported employers in quarter. From this, I identify each worker's primary employer in a quarter as the employer for which the worker worked the greatest number of hours, deferring to the employer with the longest tenure in the event of a tie. In the analysis that follows, I will be focusing on the wage effects of job loss based on the hourly wages for each of these primary employers, which is free from potential confounding effects that could be present if the average wage across multiple employers is used. One of the main benefits of a quarterly panel, as opposed to a yearly panel commonly used in studies of young worker displacement (e.g., Stevens 1997; Kletzer and Fairlie 2003), is the level of precision it affords in examining the wage dynamics of these displaced workers over time, especially given the focus on young workers who tend to experience more dramatic earnings/wage growth over relatively short periods of time due to job mobility, career advancement, etc., relative to older workers. Further, this level of aggregation allows me to construct a measure of labor market experience that evolves at the quarterly level and is more precise than conventional measures of potential labor market experience that must be used in the absence of work history data, as well as those that rely solely on a respondent's self-reported labor market experience which is subject to an evolving recall bias that grows as the respondent ages.[16]

[16] While there remains a possibility for recall bias in the weekly event history arrays, the time frame over which the bias can arise is limited to the time between survey interviews which occur at regular intervals and do not require the individual to recall employment periods far beyond the previous interview. See Appendix **??** for details on the steps taken to minimize the possibility of recall bias in this sample.

Involuntary job loss measures are defined based off of each respondent's self reported reason for why they are no longer employed with a previously identified primary employer. To avoid issues related to temporary or seasonal work, I ignore jobs that end before the respondent can accumulate at least 13 weeks (three months) of tenure. Any individuals who report a reason for job separation to be due to layoff, plant closure, or discharged/fired are considered to have involuntarily lost their job and thus make up my job loss sample. This sample is further broken down into three categories based on the type of job loss the respondent experienced, specifically layoff, plant closed, or fired. As the primary focus of this paper is on early career job loss, the analysis that follows will focus on the first involuntary job loss experienced by an individual as these are more likely to occur early in a worker's career and it avoids issues that arise when trying to separate the effect of a second job loss from the first as these are often correlated events.[17]

Finally, in order to analyze the relationship between employer learning and job loss through wage changes, I restrict my sample to individuals who have made their first long-term transition from school to the labor market prior to 2008. This transition is defined as being the first quarter in which an individual does not increase their education level the following year and will have worked at least 30 hours per week for half of the weeks during the following two years. This labor market entry definition is comparable to the one used in FG, though alternative definitions will also be considered for robustness checks. Additionally, for each worker, actual experience is defined as the number of weeks an individual has worked at least 30 hours divided by 50, and potential experience is defined as the number of quarters since an individual began their first employment spell divided by four. See Appendix **??** for further information regarding the definition of a worker's first long-term transition into the labor market, as well as a complete description of the sample construction process, as well as the methods used to create each of the relevant variables used in the study.

4.1 Creation of Residual Ability Measures

As previously discussed, using a standard ability measure is likely not the best option for studying the signaling effect of a layoff due to inherent correlations between ability measures and observable characteristics, which should be accounted for by employers when a worker is hired, regardless of any signal they may observe. From a regression standpoint, the correlation between an ability

[17] Stevens (1997) and Michaud (2018) note that the probability of involuntarily losing a job increases substantially if a worker has already experienced a prior job loss.

measure and observable characteristics will result in estimated effects of job loss by ability level that are confounded by the relationship between the effects of job loss and other characteristics, such as years of schooling. If we are willing to assume that no such correlation between observable characteristics and the effects of job loss exists, or that it can be adequately controlled for, then a standard ability measure, such as AFQT score would suffice. In practice, however, it has been well documented that the effects of job loss are heterogeneous across various demographic groups, education levels, pre-job loss occupations and industries, etc. (e.g., Fallick 1996; Farber 2017), all of which have been shown to have some form of relationship with a worker's ability, often proxied by AFQT scores (e.g., Gibbons and Katz 1992; Neal and Johnson 1996; Carneiro, Heckman, and Masterov 2005; Arcidiacono et al. 2010; Mansour 2012; Speer 2017). As such, it is necessary to purge the ability measures used in this study of their relationship with these observable characteristics.[18]

To create an ability measure that is orthogonal to the information available to the prospective employers when a worker first enters the labor market, I create a sample consisting of each individual's first period in the labor market (i.e. the first period they are employed and report a non-zero wage). Then, following FG, I define residual ability z_i^* as,

$$z_i^* = z_i - E^*(z_i \mid X_{i0}, \omega_{i0}),$$

where E^* is the linear project of an ability measure z on a vector of observable characteristics X_{i0} and the worker's first period wage ω_{i0}. FG show that z^* is equivalent to observing employers' expectation error in a worker's ability for experience levels $t > 0$, and can be used by researchers to assess the effects of employer learning.[19] In practice, I regress each worker's AFQT score on a vector of observable characteristics and their first period wage, and then use the fitted values from this regression to calculate each worker's residual AFQT score.

The vector of observable characteristics used to create the residual AFQT scores contains five

[18] These issues are highlighted by FG and Light and McGee (2015b) in the context of empirical employer learning models, with both sets of authors opting to create residual ability measures for their respective analyses.

[19] Light and McGee (2015b) use a slightly different approach than FG. They regress their z measures only on the observable characteristics used in their model, leaving out the entry period wage. The advantage of that approach is that it does not require the entry period wage to be dropped in log-wage regression models, while still purging their ability measure of any correlation to observable characteristics. However, that approach does not purge the correlation between characteristics that are only observed by the employer and the ability measure, which will complicate the interpretation of the estimated return to ability over experience, since certain aspects of learning will be correlated with these observable characteristics, meaning their $\hat{z}$ is a biased measure of employers' true expectation errors. This issue is especially problematic in this context as the characteristics observable to employers are likely to have some form of correlation with the any job loss signal, which would make it impossible to distinguish between the signaling effect of the job loss and this correlation.

education dummy variables ($<$ 12 years, 12 years, 13-15 years, 16 years, and 17+ years), an indicator for part-time status, the interaction of part-time status and each education dummy, indicators for race, sex, marital status, marital status interacted with sex, age in years (<18, 18-19, 20-21, 22-23, 23-24, 25+), birth year, current year and quarter, and the log of the worker's wage. Additionally, I include indicators for the number of employees at each worker's employer ($\leq$10, 11-50, 51-100, and 100+), as well as the interaction of each of these indicators with each worker's log wage. This is done to account for potential differences in an employer's ability to judge a worker's true ability based on the employer's size, and to address a number of recent studies which have found that the size of a worker's first employer is an important determinant of labor market career trajectories (e.g., Moscarini and Postel-Vinay 2012; Arellano-Bover 2020).

This regression accounts for roughly 40 percent of the variation in AFQT scores, which is noticeably lower than the R^2 value found in FG (53 percent of variation accounted for using their NLSY79 sample and nearly identical controls). This seems to be in line with recent empirical evidence from Altonji et al. (2012), who find that the ability distribution has widened over time, and that demographic characteristics, such as race and gender, appear to play a less predictive role in an individual's AFQT score among the more recent cohort.[20] Lastly, while $AFQT_i^*$ is mean zero by construction, to make the measure comparable to the standardized AFQT scores, it is normalized to have unit-variance.

4.2 Summary Statistics

The analysis sample consists of 4,009 unique individuals with 152,572 year-quarter wage observations. Of this sample, 821 individuals (31,624 year-quarter wage observations) make up the layoff sample, 256 individuals (10,056 year-quarter wage observations) make up the plant closure sample, and 565 individuals (21,978 year-quarter wage observations) make up the fired sample. Table 1 displays descriptive statistics for the entire sample and each of the individual job loss samples, for the quarter the respondent is identified as having entered the labor market.

