Wage Scars and Human Capital Theory*

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Abstract

A large literature shows workers who are involuntarily separated experience wage scars: their hourly earnings fall initially by an average of 15.4% and remain much lower than their non-separated counterparts more than 20 years later. We find that this reduces average life-cycle wage growth by 14.7% and increases cross-sectional wage dispersion by 17.8%. We research variants of human capital theory capable of replicating scars, highlighting a tension in producing large, persistent wage scars alongside average life-cycle wage dynamics. An examination of labor market and demographic characteristics of workers who never recover suggests many theories of wage scars are operational, but on different groups of workers.

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1 Introduction

A large empirical literature documents that workers who are involuntarily separated receive permanent wage scars.[1] We show that their hourly earnings fall initially by an average of 15.4% and remain much lower than their non-separated counterparts more than 20 years later.[2] This finding is remarkably robust. Similar large, persistent wage scars have been found to hold in several different countries and time periods. These scars have also been shown to remain after controlling for education, age, and occupational or industry changes.[3] The ubiquitous and mysterious nature of these scars is striking considering the important implications they hold.[4] We estimate that the wage consequences of involuntary separation have important effects on life-cycle wage growth and cross-sectional inequality. This result emphasizes the importance of job loss in theories seeking to understand the nature of wage determination and labor income risk. An accurate depiction of job loss is an important component in structural frameworks used to study policies that address the causes and consequences of unemployment and, on a broader scope, income inequality as a whole.

The goal of this paper is to better understand the quantitative properties for human capital models of life-cycle wage growth in relation to wage scars. We begin by analyzing the contribution of wage losses following separation to a typical empirical wage process. We find that the presence of these scars is quantitatively important: they reduce average 20-year wage growth by 14.7% and increase the cross-sectional dispersion of wages by 17.8% in comparison to a counterfactual with no separations. Next, we analyze theories of separation within structural models of life-cycle wage

[1] The literature on "scarring" usually uses "displaced" workers to refer to high-tenure male workers with strong labor force attachment. We use the term "separated" to refer to all involuntary separations regardless of tenure and/or experience at the time of separation.

[2] We use hourly earnings and wages interchangeably throughout this paper.

[3] An overview of estimates in US survey and administrative data is found in Couch and Placzek (2010) [4].

[4] Carrington and Fallick (2014) [3] provide an overview of the literature and discussion of open questions.

dynamics. The structural perspective we consider can be best understood as human capital theory following Ljungqvist and Sargent (1998) [18] in which wages grow with work experience (human capital growth) and fall following a separation (human capital loss). We test whether several theories on the cause and consequence of job loss produce wage scars in line with the empirical literature within this framework. To do so, we calibrate parameters to bring the simulated data of each model variant as close as possible to replicating both life-cycle wage dynamics and wage scars estimated in the Panel Study of Income Dynamics. We synthesize our findings on successful and unsuccessful candidate models to provide a discussion of the key properties necessary for human capital theory to be a successful candidate quantitatively and how these properties compare mechanically to successful non-human capital theories proposed in other studies.

The key lesson of this paper is that several intuitive human capital theories of wage loss after involuntary separation struggle on one or two quantitative dimensions. The first challenge for these theories is the ability, under any parameterization, to generate wage scars that are as deep and persistent as in the data. This is intuitive when considering the common modeling view of involuntary separation as a restart on the same life-cycle wage growth process but from a lower level. A persistent scar requires slow wage growth after separation so that workers do not recover. A deep initial scar requires fast wage growth prior to separation in order to have high wages from which to fall. This produces a tension when the wage growth post separation is assumed to be the same as wage growth prior to separation. We show modifications providing serial correlation in separation or lowered wage growth after separation improve the persistence of the scar.

The second challenge for these theories is in their ability to replicate the scars without producing counterfactual predictions for life-cycle wage growth and dispersion. This is particularly true for the theory that best replicates the permanent nature of the wage scar: that wage growth after separation is slower than it is prior to separation. To deliver a deep scar, the best fit calibration chooses wage growth that is three-times that of the data. When restricted to produce wage growth moments closer to the data, the largest scar it produces includes an initial wage decline that is about 50% smaller than the data and is 25% smaller than the data in terms of present discounted value. These broader life-cycle and cross-sectional outcomes are not orthogonal to the study of wage scars. They are driven by the majority of the population that are never separated. This group serves as the "reference group" to which the separated workers are compared when calculating the wage scars in the empirical literature. Therefore, a theory of wage scars is implicitly a theory of life-cycle wage growth and must be consistent with life-cycle facts. Departure from this prescription means that the reference group implicit in the standard regression specification is incorrect. If this is the case, the regression is misspecified and a new reference group should be chosen. However, if a new reference group is chosen, it means that the economist is imposing a theory of selection that separated workers are fundamentally different from the population. Then, the economist should be explicit about this theory of selection in both model and data.

We conclude by documenting additional facts on workers who recover and those who do not recover from separation. Those who recover vary from those who do not in several demographic areas as well as in occupation. Our findings on demographics support those found in the literature. We hope our findings regarding occupation will help guide future research.

Davis and von Wachter (2011) [26] conducts an analysis of a similar spirit as this paper, but with a focus on equilibrium search and matching models. They find the frictional wage dispersion provided by such models generates only a couple percentage points of the present discounted value of losses to earnings for separated workers. This is perhaps unsurprising given the findings of Hornstein, Krusell, and Violante (2011)

[10] where they show reasonable calibrations of such search models generally imply the average wage in the economy is only 5% above the lowest wage in the economy. Therefore, it would be unexpected to find a subgroup of workers earning 15% less than the average as would be required to match the magnitude of wage scars in the data. Our study instead considers wage processes that do generate life-cycle wage growth and dispersion of similar magnitudes as the data and then tests what would be required of a theory of separation to generate wage scars given these processes. We do not analyze explicitly different micro-foundations of these processes as there are many theories of wage determination one may consider. However, we discuss how some common theories, such as human capital theory, can relate to our result.