Relative to workers who are never identified as having an involuntary separation during the sample period, workers in the overall job loss sample have an average of 1.5-2 years less education,

[20] It is also possible that this smaller relationship between observable characteristics and AFQT scores could be related to the recent evidence that the return to cognitive ability has generally been decreasing over the past few decades (e.g., Castex and Dechter 2014; Beaudry, Green, and Sand 2016), though evidence from other studies using more updated data, such as Ashworth et al. (2020), among others, suggest that this may not be the case.

are 1-1.5 years younger, are more likely to be Black or Hispanic, and are less likely to be female. Table 1 also shows that, while workers in each of the job loss samples have an average AFQT score that is 10-14 points lower than the non-job loss sample, only the layoff sample has a residual AFQT score that is statistically less than the mean for the control sample. Not only is the layoff sample's standardized residual AFQT score average of -0.103 significantly lower than the sample mean, it is also an order of magnitude further from the mean in absolute terms than the other samples. This suggests that while observable characteristics account for the lower average AFQT scores reported by the plant closed and fired samples, the lower scores reported for the layoff sample cannot be accounted for based solely on observable characteristics. That is, on average, workers in the layoff sample have a lower overall ability than their observable characteristics would suggest. While this is merely descriptive, the fact that laid off workers appear to be negatively selected on unobserved ability provides some justification for employers' to use a use an observed layoff as a signal of a worker's ability, resulting in layoffs acting as a form of statistical discrimination.

Table 2 reports additional descriptive statistics for several of the key variables over the entire sample period. As would be expected, workers in each of the job loss samples have lower average career wages than the average for workers in the the non-job loss sample. Perhaps more surprisingly, despite having at least a half year or more potential experience on average, workers in each of the job loss samples average the same, or less actual experience than workers in the non-job loss sample, indicating that some workers may have had some difficulty returning to work following their job loss. Also of interest is that workers in each of the job loss samples gained around the same amount of additional education after initially entering the labor market as workers in the control sample at around half a year of additional education on average. While we may be concerned the workers in the job loss sample were more likely to re-enroll in school following their job loss, at least descriptively, the workers in the job loss sample do not appear to be disproportionately increasing their education as a means of recovering from their job loss, though I will explore this in more depth in the main empirical analysis.

5 Evidence of The Long-Term Costs of Job Loss

5.1 Wage Losses Following Job Loss

As discussed previously, it is well known that involuntary job displacement can have a profound and long-lasting impact on the labor market experiences of individuals subjected to such events (e.g., Fallick 1996; Davis and von Watcher 2011; Carrington and Fallick 2017). Beginning with the seminal worker of Jacobson et al. (1993), researchers generally have relied on worker fixed-effects models to identify the long-term effects of involuntary job loss. This traditional multi-period difference-in-differences model allows for some outcome Y, such as earnings, to be compared across displaced and non-displaced workers at the point of and after job loss. Thus, the long-term effects of involuntary job loss can be obtained by estimating the following model:

$$Y_{it} = \alpha_i + \gamma_t + \mathbf{X}_{it}\beta_1 + \mathbf{Z}_{ie_0}\beta_2 + \sum_{k \geq -2}^{6} D_{it}^{k}\delta^{k} + \epsilon_{it}, \tag{1}$$

where the outcome Y for individual i in period t depends on a worker specific fixed effect α; a time effect γ_t; worker demographics $\mathbf{X}$, including a quadratic in experience, the interaction of years of education and year indicators, and indicators for race, sex, part-time status, union membership, and urban residence, all interacted with experience and a year trend; characteristics of the worker's first employer when they entered the labor market $\mathbf{Z}_{e_0}$ which include the log of the employer's size and two-digit industry and occupation codes, all interacted with experience and a year trend; the effect of the k^{th} year relative to job loss δ_k, where D^k is an indicator for the k^{th} year relative to job loss, and a stochastic error term ϵ.[21]

Identification in this type of model comes from the assumption that, absent job loss, individuals in the job loss group would have had similar earnings/wage growth paths (or trends) as those in the control group. Generally speaking, the validity of this assumption is checked by looking at the coefficients on the pre-job loss year indicators, in this case δ_{-2} and δ_{-1}. If no pre-job loss trends are found, these coefficients should both be near zero, as ideally, these workers would otherwise be indistinguishable from non-job losers. Figure 2a shows the estimated job loss effects on log earnings for young job loser in the NLSY97 data. The figure illustrates that earnings remain

[21] Additional controls include indicators for the year an interview takes place, and indicators for job losses occurring prior to 2004 or after the start of 2008 which are used to capture any general trends in the costs of job loss associated with losing any job during those time periods, regardless of reason.

around 10 percent lower than the control group's earnings through at least six years following job loss, which is in line with prior literature.[22] Lachowska et al. (2020) show that, while hours losses account for the steep initial drop in earnings, the long-term persistence of the displacement effect can be traced to wages that remain depressed relative to observationally similar non-displaced workers. Figures 2b and 2c support this notion as hours recover quite rapidly following job loss, while wages remain around 10 percent lower than the control groups through at least six years post job loss.

Nonetheless, event-study models are likely unsuitable for studying the effects of job loss for young workers. For example, event-study models do not account for inherent differences between workers who leave or are let go from firms relative to those who stay. This can lead to biases in the estimated effects of job loss (von Wachter and Bender 2006). If some workers who lose their jobs, specifically those who are laid off, are negatively selected based on ability, then the results shown in Figures 2a-2c will be biased away from zero. In the following subsection, I attempt to investigate this notion by breaking down and comparing the effects of job loss by groups based on reason for job loss (layoff, plant closure, or fired with cause), and then again further by various definitions of above versus below average ability. Breaking down the costs of job loss in this manner should help provide some initial indications regarding the suitability of event-study frameworks for analyzing the costs of job loss for young workers.

5.2 Wage Losses By Type of Job Loss

A common method in the literature for identifying if workers who are selectively separated from their employers (layoffs or firings) are adversely selected is to compare the job loss effects of these types of separations with those due to plant closure, as plant closures should affect workers of all ability types equally (Gibbons and Katz 1991). If employers believe that workers who are selectively separated from their previous employer are adversely selected but workers who lose their job because their previous employer shut down are not, then we should see more severe job loss

[22] There are two things that must be noted with the results presented here for job losers generally. First, unlike studies of displaced workers that are concerned with workers who lose their jobs due to layoff or plant closures only, the job loss sample used here includes workers who were fired with cause. Additionally, it must be noted that only workers with more than two years of pre-job loss experience are used when estimating this event study model, and that all periods prior to the two years before job loss have implicitly been set to have a zero estimated coefficient on a year relative to job loss indicator. Forcing a zero coefficient for at least one of the pre-job loss periods is required for identification in these types of models.

effects for the selectively separated group relative to the plant closure group since the prior should be believed to be of lower ability on average than the latter. To explore this idea and break down the effects of job loss by type, I estimate the following modified version of the event-study regression from Equation (1):

$$Y_{it} = \alpha_i + \gamma_t + \mathbf{X}_{it}\beta_1 + \mathbf{Z}_{ie_0}\beta_2 + \sum_{j\in\mathcal{J}}\sum_{k=-2}^{6} D_{it}^{kj}\delta_j^k + \epsilon_{it}, \tag{2}$$

where $\mathcal{J} = \{L, C, F\}$ represents layoff, plant closure, and firing, respectively, and δ_j^k represents the effect of the k^{th} year relative to the j^{th} type of job loss on the outcome Y, all remaining variables are the same as in the previous subsection. Based on the estimation of this model, Figure 3 breaks down the long-term earnings, hours, and wage losses of workers who lose their jobs due to layoff, plant closure, and fired with cause.

Figure 3 shows that the initial earnings effect of plant closure (3d) is significantly smaller than the earnings effects of layoffs and firings (3a and 3g respectively), which would seemingly support an argument that employers believe that workers who are laid off or fired are adversely selected. The initial difference in earnings losses, however, appears to be partly explained by the smaller initial effect of plant closure on hours worked (3e) relative to the effect based on other types of job loss (3b and 3h for laid off and fired workers, respectively), which is not predicted by the general GK layoff signaling model. Furthermore, looking at the effect of plant closure on log wage (3f), it is clear that the assumption of common trends is violated as workers who lose their jobs due to plant closure experience sizable wage reductions in the year(s) *prior* to job loss, a phenomenon also noted by Stevens (1997) who analyzes the effects of job loss using data from the PSID.[23] Given that the common trends assumption is not violated in the pre-layoff period for any of the specifications (with the layoff effect on log wage (3c) being the only log wage regression without this violation), it cannot be reasonably assumed that workers who lose their jobs in a plant closure are a valid control group from which to compare laid off workers. This underscores the most prominent issue with identifying layoff signaling in this manner, if pre-event trends are present for the sample of workers who lose their job due to plant closure, then they are simply different from those who lose their

[23]Interestingly, Michaud (2018) uses a similar estimation strategy as presented here with data from the PSID, but does not document any pre-job loss trends for her sample of workers who lost their job due to a plant closure. It is possible that the differences between Michaud (2018) and Stevens (1997) in this regard are due in part to slightly different sample definitions, as well as different time frames studied in each of the samples.

jobs due to being laid off and should not be used as a direct comparison group. It is also worth noting that, while workers who are fired with cause are expected to be the most adversely selected, the noticeably large, negative pre-firing wage effects (3i) suggest that these workers have already been identified by employers as being negatively selected well before being fired, so the amount of new information gained by the firing may be ultimately be relatively small.

5.3 Evidence of Divergent Recovery Paths For Laid Off Workers

While using workers who lost their job due to plant closure proved to be an ineffective way to assess whether laid off workers are adversely selected, an alternate approach would be to split the sample of laid off workers by ability and compare the long-term layoff effects for each group. As discussed at the end of Section 3 in regard to Figure **??**, even if employers believe that laid off workers are adversely selected on average, some portion of these workers will actually be high ability workers who were unlucky enough to get caught up with the rest. If this is the case, then we should observe high ability workers recover from a layoff over time, while the effects for low ability workers will remain fairly constant. To examine this hypothesis, I consider three ability measures: each worker's standardized AFQT score, predicted AFQT score, and residual AFQT score. In order to break down the effects of job loss by type and ability, the following modified version of the event-study regression from Equation (2) is estimated:

$$Y_{it} = \alpha_i + \gamma_t + \mathbf{X}_{it}\beta_1 + \mathbf{Z}_{ie_0}\beta_2 + \sum_{a \in \mathcal{A}} \sum_{j \in \mathcal{J}} \sum_{k=-2}^{6} D_{it}^{kja} \delta_{ja}^{k} + \epsilon_{it}, \tag{3}$$

where $\mathcal{A} = \{\textit{Above Avg. Ability},\ \textit{Below Average Ability}\}$ represents above and below the sample average of a given ability measure during all respondents' first quarter in the sample, and δ_{ja}^{k} represents the effect of the k^{th} year relative to the j^{th} type of job loss for an individual in ability group a on the outcome Y.

Figure 4 displays the estimated δ_{ja}^{k}'s based on the regression described in Equation (3), with each ability measure represented separately. Note that for simplicity, throughout the remainder of this study, I focus solely on the effects of job loss on log wages, though hours and earnings effects are available upon request. Additionally, as the primary interest of this study is looking at the signaling role of layoffs, Figure 4 reports only the long-term effect of being laid off. For the sake of comparison, the estimated effects for job loss due to plant closure and fired with cause, broken down by above or below average ability types, can be found in Appendix Figure **??**.

When I split the layoff sample based on actual AFQT score, Figure 4a shows that laid off workers with above average actual AFQT scores experience similar, if not worse, layoff effects as those with below average ability. These results are remarkably similar to those found in Seim (2019)'s work looking at the effects of job loss by ability among Swedish workers. While this may seem to suggest that adverse selection and signaling do not play a major role in determining the long-term effects of layoffs, it is important to consider that employers should have some prior knowledge of a worker's ability based on observable characteristics. Thus, the real interest in this analysis comes from looking at effects based on predicted and residual AFQT scores, Figures 4b and 4c, respectively. Figure 4b shows that based on what employers can easily see about a worker's ability (based on education, gender, race, etc.) , the long-term effects of a layoff are nearly identical for high versus low predicted ability workers, which is what we would expect in a model where a layoff conveys a signal about unobserved worker ability, since this signal should be orthogonal to what is easily seen (else it would be poor signal). When splitting the sample based on the portion of ability that is orthogonal to employers' initial beliefs, as in Figure 4c, we see that while workers with above and below average residual AFQT scores experience nearly identical initial wage losses following a layoff, workers with above average residual AFQT scores gradually recover to the point where the effects of the layoff are statistically indistinguishable from zero, while workers with below average residual AFQT scores experience no noticeable recovery over the same period. This is directly in line with the prediction of divergent trends discussed at the end of Section 3.

6 Empirically Identifying Layoff Signaling

While the results of the event-study framework provide some encouraging support for one of the predictions of the layoff signaling theory, in practice they only confirm that workers with above average residual ability do a better job at recovering from the effects of a layoff than do workers with below average residual ability. There are likely a multitude of theoretical justifications for why workers with above average residual ability recover from layoffs better than those who are below average, such as better potential to rise quickly through job ladders, not to mention that higher residual ability workers may just work harder than below average workers, which could ultimately drive their wage recovery. Thus, in order to parse out the extent to which these divergent recovery paths are indeed driven by some form of layoff signaling, it is necessary to develop an empirical strategy that can address each of the individual predictions discussed in Section 3, as these predictions describe in specific detail the underlying wage dynamics that should be observed if layoff signaling is playing a major role for these workers.

In order to identify layoff signaling empirically, first consider the basic employer learning model developed by FG and AP, which can be empirically estimated using the following log wage regression equation,

$$w_{iq} = \beta_0 + \beta_s s_i + \beta_{s,t}(s_i \times t_i) + \beta_z z_i^* + \beta_{z,t}(z_i^* \times t_i) + f(t_i) + \mathbf{X}_{iq} + \epsilon_{iq}, \tag{4}$$

where w_{iq} is the log wage of worker i at the main employer during quarter q; s_i is years of education for worker i; t_i is a measure of total years of experience, z_i^* is a residualized ability measure, such as AFQT score; $f(t_i)$ is a cubic in experience; $\mathbf{X}$ is a vector of controls including indicators for each year-quarter pair, indicators for year interacted with education (base year of 2015), indicators for race, union status, female, entry age, and part-time status, as well as indicators for entry quarter two-digit industry.

The key intuition behind this regression is that if the standard employer learning models are correct, then if z_i^* is a residualized ability measure, we would expected β_z to be zero and $\beta_{z,t} > 0$ as the effect of the unobserved component of ability is learned by the labor market, and is thus factored into the wage equation. Additionally, as the ability measure is orthogonal to information available to the employers when the worker first enters the labor market, $\beta_{s,t}$ should be equal to zero as the labor market returns to education should be fully captured in the first period as it is fully observed by the market.[24]

Now, to see how this general framework can be used to identify layoff signaling, observe that

[24] Technically these implications only hold for the FG model. In the EL-SD model developed in AP, where z_i is used in place of z_i^*, the expected coefficients have a slightly different interpretation, and this interpretation will be useful when interpreting the estimates from the asymmetric learning model developed in Section 3. In the EL-SD model, β_3 need not equal zero as some portion of ability related to, e.g. education, is observed by the market. Given that education, and the ability measure are likely correlated in the model, if employers have an underlying belief about a worker's ability, conditional on some observed variable (education), we should find $\beta_4 > 0$, while $\beta_2 < 0$ as the market shifts the weight it puts on the relationship between education and ability when a worker first enters the market to the observed productivity signals for the worker overtime. That is, as a worker gains more experience, the market should have a better understanding of her innate ability, and will no longer need to rely on its beliefs about ability, given observed education.

Equation (4) can be augmented in the following way,

$$\begin{aligned}\omega_{iq} = \ & \beta_0 + \beta_s s_i + \beta_z z_i^* + \beta_{s,t}(s_i \times t_i) + \beta_{z,t}(z_i^* \times t_i) + \beta_d d_{it_0} + \beta_{z,d}(z_i^* \times d_{it_0}) \\ & + \beta_{z,t'}(z_i^* \times d_{it_0} \times t_i') + \beta_{z,t_0}(z_i^* \times d_{it_0} \times t_0) + \beta_{z,t_0,t'}(z_i^* \times d_{it_0} \times t_0 \times t_i') \\ & + f(t_i) + \tilde{f}(t_0, t_i') + \mathbf{X}_{iq} + \epsilon_{iq},\end{aligned} \tag{5}$$

where $d_{it_0} = \mathbb{1}(t \geq t_0)$ is an indicator for all periods following a layoff, t_0 represents years of pre-layoff experience, t_i' represents post-layoff experience for worker i, and $\tilde{f}(t_0, t_i')$ is a function of pre- and post-layoff experience. Under additional asymmetric information assumptions that we may be concerned are at play in the background of the implications discussed in Section 3, this equation can be modified to include the interaction of z^* and x_c (tenure on worker's current job) or the interaction of z^* and j_c^s (the length of a worker's current job spell), which addresses and expands upon the empirical estimation frameworks of Schönberg (2007) and Pinkston (2009), respectively.