Recent quantitative theory papers attempting to generate these wage scars include Jarosch (2014) [12], Krolikowski (2013) [16] Michaud (2017) [22], and Burdett, Carrillo-Tudela, and Coles (2015) [1].[5] Michaud (2017) provides a theory of asymmetric employer learning, fitting the model to statistics related to cross-section wage dispersion, life-cycle wage growth, and differences among types of separated workers. Jarosch (2014) [12] develops a job-ladder model targeting a variety of cross-sectional statistics but not variance in outcomes amongst separators. Krolikowski (2013) [16] similarly uses a job ladder model and targets the aggregate mean-min wage ratio. Burdett, et al. (2015) [1] study wage scars within a model where wages arise from an optimal contracting problem with on-the-job search. They estimate their model separately for low-skill and high-skill workers, finding higher rates of separation for the former group. They provide many cross-sectional statistics related to the control group as well. As in this paper, Huckfeldt (2016) [9] follows the methodology of Stevens (1997) [25] to consider all separated workers. He provides a human capital theory related to occupation to generate wage scars.

This literature makes evident that an array of different theories are capable of

[5] Jung and Kuhn (2012) [14] is related but does not display statistics on model fit to cross-sectional wage statistics; they instead focus on worker flows.

degrees of quantitative success in replicating empirical wage scars. Yet, these theories vary greatly in their key mechanisms and implications. Michaud (2017) [22] and Burdett, Carrillo-Tudela, and Coles (2015) [1] feature selective separation for low productivity workers where productivity is interpreted as a fixed worker-specific trait. Jarosch (2014) [12] and Krolikowski (2013) [16] also feature selective separation, but on a job-specific, rather than a worker specific, trait. All of the papers feature "skill" or worker-specific productivity loss at separation except Michaud (2014) [22] who replicates the scars without any changes in productivity at all. Finally, all feature rich theories of wages in which a separation changes the match surplus and/or the share paid to the worker beyond what would be expected from changes in productivity alone. One purpose of this paper is to go back and understand if and why such rich models are needed. Could a more nuanced view of classic human capital theory alone fair well?[6] We add to this literature by demonstrating varying levels of quantitative success for human capital theory when combined with serially correlated separations. This finding supports the idea that more micro-evidence in conjunction with structural modeling is necessary to parse between the multiple successful theories and determine which ones play the most quantitatively important roles. In this spirit, we present additional facts on those that recover and those that do not before concluding.

2 Empirical Wage Scars

To motivate the rest of the paper and to establish the parameters which will be used throughout the paper, we estimate the effect of involuntary job loss at time $t - n$ on the natural log of real hourly earnings (w_t) wage scars using the Panel Study

[6] Ljungqvist and Sargent (1998) [18] is related, but with a slightly different objective. They target life-cycle facts and wage losses relative to workers' own past wages, not relative to the reference comparison group in the empirical literature that provides the permanent scars to which this paper is using for reference.

of Income Dynamics (PSID) through the 2015 wave of data.[7] We use the strategy given in Jacobson, LaLonde, and Sullivan (1993) [13] which develops the standard event study regression framework while incorporating insights from the literature in arriving at the following equation for individuals indexed by i:

$$ln(w_{i,t}) = \Phi\mathbf{X}_{i,t} + \Theta\mathbf{E}_{i,t} + \sum_{n=-2}^{19}\beta_{t-n}D1_{i,t-n} + \gamma_1 D1_{i,20+} + \sum_{j=2}^{5}\gamma_j Dj_i + \delta_t y_t + \zeta_i + \eta_s S + \epsilon_{i,t} \quad (1)$$

The key variables in this estimation are those related to the time since separation and indicator variables on whether the worker has been separated more than once.[8] The dummy variables indicating time from first involuntarily separation $D1_{i,t-n}$ in year $t-n$ closely resemble the strategy put in place by Ruhm (1991) [24] and used elsewhere in the literature (Couch and Placzek (2010) [4], Jacobson, LaLonde, and Sullivan (1993) [13], Stevens (1997) [25]). Note that the separation variable $D1_{i,n}$ includes separate dummies for two years prior to separation, the year of each separation, and each of the first through 19 years following the first separation (ie: $n \in \{-2,-1,0,1,...,19\}$). Our estimation also includes a dummy indicating that it has been at least 20 years since that first separation. As Stevens (1997) [25] points out, multiple separations are important in understanding the effects of wage scars. Therefore, we control for multiple separations with a dummy for whether the worker has been separated at least twice, at least three times, at least four times or at least five times with Dj_i where j takes the appropriate values two through five.

The independent variables include labor force experience, non-time stationary observable characteristics such as union participation and a vector of dummies related to educational attainment along with fixed effects for the year, state, and individual.

[7] Please see the appendix for details on data selection along with the summary statistics.

[8] See the appendix on the timing of separations as well as more technical details on the construction of variables.

The labor force experience variable and its quadratic along with union participation make up the vector ($\mathbf{X}$).[9] Dummies for educational attainment ($\mathbf{E}$) include those indicating less than 12 years of education, more than 12 years of education, a four year college degree, or some graduate school. Year fixed effects (y_t) along with state fixed effects ($\mathbf{S}$) are included to control for macroeconomic conditions. Individual fixed effects are represented with the parameter ζ_i.