The key aspects of this regression model are in how it relates to the predictions about the combined return to ability following a layoff discussed in Section 3. In this regression model, β_{zt} represents the experience-ability profile for workers for whom $d_{it_0} = 0$ and is analogous to the $\beta_{z,t}$ term from Equation (4) for the sample of non-laid off workers; $\beta_{z,d}$ represents the experience-invariant layoff signal; $\beta_{z,t'}$ represents the return to the post-layoff experience-ability profile; β_{z,t_0} represents the return to the pre-layoff experience-ability profile; and $\beta_{z,t_0,t'}$ represents the way in which pre- and post-layoff experience interact with each other and the ability measure. If a layoff truly conveys a negative ability signal, the predictions discussed in Section 3 suggest that a layoff will disproportionately hurt high residual ability workers ($\beta_{z,d} < 0$ - prediction (i)), while the return to the residual ability-experience profile will be greater for laid off workers with both pre- and post-layoff experience ($\beta_{z,t'}, \beta_{z,t_0} > \beta_{zt} > 0$ - predictions (ii) and (iii)), and the increased return to the residual ability-post-layoff experience profile will decrease in pre-layoff experience ($\beta_{z,t_0,t'} < 0$ - prediction (iv)). For a complete discussion of this type of estimation framework, and how it relates to the broader employer learning literature, see VanderBerg (2020).

6.1 Empirical Model Estimation

Table 3 reports estimates based on the predictions regarding the signaling role of layoffs discussed in Section 3. Column 1 reports the traditional employer learning model estimates based on Equation (4), while Column 2 reports the same model with the inclusion of an ability-job loss variable.

Comparing the estimated coefficients on AFQT*× Total Exp/10 tests the prediction that the AFQT-experience profile is different between the two estimation models. The difference between the two estimates indicates that when the AFQT-job loss interaction variable is added, the return to a standard deviation increase in residual AFQT score after 10 years of potential labor market experience increases from 0.027 log points to 0.034 log points, with both estimates significant at the 0.1% significance level. While this finding is encouraging, the model also included the interaction between residual AFQT score and an indicator for job loss due to plant closure, with the coefficients for both this and the layoff interaction very imprecisely estimated and indistinguishable from zero.

The rest of the columns in Table 3 illustrate the complex relationship between the layoff signal and pre- and post-layoff experience, culminating in Column 5 which estimates the main estimation model discussed above in Equation (5). Column 3 adds an interaction between residual AFQT score and post-layoff experience. When the post-experience interaction is added, the coefficient on the layoff-AFQT interaction is negative (-0.026 log points) and significant, however the interaction between AFQT score and post-layoff experience is not, though the sign is correct. The bigger issue with the estimates in Column 3 is that the interaction between closed and AFQT is negative (-0.043 log points), which could suggest that job loss in general hurts higher ability workers more than lower ability workers. This issue is no longer present when the interaction between pre-layoff experience and AFQT score is added to the regression model in Column 4, with all three main layoff-AFQT coefficients as predicted by the model, however they are imprecisely estimated.

Turning attention now to Column 5, which provides estimates for the coefficients from the full regression model in Equation (5). Under this specification, the interaction between layoff and AFQT is negative (-0.052 log points) and significant, while the pre-layoff experience-AFQT interaction is positive (0.009 log points) and significant at the 5% level. Similarly, the post-layoff experience-AFQT interaction is also positive (0.012 log points) and significant (at the 1% level), and it is estimated precisely enough to be statistically different from the estimated AFQT-exp interaction for the non-job loser sample. Additionally, the interaction between AFQT score and pre- and post-layoff experience is negative (-0.002 log points) and significant (at the 5% level). All of these coefficients match the predictions of the learning model developed in this paper. A similar result is not found for the sample of worker who lost their jobs due to plant closure, which suggests that the estimated coefficients from this regression provide strong evidence in support of the signaling role of layoffs.

In literal terms, the estimates in Column 5 in Table 3 indicate that among the sample of laid off workers, a standard deviation increase in residual AFQT score decreases wages following a layoff by roughly five percent, with this effect decreasing by just under one percentage point per year of pre-layoff experience (or 9 percentage points over 10 years). Following a layoff, a standard deviation increase in residual AFQT score is associated with a nearly 12 percent increase in wages 10 years after the event, with this effect decreasing by around two percentage points per year of pre-layoff experience. These estimates generally back up the predictions of the conceptual framework discussed previously, and lend support to the idea that signaling is playing a role in the overall costs of job loss for young laid off workers, especially during the first five years or so of labor market experience.

6.1.1 Results For Alternate Sample

Table 4 provides estimation results based on Equation (5) for different samples and control specifications. Column 1 shows the results from the main specification discussed above. As discussed previously, changing education level may bias the estimated ability-experience profile for the total sample, and this same logic holds for the estimated effects of the layoff-ability interactions. Thus, Column 2 repeats the main specification above while excluding observations for workers who change education levels beginning two years prior to the reported change to account for decreased labor market participation due to re-enrollment during the period. While less precise and slightly smaller, the results in Column 2 on quantitatively similar to those found in the main specification. As there may be concerns that these results are being driven by high-ability workers losing their jobs during the Great Recession, Columns 3 and 4 of Table 4 repeat the specifications of Columns 1 and 2 respectively, and again report quantitatively similar results.[25] Finally, as the main specification allowed for observable characteristics to interact with the job loss experience profile, Columns 5-9 repeat the estimation of the models in Columns 1-4 without including the interaction controls. Again, these results are quantitatively similar to the preferred specification in Column 1 and generally significant. Taken together, the general consistency of the results across model specifications and samples reinforces the notion that the layoff-ability effects are driven by the signaling nature

[25]See Farber (2017) for more information on the differences in the impact of involuntary job loss prior to and after the Great Recession.

of layoffs.

Additional robustness checks can be found in Appendix ??. Appendix Tables ?? and ?? reproduce the model from Table 3, ignoring job loss due to firing and all job losses other than layoffs respectively. The main findings still hold. Appendix Tables ?? and ?? replicate the model from Table 3 but exclude the first period wage from the construction of the residual AFQT scores. The primary results are insensitive to this exclusion, though the residual AFQT score variables is no-longer insignificant on its own, likely picking up the effects of workers' characteristics that are only observed by employers and are correlated with ability (as noted in Footnote 19). Appendix Tables ?? through ?? replicate the model from Table 5 using the restrictions discussed above for the tables replicating the results from Table 3, again, the results are generally insensitive to these sample and variable definition changes.

6.1.2 Results Based on Asymmetric Employer Learning Models

Given that the signaling role of job loss is directly tied to asymmetric employer learning, it is necessary to assess how the predictions discussed in Section 3 change under different asymmetric information empirical frameworks. Tables 5 and ?? present results of the primary estimation model for log-wage and wage levels respectively when accounting for tenure and job spell. These comparable to the asymmetric employer learning tests of Schönberg (2007) and Pinkston (2009), using residual AFQT scores instead of actual.[26] The inclusion of tenure and job spell length variables in the main specification results in minimal changes to the primary estimates, with significant coefficients on the primary variables of interest appearing in each specification, with the exception of the model in column 12 of Table 5 which includes both tenure and job spell length, as well as their interactions with experience, and even here the only coefficient that is no longer significant is the the interaction between pre- and post-layoff experience and AFQT score. In terms of the implications for asymmetric employer learning, the results under the log-wage specification generally back up the predictions of Pinkston's model, though the effect of job spell interacted with residual AFQT score is significantly weakened by the inclusion of the layoff-AFQT variables, indicating that for this sample, asymmetric information is coming through via signaling regarding the type of job loss, as opposed to differences in learning occurring after a generic job loss.

[26]Estimation models based on Schönberg (2007) and Pinkston (2009) using actual AFQT score can be found in Appendix Tables ?? and ??.

7 Conclusion

In this paper, I examined the extent to which ability signaling explains the long-term wage losses suffered by young workers who experience layoffs. To investigate this phenomenon, I describe a number of predictions derived from theory that provide clear empirical implications regarding the nature of how the relationship between ability and experience evolves over time. These implications allowed for both a straightforward analysis of the long-term effects of job loss wherein the notion of divergent recovery paths was explored, as well as a more intricate empirical strategy based on an augmentation of the traditional employer learning models of FG and AP.

Using data from the National Longitudinal Survey of Youth 1997, the empirical analysis in this paper provides fairly strong evidence in support of ability signaling following a layoff, but not a plant closure. This finding supports the notion that employers may use an observed layoff as a signal that a worker is of lower unobserved ability. As predicted by the model, this signal is greatest early in a labor market career when information on the worker is likely to be imperfectly known by the market. These results help explain some of the persistence in the wage losses of displaced workers, as these losses may be due to the market correcting its valuation of the productive ability of a worker, which should remain fairly persistent if the worker was in fact revealed to be of lower ability than had previously been expected. Further, the way in which high ability workers gradually recover from the effects of a layoff resulted in clear divergent recovery paths when empirically investigating this hypothesis using a traditional event-study framework.

The results found in this paper fit well into the literature on the signaling role of job loss (e.g. Gibbons and Katz 1991; Michaud 2018), as well as the general literature on asymmetric employer learning (e.g. Pinkston 2009; Kahn 2013). While the underlying findings are the primary focus of the paper, the methodology used, as well as the focus on how the information on worker ability evolves with experience are fairly novel in this literature, and should provide additional avenues of future research on this and related topics. An area of future work based on the methodologies used in this paper would be to expand the ability parameters across a number of additional dimensions, as the idea of worker's possessing multidimensional abilities has grown in popularity in recent years.

The next step in this work will be to further the analysis to be able to recover some sense of the magnitude of the role that signaling plays in the overall costs of job loss for young workers. To do so will involve a careful analysis of the costs of job loss, by ability type, for workers across the experience spectrum as well as across varying periods since they experienced a layoff. While more work needs to be done on this particular aspect of the work before more definitive statements can be made, being able to recover the relative contribution of signaling to the overall costs of job loss will likely have significant policy implications. Depending on the extent to which signaling affects the overall cost of job loss, future policy may be more well suited to focus on measures that can prevent young job loss in the first place, as opposed to attempting to find ways to help the workers recover after a job loss.

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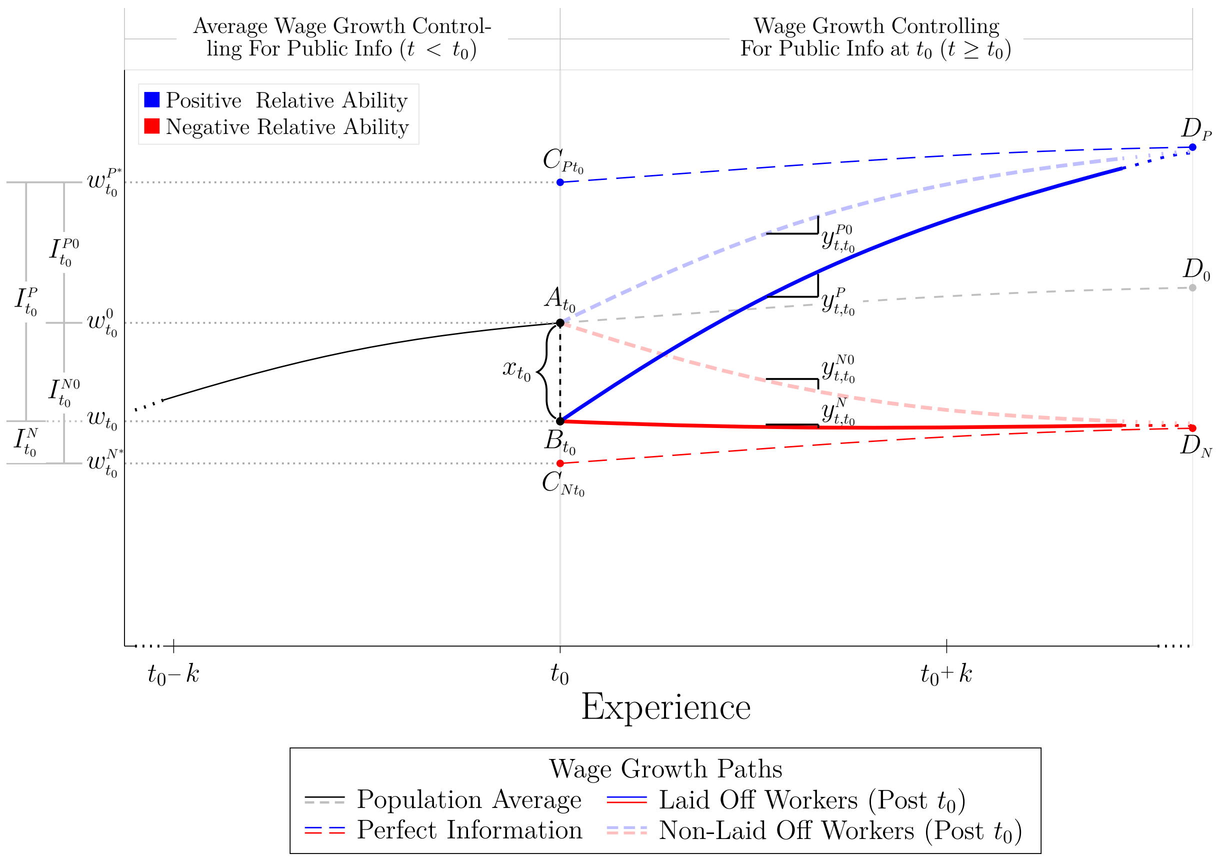
Figures

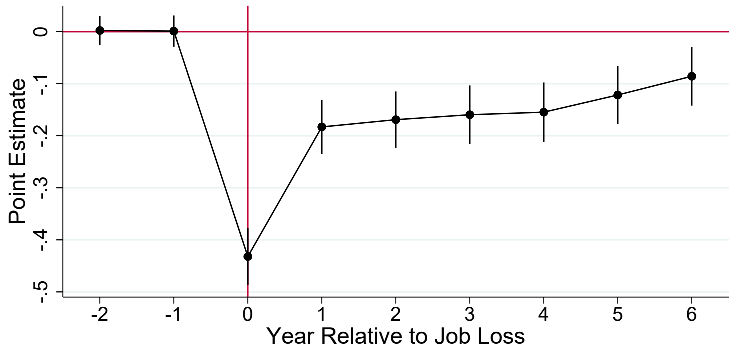
Figure 1: Wage Learning Profile
Generalized Wage Growth Path



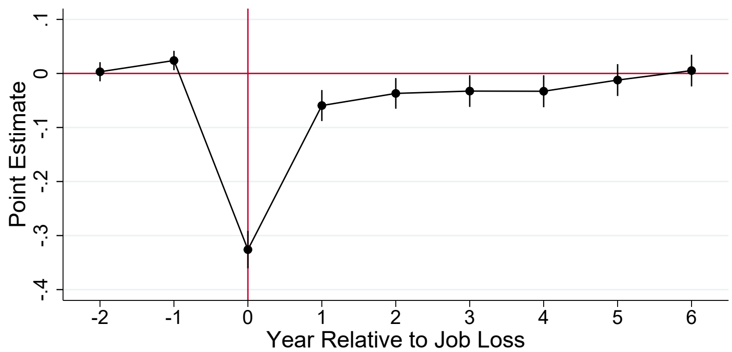
Notes: This figure shows the post-layoff wage paths for a "type-P" worker with positive relative ability (blue), compared to a "type-N" worker with negative relative ability (red), after controlling for public information prior to the layoff. Following a layoff signal, as more information becomes available, employers rapidly correct their beliefs about the type-P worker, while gradually confirming their beliefs about type-N worker. Opaque dashed blue and red lines illustrate the counterfactual wage paths for type-P and type-N workers, respectively, had they not been laid off. As public information is assumed to converge on full information as experience grows, all wage paths for a given worker eventually converge on their full information wage (given by the solid dashed lines).