We choose real hourly wages as the dependent variable for several reasons. First, we are interested in permanent scars of unemployment and not the transitory effects. For this reason, we do not include total earnings because they would take into account losses during the period an individual is unemployed; these are temporary losses. Additionally, total earnings may be less following a job loss because an individual may choose to work reduced hours for a variety of reasons.[10] Again, this is a temporary effect. Finally, hourly wages are more likely to be related to human capital dynamics, the focus of this paper.

The lasting scar from job loss is quite clear in Figure 1. This figure depicts the scar from the initial separation. The x-axis accounts for the years since separation and the y-axis depicts the percentage loss in real hourly earnings that will be used in our estimates going forward.[11] The dashed lines represent the 95% confidence intervals on these changes.[12]

These results are similar to those found in the literature. Huckfeldt (2016) [9] uses PSID data with different restrictions in showing that hourly wages drop 13% versus our 15.4% after one year of separation.[13] The impacts of separation are documented through ten years where the loss is still at 7%. [9] Davis and von Wachter (2011) [5]

[9]Please see Kambourov and Manovskii (2009) [17] for the algorithm on constructing and cleaning the experience variable.

[10]We run our estimation on log hours and find that separated workers recover to their expected hours worked in the third year after separation.

[11]These losses are computed as $e^{\beta_{t-n}} - 1$

[12]Please see the appendix for the coefficients estimated from equation 1.

[13]Our results through ten years are also very similar to those of Huckfeldt (2016) [9] when the dependent variable is annual earnings.

use data from the social security administration and show losses in average earnings to be a little more than 10% upon separation with losses at over 5% twenty years after separation.

3 Role of Separation in Empirical Models of Wage Processes

In this section we estimate how much separation and the accompanying wage scars contribute to individuals' wage risk over the life-cycle, cross-sectional wage dispersion, and other statistics. We provide estimates of a typical empirical wage process incorporating the observed separation hazards and wage scars found in the PSID. We then run a counterfactual simulation in which we shut down the separation hazard. We compare the two to understand the role of separation in wage outcomes.[14]

The general empirical process for wages of non-separated workers is specified according to a commonly used form:[15]

$$ln(w_{it}) = \alpha_i + \beta_1 exp + \beta_2 exp^2 + z_{it} + \epsilon_{it} \tag{2}$$

The dependent variable is log wages. The independent variables include individual fixed effects, a quadratic in experience, a persistent shock z_{it}, and a transitory shock ϵ_{it}. Specifically, the persistent shock follows an AR(1) process:

$$z_{it} = \rho z_{i,t-1} + \eta_{it}$$

[14]This exercise complements prior work on sources of life-time income inequality and risk (ex: Low, Meghir, and Pistaferri (2010) [19], Blundell, Pistaferri, and Preston (2008) [2], Hornstein, Krusell, and Violante (2011) [11],Guvenen (2009) [8]). The distinction is that we specify that unemployment has persistent effects on wages independent of realized shocks in the general wage process and thus isolating how much variance is related to these separations.

[15]This income process is widely used in partial equilibrium models concerned with insurance, credit, and inequality, among other applications.

It is assumed that all individuals start with $z_{i0} = 0$ and that the innovations are iid across individuals.

We estimate the parameters of this income process using simulated method of moments. The simulated wage paths of non-separated workers are provided by the empirical wage process in equation 2. Wages of separated workers follow that of the non-separated, except they are reduced by exactly the same magnitudes we estimate in the data: the non-parametric estimates of the 20 years of wage scars following the first loss plus the two extra constant terms following the second and third loss. Separation occurs with a hazard function that we estimate in the data, of the following form for a worker of experience t with at least d past separations $d \in 0, 1, 2, 3$:

$$\xi(d,t) = \lambda_0(e^{\phi t} + \sum_{d=1}^{3}(\lambda_d)D_d)$$

This specification includes a baseline hazard λ_0, plus an estimated negative effect of age ϕ, and positive effect of past separations λ_d, where $D_d = 1$ is the dummy for past separations.

The targeted statistics in the estimation are typical and chosen to be informative about different parameters. The first is a set of regression coefficients from the following regression run in both data sets:

$$ln(w_{it}) = \alpha_i + \beta_1 exp + \beta_2 exp^2 + \epsilon_{it}$$

The values of β_1 and β_2, which describe life-cycle wage growth, as well as the standard deviation of the individual fixed effects α_i are included in the targets.[16] We also include two targets related to the residual wages from this regression: the standard deviation of residual wages for individuals with 5 years and 30 years of experience. Statistics informative about the AR(1) process deal with higher-order

[16] We also add the same constant to wages in the model as calculated in the data regression.

serial correlations of the wage process. Define $Scorr(n)$ to be the n^{th} serial correlation. We target three statistics: $Scorr(1)$, $Scorr(1) - Scorr(2)$, and $\frac{Scorr(2)-Scorr(3)}{Scorr(1)-Scorr(2)}$.[17]

Our resulting parameter estimates are listed in Table 1 and the fit to targeted statistics is shown in Table 2. Our estimates are comparable to the literature employing other estimation techniques.[18]

In order to analyze how separation affects wage inequality, we perform a counterfactual simulation. We simulate data from the wage process using the parameters estimated above, but with the separation hazard set to zero. We interpret this counterfactual as a world where we remove the estimated wage effects of separation. We report a comparison of moments with and without separation in Table 3.

We find the presence of wage scarring following separation reduces average 20 year wage growth by 14.7%. It also increases the cross-section dispersion, measured as the standard deviation of estimated individual fixed effects, by 17.8%.