Figure 2: Effects of Job Loss

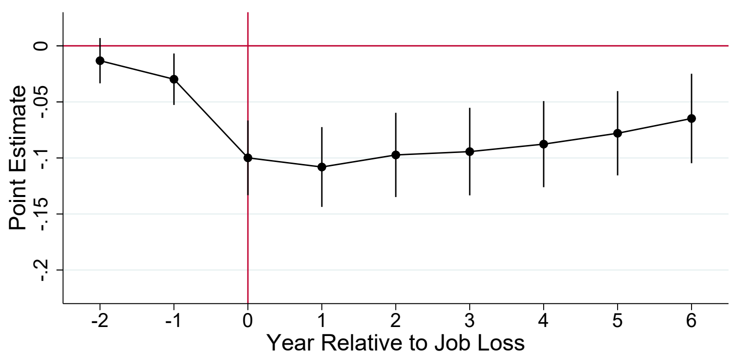
(a) Job Loss Effect on Log Earnings



(b) Job Loss Effect on Log Hours

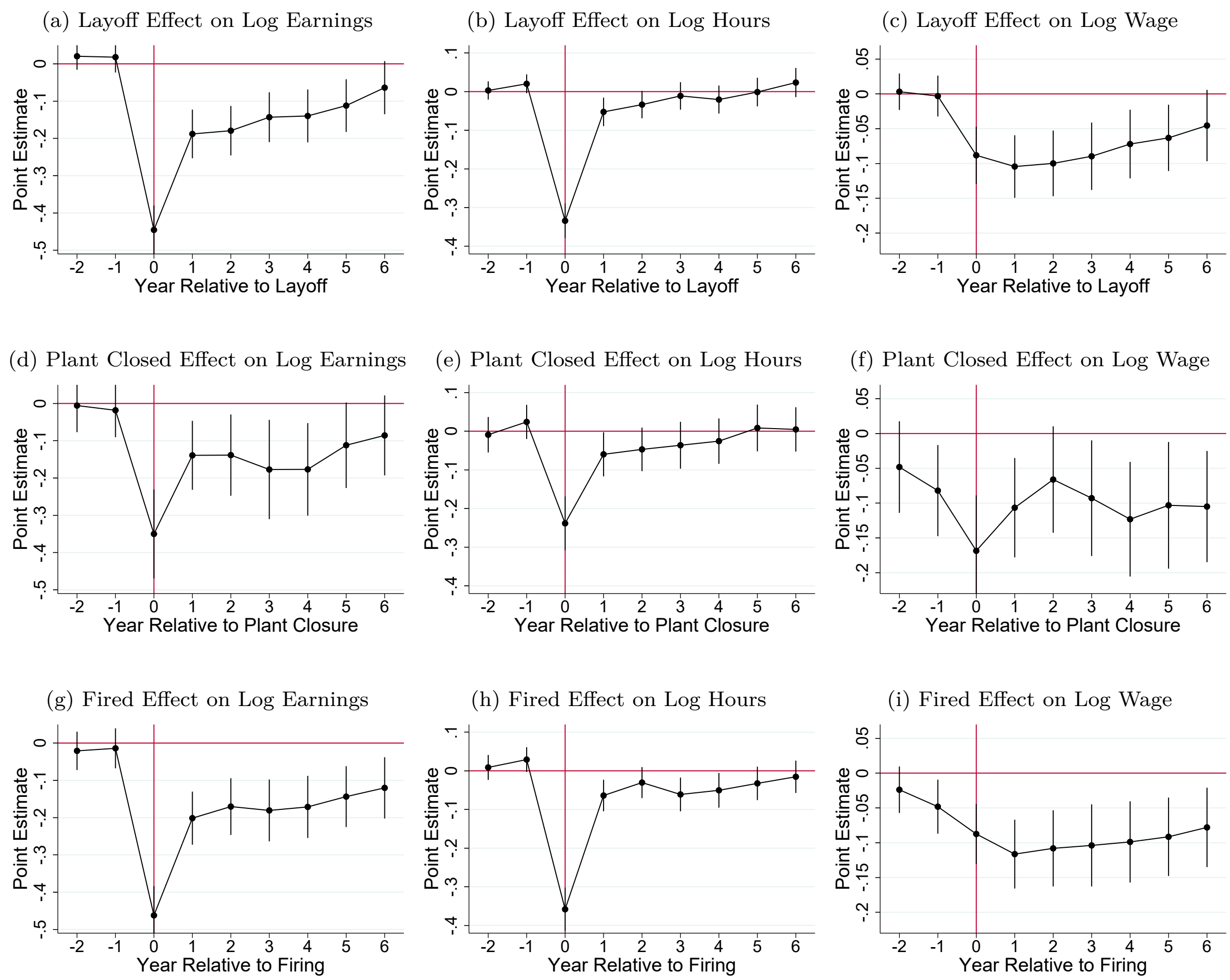


(c) Job Loss Effect on Log Wage



Notes: Sub-figures (a), (b), and (c) report the estimated δ^ks - effects of job loss on log earnings, log hours, and log wages, respectively, pooled at the year level - based on equation (1). Whiskers denote 95-percent confidence intervals based on standard errors clustered at the individual worker level. All workers in the job loss sample have an implied zero coefficient on an indicator for more than two years prior to job loss (not shown). All workers with two years of experience or less at the time of job loss are excluded from these regressions to ensure identification.

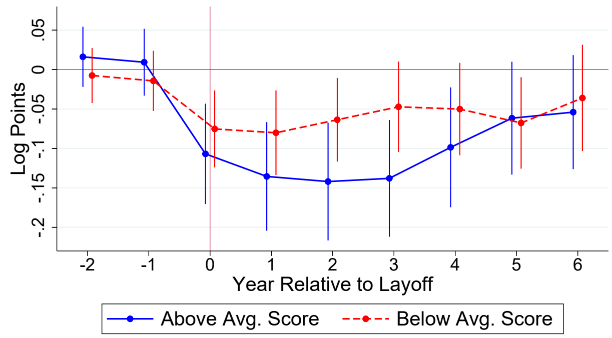
Figure 3: Effects of Job Loss by Type



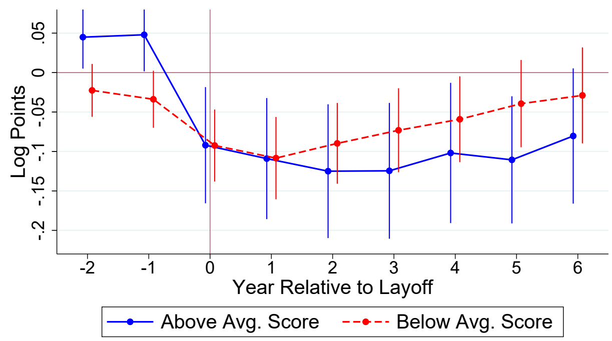
Notes: Sub-figures (a) - (c), (d) - (f), and (g) - (i) report the estimated δ^ks - effects of job loss on log earnings, log hours, and log wages for workers who lose their job due to layoff, plant closure, or firing, respectively, pooled at the year level - based on equation (2). Whiskers denote 95-percent confidence intervals based on standard errors clustered at the individual worker level. All workers in the job loss sample have an implied zero coefficient on an indicator for more than two years prior to their respective form of job loss (not shown). All workers with two years of experience or less at the time of job loss are excluded from these regressions to ensure identification.

Figure 4: Log Wage Effects of Layoff Grouped By Different Definitions of Ability Levels

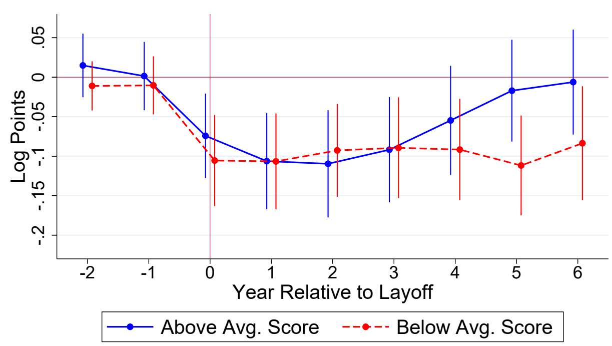
(a) High vs. Low Actual AFQT Score



(b) High vs. Low Predicted AFQT Score



(c) High vs. Low Residual AFQT Score



Notes: Sub-figures (a) - (c) report the estimated δ^ks - effects of a layoff on log wages, split by whether the worker is above or below average AFQT score, predicted AFQT score, or residual AFQT, respectively, pooled at the year level - based on splitting equation (2) by above or below average ability definitions. Whiskers denote 95-percent confidence intervals based on standard errors clustered at the individual worker level. All workers in the job loss sample have an implied zero coefficient on an indicator for more than two years prior to their respective form of job loss (not shown). All workers with two years of experience or less at the time of job loss are excluded from these regressions to ensure identification.

Tables

Table 1: Entry Quarter Summary Statistics

	Whole Sample	Layoff	Closed	Fired	No Job Loss
Wage	12.641	11.805	11.083	10.477	13.617
	[8.310]	[6.036]	[4.676]	[4.279]	[9.750]
Log Wage	2.418	2.386	2.332	2.283	2.471
	[0.465]	[0.392]	[0.383]	[0.365]	[0.507]
Years of Education	13.415	12.872	12.652	12.292	13.954
	[2.200]	[1.925]	[1.875]	[1.621]	[2.270]
Age	20.640	20.328	19.945	19.729	21.041
	[2.285]	[2.201]	[2.187]	[2.074]	[2.276]
Female	0.488	0.353	0.465	0.480	0.540
	[0.500]	[0.478]	[0.500]	[0.500]	[0.499]
Black	0.242	0.308	0.258	0.278	0.209
	[0.428]	[0.462]	[0.438]	[0.448]	[0.406]
Hispanic	0.205	0.230	0.266	0.200	0.191
	[0.404]	[0.421]	[0.443]	[0.400]	[0.393]
Part-Time	0.172	0.153	0.211	0.191	0.169
	[0.377]	[0.361]	[0.409]	[0.394]	[0.375]
Union	0.097	0.096	0.074	0.078	0.105
	[0.296]	[0.295]	[0.263]	[0.268]	[0.306]
Urban	0.783	0.805	0.793	0.770	0.777
	[0.412]	[0.396]	[0.406]	[0.422]	[0.416]
Size of Employer	341.374	324.376	174.500	244.092	388.539
	[2016.3]	[1419.1]	[494.8]	[909.1]	[2440.9]
AFQT Score	162.890	154.909	159.123	157.249	167.412
	[31.09]	[31.41]	[32.37]	[30.58]	[30.14]
Standardized AFQT Score	-0.000	-0.257	-0.121	-0.181	0.145
	[1.000]	[1.010]	[1.041]	[0.983]	[0.969]
Std. Residual AFQT Score	-0.000	-0.103	0.084	0.080	0.007
	[1.000]	[1.032]	[1.103]	[1.076]	[0.955]
Above Avg. AFQT Score (proportion)	0.554	0.448	0.477	0.480	0.616
	[0.497]	[0.498]	[0.500]	[0.500]	[0.486]
Above Avg. Residual AFQT (proportion)	0.535	0.493	0.566	0.558	0.540
	[0.499]	[0.500]	[0.497]	[0.497]	[0.499]
Length of Time in Sample (years)	13.648	14.202	14.548	14.761	13.093
	[3.023]	[2.867]	[2.931]	[2.699]	[3.028]
Total Observations	4,009	821	256	565	2,367

Note: Standard deviations in brackets.
Source: Author's tabulations of NLSY97 data. See Section 4 for information regarding the construction of the sample presented here.

Table 2: All Year-Quarter Summary Statistics

	Whole Sample	Layoff	Closed	Fired	No Job Loss
Wage	18.241	16.655	16.234	14.419	19.976
	[12.030]	[10.021]	[11.023]	[9.005]	[13.071]
Log Wage	2.762	2.701	2.651	2.563	2.845
	[0.513]	[0.455]	[0.498]	[0.436]	[0.533]
Age	27.476	27.317	26.989	26.877	27.736
	[4.254]	[4.304]	[4.361]	[4.342]	[4.178]
Potential Experience	7.047	7.238	7.290	7.369	6.871
	[3.991]	[4.083]	[4.125]	[4.145]	[3.892]
Actual Experience	6.101	6.040	6.134	6.018	6.139
	[3.582]	[3.545]	[3.607]	[3.524]	[3.607]
Years of Education (at Entry)	13.398	12.821	12.717	12.300	13.952
	[2.162]	[1.883]	[1.816]	[1.576]	[2.234]
Years of Education (Current)	13.718	13.127	13.000	12.616	14.282
	[2.301]	[2.022]	[1.874]	[1.700]	[2.391]
Current Job Spell Length	3.396	2.275	2.574	2.247	4.171
	[3.178]	[2.273]	[2.545]	[2.301]	[3.464]
Tenure With Current Employer	2.854	1.995	2.174	1.975	3.453
	[2.862]	[2.131]	[2.279]	[2.134]	[3.140]
Total Year-Quarter Observations	152,572	31,624	10,056	21,978	88,914

Note: Standard deviations in brackets.
Source: Author's tabulations of NLSY97 data. See Section 4 for information regarding the construction of the sample presented here.

Table 3: Layoff versus Plant Closed
Log Wage Regressions Using Potential Experience

Independent Variable	(1) Log Wage	(2) Log Wage	(3) Log Wage	(4) Log Wage	(5) Log Wage
Education	0.098***	0.096***	0.094***	0.094***	0.093***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Educ × Total Exp/10	0.003	-0.003	-0.001	-0.001	0.000
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
AFQT*	-0.001	-0.002	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
AFQT* × Total Exp/10	0.027***	0.034***	0.030**	0.029**	0.029**
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
Layoff × AFQT*		-0.013	-0.021	-0.026	-0.052*
		(0.013)	(0.013)	(0.022)	(0.023)
Layoff × AFQT* × Post Exp			0.002	0.005*	0.012**
			(0.003)	(0.002)	(0.004)
Layoff × AFQT* × Pre Exp				0.002	0.009*
				(0.004)	(0.004)
Layoff × AFQT* × Post × Pre Exp					-0.002*
					(0.001)
Closed × AFQT*		0.004	-0.043++	0.017	0.026
		(0.020)	(0.022)	(0.040)	(0.043)
Closed × AFQT* × Post Exp			0.009*	0.010**	0.007
			(0.004)	(0.004)	(0.008)
Closed × AFQT* × Pre Exp				-0.012	-0.014++
				(0.008)	(0.008)
Closed × AFQT* × Post × Pre Exp					0.001
					(0.002)
R^2	0.381	0.391	0.393	0.394	0.395
Observations	153,241	153,241	153,241	153,241	153,241
Individuals	4,009	4,009	4,009	4,009	4,009
No. of Layoffs	.	774	774	774	774
(Avg. Year)	(.)	(2007.32)	(2007.32)	(2007.32)	(2007.32)
No. of Plant Closings	.	227	227	227	227
(Avg. Year)	(.)	(2007)	(2007)	(2007)	(2007)

Cluster-robust standard errors in parentheses are computed at the individual worker level
+ $p < 0.10$, ++ $p < 0.075$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors are clustered at the individual worker level. The first year of potential experience is dropped from the analysis as this was used to create the residual ability measures. All models include a quadratic in pre- and post- job loss potential experience, indicators for each type of job loss, pre-job loss experience interacted with post-job loss experience, indicators for if the job loss took place between 2008 and 2010 or after 2010, a vector of year-quarter indicators, education interacted with a vector of year indicators, indicators for race, female, union status, part-time status, two-digit entry industry, and the log number of employees at the workers entry job, all interacted with a cubic time trend. The base year for the year indicators and time trends is 2017. Additionally, with the exception of the two-digit entry industry dummies, each individual control above is also interacted with a quadratic in pre- and post-job loss potential experience.