4 Testing Candidate Models of Wage Scars

4.1 Baseline Learning-by-Doing Model of Human Capital

We build upon a simple life-cycle wage model of learning-by-doing similar to Ljunqvist and Sargent (1998) [18] (LS). Workers differ in human capital $h \in \{h_0, h_1 ... h_N\}$ and their age t. They begin their careers at h_0 and accumulate skills sequentially. Each period they are employed, a worker with human capital h_j will see his human capital next period increase: $h' = h_{j+1}$. Human capital determines each worker's efficiency units of labor. We normalize the consumption paid per efficiency unit to one, implying

[17] This is a typical estimation strategy as detailed in Guvenen (2009) [8].

[18] For example, Floden & Linde (2001) [6] use GMM on PSID data and find $\rho = 0.9136$ versus our $\rho = 0.9213$, $\sigma_\eta = 0.206$ versus our 0.2709 and $\sigma_\alpha = 0.2052$ versus our 0.2120. Some of the discrepancy is from our inclusion of iid transitory ϵ_{it} shocks and differences in sample construction including the time-span of our data.

a worker's total period income is equal to their human capital h.[19] Workers are separated to unemployment with age-dependent probability $\delta(t)$. Upon separation, workers lose a portion τ of their skills and return to the gridpoint $h' = floor(\tau h_j)$ with probability γ. The wage progression of a worker can then be defined as a function of age t and current human capital h_j, $j < N$:

$$w'(h_j, t) = \begin{cases} w(h_{j+1}, t+1), & \text{with probability } (1 - \delta(t); \\ w(floor(\tau h_j), t+1), & \text{with probability } \delta(t)\gamma; \\ w(h_j), & \text{otherwise.} \end{cases}$$

4.2 Calibration

We consider a time period of one year. The deterministic career span of our agents is 35 years. For the baseline model, we choose the probability of separation to match the separation hazards to unemployment as a function of labor market experience calculated in our PSID sample. This leaves three parameters to calibrate: s, the value of each human capital step; τ, probability of human capital depreciation at separation; and δ percent of human capital loss if depreciation occurs. Our first exercise targets coefficients in the wage scar equation alone: the initial and 15-year value of the scar as well as the present discounted value.[20] In this way, we give the model the best shot at replicating the scars before examining whether ancillary implied life-cycle wage statistics are factual. We consider a range of step values from

[19] The drop in wages in the full LS model is affected by choices of the worker that we do not explicitly model here. Workers sample one exogenous draw of an additional match specific component of wages each period of unemployment and choose whether to accept it or search again next period. Our estimation serves the purpose of showing how large this drop is in the best fit. It remains innocuous in relation to this model because the match specific component does not affect wage scars through selection into unemployment as in Mortensen-Pissarides (1994) since all separation is exogenous.

[20] The wage regression in our model includes experience and experience-squared, the first fifteen years of dummies following separation, the dummy for the second separation, the dummy for third separation and individual fixed effects. The wage regression in the data includes additional demographic controls, year fixed effects, etc.

$s = 0.01$ to $s = 0.1$. For each, we calibrate remaining parameters to minimize the weighted distance between these statistics calculated for model simulated data and the analogous statistics in the PSID sample. We choose the set of parameters across s-values that minimizes this distance. These parameters are available in Table 4.

The results for the model are shown in Figure 2, which corresponds to Table 5. The baseline model replicates both the initial drop in wages following separation as well as the total present discounted value of lost wages. However, inspection of Figure 2 shows that the wage scar is not adequately persistent. Separated workers have a clear trajectory towards recovery approaching 15 years. The separated workers that are re-employed recover lost human capital through the same process that delivered their initial high pre-separation wages. That delivers high wages for the reference group to which they are compared. This mechanism can be seen in the predictions of the baseline for wage growth. The best fit to the scar chooses life-cycle wage growth that is 11% greater than that seen in the PSID.

4.3 Alternative Specifications

We re-calibrate the model for a series of modifications on the baseline model of ex-ante homogenous agents with random separation. We make two types of modifications. In the first set, we depart from the random separation specification to provide serially correlated separations. We do this because of the finding in Stevens (1997) [25], replicated in this paper, that multiple separations are important for understanding the wage scar. We achieve serially correlated separations in two ways. In the first, we specify that only low-wage workers face a separation hazard. This ties the human capital theory directly to the serial correlation of separations. The next is agnostic and mechanical: we modify the separation hazard to mechanically be serially dependent. The second modification allows a separation to permanently reduce the worker's future wage growth rate (γ) without any implication for the future unemployment hazard.

(a) **Baseline** (*Red Solid Line labeled "Baseline" in Figures 2 & 3.*) See previous subsection.

(b) **Selection of Low Wage Workers** (*Solid-diamond line labeled "Selection". Select in Figures 2 & 3.*) We now consider the case where only workers below a given current wage threshold face separation hazards. This specification is related to business cycle theory building from Ljungqvist and Sargent (1998) [18]. The view of this theory is that match destruction is endogenous and occurs when match productivity falls below a certain threshold. Match productivity is a combination of worker, match, aggregate, and firm components, and so low productivity workers are more likely to be in a match that falls below the threshold and face a higher separation probability.

(c) **Separation Changes Workers - Correlated Separation** (*Solid-square line labeled "Serial Separations" in Figures 2 & 3.*) We modify our baseline such that separated workers are likely to suffer multiple separations. We introduce a new parameter $\lambda \geq 1$ indicating how much each separation a worker experiences increases the hazard of future separation. These probabilities are estimated directly from the data. The first separation increases the probability of a second separation by 2.17 times, the second separation increases the probability of a subsequent separation by 1.15 times, and three or more separations increase the probability of subsequent separation by 1.49 times (see Table 1). This modification is best viewed as human capital theory combined with a job ladder model where the "bottom rung" accessible to unemployed workers is "slippery" or has a higher separation rate.

(d) **Permanently Lowered Wage Growth** (*Solid-circle line labeled "Lowered Wage Growth" in Figures 2 & 3.*) We modify our baseline such that separated workers' probability of moving up the skill ladder is permanently lowered to zero. We still calibrate the amount of skills lost (τ) to best fit our targets, but set the hazard rate of future skill accumulation (γ) only for workers who are separated.[21] This modification is an extreme view of human capital theory. The worker changes not only in her current skill level, but in her ability to ever gain skills again.

The extensions (b) and (c) that provide serial correlation in separation are qualitatively similar to the baseline model. They replicate the targets including the initial decline and present discounted value of the wage scar, but do not produce permanent wage scars. However, they do fare slightly better in generating persistence. This is because the wage process after the first separation is fundamentally different from the wage process prior to separation by the fact that a separation and its corresponding consequences become more likely. An interesting corollary result is that the three specifications differ in the amount of skills lost at separation. The baseline in the highest (54%), followed by correlated separations (29%), and then selected separations (7%). This makes sense. Correlated separations deliver similar net skill losses over several separations while selection adds that workers with low wages are more likely to experience these events which imply that less of a skill loss is necessary.

Extension (d) involving a permanent removal of future human capital growth performs fundamentally different than the other three cases. As one would expect, it replicates the permanent nature of the scar. However, there is a trade-off in the depth of the scar. It provides an initial fall of about half of the target and underpredicts the present discount value of the scar. Most striking is that this specification chooses non-targeted life-cycle margins that are wildly counterfactual. It generates wage growth in excess of three-times that seen in the data. This is done in an attempt

[21] The γ provided in the parameter tables is the human capital process prior to separation and for the never separated workers.

to provide a deep initial scar. The separation hazards are chosen directly to match PSID estimates, implying high hazard rates for the initial few years of experience. Therefore, fast wage growth is required during these early years to provide a place from which wages may fall in comparison to the reference group with individual fixed effects.

4.4 Targeting Life-Cycle Wage Growth and Scars

In the prior section we gave the model the best shot at replicating the wage scars even if counter-factual life-cycle statistics were produced. We now quantitatively explore the tension introduced when attempting to produce factual life-cycle wage growth patterns along-side the permanent scar. To do so, we re-estimate specifications (a)-(d) adding a few key life-cycle statistics as targets. These include the mean wage growth in the first 5 years and the first 30 years of experience. As discussed, these two statistics are important for generating the depth of the initial scar and discipline the speed of the wage recovery. We also display, but do not target, the standard deviation of wages at 30 years experience.

The baseline specification along with the serial separation specification produce smaller wage scars when they are required to replicate life-cycle moments. However, they still perform relatively well in these dimensions but of course remain unable to produce a permanent scar. Specification (b) with selection of low wage workers performs rather poorly in that it over-predicts both the initial scar and the present value of the scar. The present value of the scar is over-predicted by about 30%. There is "too much" selection in that this specification would perform better if a mix of both low-wage and random workers faced separation instead of only low-wage workers. Finally, the depth of the scar in specification (d) falls when required to generate factual life-cycle wage growth. It is also interesting that this specification generates wage dispersion two to four times that of the other theories. It leaves only one-quarter of the residual wage dispersion in the data to be explained by factors other than separations.

5 Discussion of Results

Relationship to the Results in Ljunqvist and Sargent (LS) (1998) Our analysis differs from LS. We calibrate our model by targeting life-cycle wage growth facts and the wage scar regression coefficients. The wage scars presented in Figure 15 of the LS paper are not filtered through a regression analysis as we have done here. The difference is that the regression analysis compares separated workers' future wages to a reference group of similar workers that were not separated. The figure in LS compares a worker's future wages to their past, pre-separation wages. Including the quadratic in experience improves the wage scar fit of the basic LS model since the separated workers are compared to a parametric quadratic that predicts constant wage increases with experience. On the other hand, the inclusion of individual fixed effects reduces the magnitude of the scar and worsens the fit of the basic model. Instead of comparing the separated individuals to the average worker, it compares separated individuals to their average life-time earnings which is lower than the average across all workers.

It is intuitive that the baseline LS framework does not produce permanent scars without additional ingredients.[22] Examining Figure 15 in their paper, which shows the wage path of the average separated worker, one sees a consistent upwards recovery in wages. This is because the general human capital accumulation process provides a

[22]This does not imply the results of LS are not useful. The turbulence they describe, the importance of considering how workers' behaviors are affected and the fact that unemployment insurance relates to past wages, which are often higher than future wages for separated workers, are promising margins to consider in analyzing how these scars vary over time and across countries. Our only point is that a modification of this theory on top of the instantaneous human capital loss is necessary to match both the persistent wage scars and life-cycle wage growth patterns in data.

concave life-cycle profile in wages.[23] This intuition holds for other micro-foundations, such as some models of search and matching, that provide concave life-cycle wage growth on average. Although workers suffer an instantaneous reduction in wages upon separation, they should recover as long as they have access to the same process through which they accumulated their initial high wages.

Main Results and Promising Theories The main conclusion of our analysis highlights a tension between producing deep, persistent wage scars alongside life-cycle wage statistics. On the one hand, extensions where the wage and employment process changes after first separation improve upon the baseline model in their ability to generate a scar with the high persistence documented in the data. On the other hand, these extensions struggle to produce the correct magnitude of the wage scar when they are required to be consistent with observed pre-separation wage growth and wage growth patterns of the reference group of never separated. We now discuss the implications of these findings for future research.

The takeaway from our study for future research depends on what one wants. If one would simply like to embed a quantitative process for wages that replicates both life-cycle wage patterns as well as the depth and present value of wage losses following separation, then the baseline Ljungqvist and Sargent type of model can do the job more than adequately. However, if one would like to have a deeper understanding of why the scars are so persistent, then theories where a separation is a restart on the bottom rung of the pre-separation wage process leave something to be desired. Instead, we have shown that theories where separation somehow changes the worker's future prospects by lowering wage growth or raising the incidence of future separation are promising.

[23] In their specification, it takes an average of less than eight years to move from the lowest wage in the economy to the highest. This implies that wages of the average separated workers should recover in a maximum of eight years.

Recently, the literature has developed a couple classes of theories in which separation changes a worker's future prospects. One class features variants upon job ladder models. Krolikowski (2014) and Jarosch (2014) [12] interpret the job ladder as a match productivity. Workers hired from unemployment start in low-productivity matches that are also vulnerable to destruction. Huckfeldt (2016) [9] provides evidence of an occupation ladder. He shows that a large component of wage scarring for displaced workers is a consequence of switching to lower paid occupations.[24]

Another class of models generates wage scars via a form of selection that is more akin to model variant (d) than model variant (c). In the successful theories of Michaud (2017) and Burdett, et al. (2015) [1], the scars are generated by endogenous selection of a "low-type" worker. However, in both cases, this selection on type is not captured by the individual fixed effect as in the regression they run on model generated data. In Burdett, et al. (2015) [1], the fixed characteristic has dynamic impact through a heterogenous wage growth and separation process. In the learning story of Michaud (2017) [22], the fixed heterogeneity is not known to employers at the beginning of a worker's career. This leads to a time-varying impact through the dynamics of an employer learning about the trait through observations of workers' output.

6 Ancillary Evidence: Who Recovers from Separation?

In this section, we document the characteristics for workers that recover from wage scars for guidance on further advancements in theory. We consider two subsets of the 1,124 workers that were separated once: those with residual wages after separation in the top quartile and those in the bottom quartile. Wage residuals are calculated every

[24] His analysis differs from ours in how he calculates wage losses and in that the group of "displaced" workers is more restrictive than our designation of involuntarily separated workers.

year after the separation. We then calculate the mean wage residual after separation for these workers to sort them into their respective quartiles.

The workers in the top quartile make up those that we can consider having avoided the scar. The mean of the average wage residual for the top quartile after separation is 0.58. The minimum average wage residual is 0.25. This is a higher magnitude than the scar coefficients found earlier, implying no worker in this group experiences a wage scar. The mean of the average wage residual for the bottom quartile of separated workers is -0.72 and the maximum value for these workers is -0.48. These are workers that certainly do not recover from their first and only separation.

The fact that so many separated workers have such high average wage residuals suggests that several of these involuntarily separated workers move beyond recovery after separation. This is difficult for human capital theory to reconcile unless the theory works differently for different types of workers. Table 8 and Table 9 provide a convenient resource to guide future researchers in this area.

Table 8 indicates that workers from some occupations are more prone to recovery than others. This is clear when examining the occupations for workers who recover. These workers are craftsmen, technical workers, or in management. These make up the biggest portions for these workers before and after separation. Not many workers who do not recover find themselves in these occupations. This can be consistent with a "job ladders" mechanism as in Jarosch (2014) [12] and Krolikowski (2013) [16].

Additionally, separated workers who recover and those who do not recover vary along several other dimensions as shown in table 9. Workers who recover are 94% white and 92% male. Workers who do not recover, on the other hand, are 80% white and 63% male. Education levels are also clearly different where 44% of workers who recover have a college degree while this percentage is 14% for those that do not recover.[25]

[25] Carrington and Fallick (2014) [3] provide an overview of empirical findings related to Table 9.

7 Conclusion

Understanding the long-lasting effects of job loss on wages is important for understanding income risk and how this contributes to income inequality. We estimated that job loss accounts for 17.8% of cross-sectional wage dispersion and is an important contributor to individuals' wage risk over the life-cycle. We then used structural models to highlight two potential quantitative challenges for human capital in replicating the empirical paths of wages after job loss. We first showed that some intuitive theories struggle to provide a scar that is both as deep and as persistent as scars in the data. We then showed the difficulty for some theories in delivering large wage scars while maintaining life-cycle wage growth and dispersion implications that are quantitatively in line with the data. Notable examples included the intuitive theory where individuals' wages are permanently low after a separation. This theory struggles to deliver the depth of the wage scar observed in the data because of the individual-fixed effects that are included in these regressions. Another intuitive theory is to model a separation as a re-start along the same pre-separation wage growth process, but at a lower wage. This theory does not produce a persistent enough wage scar when required to be in line with observed life-cycle wage growth. Finally, we provided ancillary evidence on characteristics of workers who recover versus those who do not and noted that these facts could guide improvements in theories for worker separation and wage determination.

We hope this paper influences the literature in the following ways. We have made the importance of understanding wage scars evident and facilitated future work aimed at that goal. We hope that these future works will target and make transparent the model fit with regards to both separated workers and the reference group to which their wages are compared: the non-separated workers. This will facilitate synergistic advancements on this topic by allowing for better comparisons of the strengths and weaknesses of different theories and modeling approaches. Finally, we hope the fact that we have just added a modification of simple human capital theory to the growing list of theories capable of replicating empirical wage scars increases the demand for direct micro-evidence to parse between the competing theories of wage scars.

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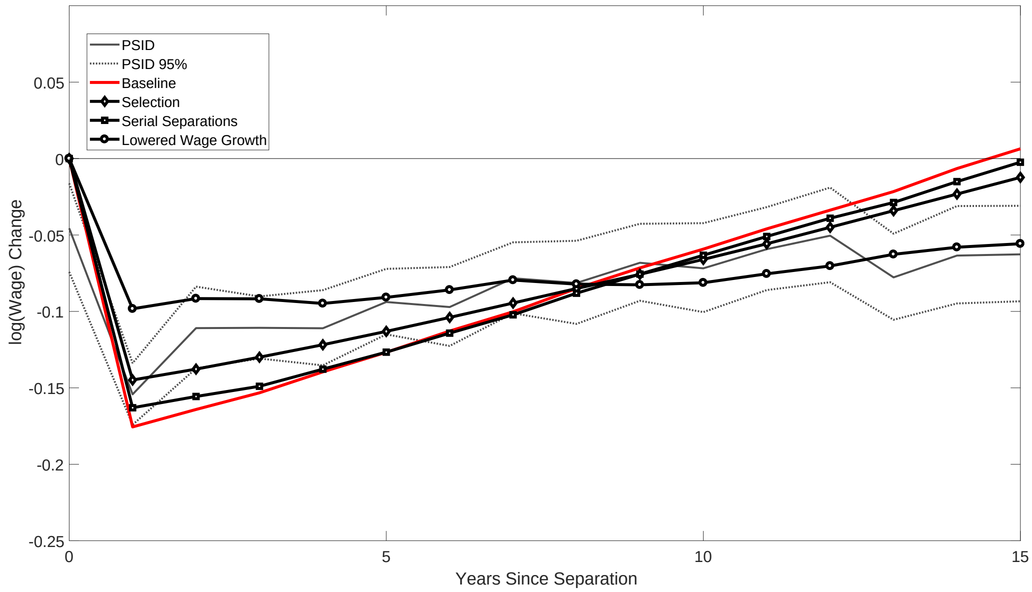
Figure 1: Estimated Wage Effect of Separation

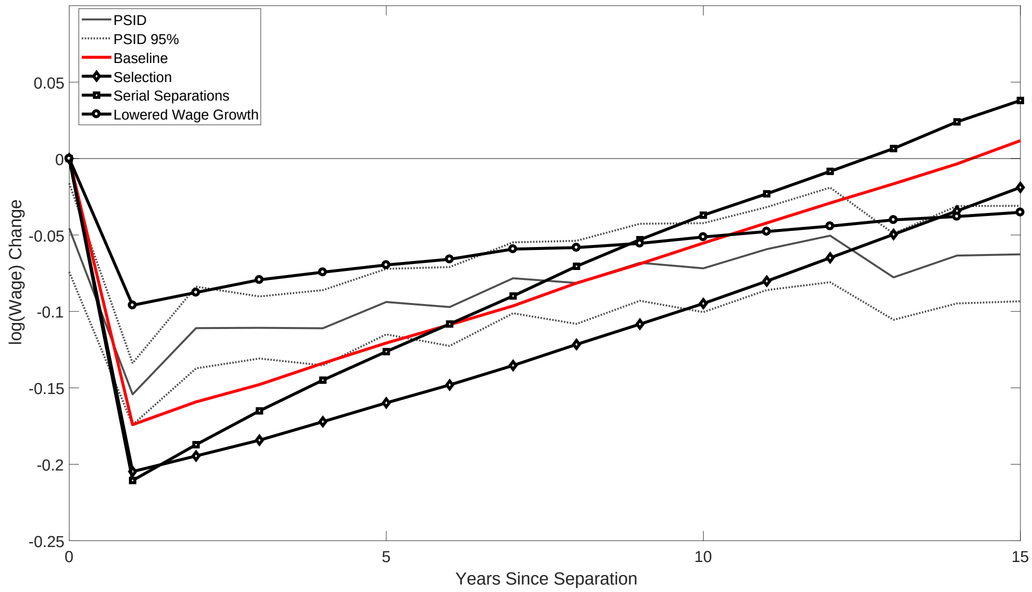
The solid line indicates the values for $\exp(\beta_{t-n})$ from equation 1 with log hourly earnings as the dependant variable. The dashed lines indicate the 95% confidence intervals.

Figure 2: Model Fit- Targeting Scar Coefficients Only



These lines come from section 4.3. "Baseline" is the learning-by-doing model of human capital. "Selection" is a modification of Baseline with only low-wage workers facing a separation hazard. "Serial Separations" is a modification of Baseline where the probability of future separations increase after each separation. "Lowered Wage Growth" is a modification of Baseline where workers have no wage growth after separation.

Figure 3: Model Fit- Targeting Scar Coefficients & Life/Cross Section Wage Statistics



These lines come from section 4.3. “Baseline” is the learning-by-doing model of human capital. “Selection” is a modification of Baseline with only low-wage workers facing a separation hazard. “Serial Separations” is a modification of Baseline where the probability of future separations increase after each separation. “Lowered Wage Growth” is a modification of Baseline where workers have no wage growth after separation.

Table 1: Empirical Wage Process- PSID Estimates

Parameter	**No Separations**	(Std. Err.)	**With Separations**	(Std. Err.)
Return to *Exp*	0.0218	(0.0010)	0.0237	(0.0013)
Return to Exp^2	-0.0006	(0.0000)	-0.0007	(0.0000)
AR(1) persistence (ρ)	0.9213	(0.0112)	0.8996	(0.0333)
std AR(1) innov. (σ_η)	0.2709	(0.0063)	0.3146	(0.0047)
std transitory shock (σ_ϵ)	0.2505	(0.0034)	0.1608	(0.0077)
std permanent level (σ_α)	0.2120	(0.0146)	0.1334	(0.0049)
Initial Separation Hazard (λ_0)	0.0	(n.a.)	0.9582	
Additional Separation Hazards				
After One Separation (λ_1)	0.0	(n.a.)	2.1686	(0.1308)
After Two Separations (λ_2)	0.0	(n.a.)	1.1495	(0.1002)
After 3+ Separations (λ_3)	0.0	(n.a.)	1.4888	(0.1551)

Table 2: Empirical Wage Process: Model Fit to PSID Targets

Full Model Estimation-Fit			
Moment	**Data**	**No Separations**	**With Separations**
Return to *Exp*	0.015	0.011	0.010
Return to Exp^2	-0.0004	-0.0003	-0.0003
Resid. Wages, 5 yr Exp (std)	0.510	0.510	0.510
Resid. Wages, 30 yr Exp (std)	0.531	0.521	0.529
Wages (Scorr(1))	0.933	0.877	0.869
Wages (Scorr(1)-Scorr(2))	0.039	0.139	0.167
Wages ($\frac{\text{Scorr(2)-Scorr(3)}}{\text{Scorr(1)-Scorr(2)}}$)	0.866	0.872	0.825
Individ. Fixed Effects (std)	0.483	0.462	0.451

Note: Return to experience and experience-squared are coefficients in the regression on model generated data.

Table 3: Role of Separation in the Wage Process

Counterfactual Simulation-Turn off Separation			
Statistic	**No Separation**	**Separation**	**Effect of Sep**
	(Std. Err.)	(Std. Err.)	
20 yr wage growth (mean)	0.395	0.340	-14.7%
	(0.024)	(0.021)	
Resid. Wages, 5 yr Exp (std)	0.483	0.510	+5.6%
	(0.012)	(0.011)	
Resid. Wages, 30 yr Exp (std)	0.496	0.529	+6.7%
	(0.014)	(0.012)	
Wages (Scorr(1))	0.831	0.869	+4.6%
	(0.004)	(0.004)	
Individ. Fixed Effects (std)	0.437	0.515	+17.8%
	(0.011)	(0.012)	

The counterfactual uses the model parameters from the estimation of the model with separation, but then sets separation hazard to zero.

Table 4: Parameter Estimates- Targeting Scar Coefficients Only

Parameter Estimates	Baseline	Selected Separation	Correlated Separation	No Growth
Skills (s)	0.021	0.011	0.024	0.17
Skill Loss Prob. (γ)	0.50	0.45	0.51	0.71
Percent Skills Lost (τ)	0.54	0.07	0.29	0.96

See Section 4.3 for the specification of each model.

Table 5: Model Fit- Targeting Scar Coefficients Only

Moment	Data	Baseline	Selected Separation	Correlated Separation	No Growth
5 year wage growth (mean)	0.12	0.09	0.05	0.11	0.56
30 year wage growth (mean)	0.49	0.60	0.32	0.59	1.72
30 year wage dispersion (stdev)	0.53	0.02	0.01	0.09	0.76
Initial wage scar (%)	-0.15	-0.16	-0.14	-0.16	-0.09
PDV 15 year Wage Loss (mean)	-0.93	-0.92	-0.89	-0.94	-0.86

See Section 4.3 for the specification of each model.

Table 6: Parameter Estimates- Targeting Scar Coefficients & Life/Cross Section Wage Statistics

Parameter Estimates	Baseline	Selected Separation	Correlated Separation	No Growth
Skills (s)	0.02	0.02	0.031	0.059
Skill Loss Prob. (γ)	0.48	0.35	0.88	0.89
Percent Skills Lost (τ)	0.98	0.02	0.94	0.99

See Section 4.3 for the specification of each model.

Table 7: Model Fit- Targeting Scar Coefficients & Life/Cross Section Wage Statistics

Moment	Data	Baseline	Selected Separation	Correlated Separation	No Growth
5 year wage growth (mean)	0.12	0.09	0.07	0.13	0.19
30 year wage growth (mean)	0.49	0.49	0.45	0.51	0.53
30 year wage dispersion (stdev)	0.53	0.10	0.10	0.20	0.41
Initial wage scar (%)	-0.15	-0.16	-0.19	-0.18	-0.08
PDV 15 year Wage Loss (mean)	-0.93	-0.87	-1.26	-0.81	-0.70

See Section 4.3 for the specification of each model.

Table 8: Occupation Distribution

	Not Separated	Recover Before	Recover After	Do Not Recover Before	Do Not Recover After
Technical	21.1%	31.3%	26.0%	4.1%	3.6%
Management	12.0%	23.3%	20.8%	9.2%	7.3%
Sales	2.4%	5.7%	2.2%	12.2%	6.7%
Clerical	10.1%	4.0%	4.1%	19.4%	13.9%
Craftsman	24.8%	18.8%	31.2%	4.1%	9.7%
Operatives	12.3%	8.5%	9.7%	14.3%	20.5%
Transport	5.0%	2.8%	2.4%	7.1%	7.3%
Laborers	4.3%	2.3%	2.0%	10.2%	9.7%
Farm Work	0.5%	0.0%	0.2%	3.1%	1.8%
Service	7.6%	3.4%	1.4%	15.3%	19.3%
Housework	0.2%	0.0%	0.0%	1.0%	0.3%

"Recover"("Do Not Recover") refers to workers in the top-quartile (bottom-quartile) of post separation residual wages.

Table 9: Summary Statistics

	Not Separated	Separated*	Recover*	Do Not Recover*
White	89.62%	87.49%	94.00%	79.52%
Male	82.56%	82.71%	92.03%	63.05%
Age	40.03	33.80	35.89	35.60
Experience	16.29	10.32	11.28	10.62
Unemployed Duration		34.33	25.50	34.61
Years Education	13.54	12.81	14.02	12.62
College Graduate	32.41%	18.81%	43.80%	14.23%
Firm Tenure	9.84	3.24	3.27	2.41

* Statistics at Separation
"Recover"("Do Not Recover") refers to workers in the top-quartile (bottom-quartile) of post separation residual wages.