Table 4: Layoff versus Plant Closed - Robustness Checks
Log Wage Regressions Using Potential Experience

Independent Variable	(1) Log Wage	(2) Log Wage	(3) Log Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage	(7) Log Wage	(8) Log Wage
Education	0.093***	0.088***	0.096***	0.092***	0.099***	0.095***	0.102***	0.098***
	(0.021)	(0.024)	(0.022)	(0.025)	(0.021)	(0.024)	(0.022)	(0.025)
Educ × Total Exp/10	-0.000	-0.000	0.001	-0.002	-0.001	-0.000	0.000	-0.001
	(0.017)	(0.020)	(0.017)	(0.020)	(0.017)	(0.020)	(0.017)	(0.020)
AFQT*	-0.000	0.002	-0.000	0.002	0.000	0.002	0.000	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
AFQT* × Total Exp/10	0.031**	0.035**	0.032**	0.035**	0.031**	0.035**	0.031**	0.035**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)
Layoff × AFQT*	-0.051*	-0.050*	-0.048	-0.051+	-0.053*	-0.053*	-0.057+	-0.068*
	(0.023)	(0.024)	(0.031)	(0.031)	(0.023)	(0.024)	(0.032)	(0.033)
Layoff × AFQT* × Post Exp	0.012**	0.010*	0.014*	0.014*	0.012**	0.011*	0.015**	0.016*
	(0.004)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)
Layoff × AFQT* × Pre Exp	0.009*	0.008	0.003	0.004	0.008*	0.008+	0.006	0.011
	(0.004)	(0.005)	(0.011)	(0.011)	(0.004)	(0.005)	(0.012)	(0.013)
Layoff × AFQT* × Post × Pre Exp	-0.002*	-0.002	-0.003	-0.004	-0.002*	-0.002++	-0.004	-0.005+
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Closed × AFQT*	0.034	-0.012	0.045	0.009	-0.018	-0.072	0.013	-0.042
	(0.043)	(0.046)	(0.059)	(0.064)	(0.046)	(0.055)	(0.058)	(0.065)
Closed × AFQT* × Post Exp	0.006	0.012	0.007	0.015	0.018	0.027	0.020	0.036+
	(0.008)	(0.013)	(0.010)	(0.017)	(0.013)	(0.018)	(0.016)	(0.021)
Closed × AFQT* × Pre Exp	-0.015*	-0.007	-0.011	-0.004	-0.003	0.007	-0.004	0.008
	(0.008)	(0.008)	(0.015)	(0.017)	(0.008)	(0.010)	(0.015)	(0.017)
Closed × AFQT* × Post × Pre Exp	0.001	0.001	-0.000	-0.001	-0.002	-0.002	-0.003	-0.006
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)	(0.006)
Fired × AFQT*	-0.047+	-0.048	-0.025	-0.017	-0.044	-0.044	-0.025	-0.025
	(0.027)	(0.031)	(0.034)	(0.038)	(0.027)	(0.031)	(0.034)	(0.038)
Fired × AFQT* × Post Exp	0.006	0.014**	0.007	0.014*	0.005	0.013**	0.005	0.013*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Fired × AFQT* × Pre Exp	0.004	0.002	0.000	-0.008	0.003	0.002	-0.001	-0.007
	(0.006)	(0.007)	(0.011)	(0.012)	(0.006)	(0.007)	(0.011)	(0.012)
Fired × AFQT* × Post × Pre Exp	-0.000	-0.003*	-0.001	-0.003	-0.000	-0.003*	-0.001	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Controls for Interactions	Yes	Yes	Yes	Yes	No	No	No	No
Drops if Education Changes	No	Yes	No	Yes	No	Yes	No	Yes
Removes Job Losses After 2007	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.395	0.398	0.407	0.409	0.388	0.389	0.400	0.401
Observations	153,241	122,013	139,542	111,970	153,241	122,013	139,542	111,970
Individuals	4,009	3,996	4,005	3,992	4,009	3,996	4,005	3,992
No. of Layoffs	774	655	354	319	774	655	354	319
(Avg. Year)	(2007.32)	(2007.09)	(2004.13)	(2004.14)	(2007.32)	(2007.09)	(2004.13)	(2004.14)
No. of Plant Closings	227	194	122	111	227	194	122	111
(Avg. Year)	(2007.12)	(2006.87)	(2004.42)	(2004.40)	(2007.12)	(2006.87)	(2004.42)	(2004.40)
No. of Firings	527	445	315	281	527	445	315	281
(Avg. Year)	(2006.40)	(2006.14)	(2004.13)	(2004.04)	(2006.40)	(2006.14)	(2004.13)	(2004.04)

Cluster-robust standard errors in parentheses
$^{+}$ $p < 0.10$, $^{++}$ $p < 0.075$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors are clustered at the individual worker level. The first year of potential experience is dropped from the analysis as this was used to create the residual ability measures. All models include a quadratic in pre- and post- job loss potential experience, indicators for each type of job loss, pre-job loss experience interacted with post-job loss experience, indicators for if the job loss took place between 2008 and 2010 or after 2010, a vector of year-quarter indicators, education interacted with a vector of year indicators, indicators for race, female, union status, part-time status, two-digit entry industry, and the log number of employees at the workers entry job, all interacted with a cubic time trend. The base year for the year indicators and time trends is 2015. Columns 1-4 report results for estimation that include each individual control above interacted with a quadratic in pre- and post-job loss potential experience, while columns 5-8 do not include these controls. Columns 2, 4, 6, and 8 drop respondents two years prior to any education level changes. entering the labor market. Columns 3, 4, 7, and 8 drop respondents who lose their job for the first time in 2008 or later.

Table 5: Controlling for Job Spell Length and Tenure
Log Wage Regressions Using Potential Experience

Independent Variable	(1) Log Wage	(2) Log Wage	(3) Log Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage	(7) Log Wage	(8) Log Wage	(9) Log Wage	(10) Log Wage	(11) Log Wage	(12) Log Wage
AFQT*	-0.002	0.002	-0.008	-0.002	-0.003	0.001	-0.010	-0.005	-0.002	0.002	-0.009	-0.003
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
AFQT* $\times$ Total Exp/10	0.027^{**}	0.037^{**}	0.034^{***}	0.042^{**}	0.028^{**}	0.033^{**}	0.035^{***}	0.040^{**}	0.027^{**}	0.037^{**}	0.035^{***}	0.043^{**}
	(0.009)	(0.013)	(0.010)	(0.014)	(0.009)	(0.013)	(0.010)	(0.013)	(0.009)	(0.013)	(0.010)	(0.014)
AFQT* $\times$ Spell Length/10	0.006	-0.008	0.033	0.010					-0.003	-0.015	0.001	-0.021
	(0.014)	(0.016)	(0.028)	(0.029)					(0.022)	(0.023)	(0.052)	(0.053)
AFQT* $\times$ Exp $\times$ Spell Length/10			-0.003	-0.002							-0.000	0.001
			(0.002)	(0.002)							(0.004)	(0.004)
AFQT* $\times$ Tenure/10					0.012	0.001	0.047	0.029	0.014	0.011	0.045	0.044
					(0.015)	(0.016)	(0.030)	(0.030)	(0.024)	(0.024)	(0.057)	(0.057)
AFQT* $\times$ Exp $\times$ Tenure/10							-0.003	-0.003			-0.003	-0.003
							(0.003)	(0.002)			(0.005)	(0.005)
Layoff $\times$ AFQT*		-0.048^{*}		-0.046^{*}		-0.050^{*}		-0.048^{*}		-0.048^{*}		-0.047^{*}
		(0.022)		(0.022)		(0.023)		(0.022)		(0.022)		(0.022)
Layoff $\times$ AFQT* $\times$ Post Exp		0.010^{*}		0.010^{*}		0.011^{**}		0.012^{**}		0.010^{*}		0.011^{*}
		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)
Layoff $\times$ AFQT* $\times$ Pre Exp		0.007^{+}		0.007		0.008^{+}		0.008^{+}		0.007^{+}		0.007
		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)
Layoff $\times$ AFQT* $\times$ Post $\times$ Pre Exp		-0.002		-0.002		-0.002^{+}		-0.002^{+}		-0.002		-0.002
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
R^2	0.398	0.407	0.398	0.407	0.395	0.405	0.395	0.405	0.400	0.408	0.400	0.409
Observations	153,241	153,241	153,241	153,241	153,241	153,241	153,241	153,241	153,241	153,241	153,241	153,241
Individuals	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009
No. of Layoffs	.	774	.	774	.	774	.	774	.	774	.	774

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: