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(Article begins on next page)

Macroeconomic Conditions at Entry and Injury Risk at the Workplace*

Roberto Leombruni

University of Turin, Italy
roberto.leombruni@unito.it

Tiziano Razzolini

University of Siena, Italy
tiziano.razzolini@unisi.it

Francesco Serti

IMT School of Advances Studies - Lucca, Italy
Universidad de Alicante, Spain
francesco.serti@gmail.com

Abstract

Using a unique dataset from Italy, we show that the local unemployment rate at entry has a persistent positive effect on severe and non-severe workplace injuries of young workers. Entrants during recessions, although receiving marginally higher entry wages, also experience slower wage growth. The observed pattern in the differences between severe and non-severe injuries indicates that entrants during recession may underreport non-severe workplace injuries. Our findings suggest that workers entering during recession are persistently locked into low quality jobs and that the mix of hazardous tasks endogenously adjusts to the business cycle.

Keywords: work-related accidents; business cycle; young workers

JEL classification codes: J28; J60; J81

I Introduction

The macroeconomic conditions encountered by workers entering the labor market for the first time may persistently affect their future labor market outcomes. The existing

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evidence (Oyer, 2006; Genda et al., 2010; Kahn, 2010; Kwon et al., 2010; Oreopoulos et al., 2012; Brunner and Kuhn, 2014) mainly focuses on the wages prospects of young entrants. Little attention has been devoted to other non-pecuniary determinants of job quality, such as the level of workplace safety. These job attributes may represent an important channel of adjustment to negative shocks, particularly in contexts where wages are rigid and regulated by strict institutional rules.

This paper studies the impact of unemployment at entry on workplace safety for a sample of young Italian-born, low- and medium-skilled men who began their first employment between 1994 and 2003. We use a unique dataset that combines work histories from Italian administrative data (Work Histories Italian Panel, WHIP) with individual work-related injuries from the Italian Workers' Compensation Authority (INAIL).

Our main finding is that negative labor market conditions at entry are associated with a persistent increase in work-related accidents. This effect cannot be simply attributed to a lower accumulation of experience and/or tenure, as we find no significant effect of initial conditions on time worked (conditional or unconditional on being employed) and find very small negative effects on tenure only in the long run. Our results are robust to restricting the analyses to severe injuries, which, due to their consequences and immediate care needs, are not subject to reporting bias (Boone and van Ours, 2006; Boone et al., 2011), and to using as a dependent variable a measure of the risk imposed by the working environment, which is not affected by either workers' behavior in the job or variations of firms' injury prevention investments over the business cycle.

An analysis based only on earnings could be particularly misleading in labor markets,

such as the Italian one, that are characterized by downward wage rigidity and a large shadow economy (approximately 23% of Italian official GDP, according to Orsi et al., 2014). In these economies, recessions may push relatively less productive workers into the underground economy, leaving only better-paid workers in the formal sector. Indeed, by using the Survey on Household Income and Wealth (SHIW), we find that the likelihood of a young worker beginning her career in an informal (low-paid) job increases significantly during recessions. We show that this a selection mechanism could explain why, in the administrative dataset, we observe that workers who entered during recessions receive slightly higher average entry wages. To the extent that working conditions and wages are relatively worse in the underground economy, our results should provide a lower bound estimate of the impact of starting conditions on the time spent by new workers in low-quality jobs offering relatively fewer career prospects.

Using a canonical graphical analysis, we show that our findings are consistent with a scenario in which entrants during recessions become relatively more willing to bear risk, and firms react by offering wage-job safety bundles characterized by a lower compensation for risk. In the presence of downward wage rigidity, these endogenous responses to recessions are able to explain both the higher average wages and injury risk observed in the formal sector and the detected countercyclical pattern of the underground economy.

Finally, our evidence on lower levels of job safety represents an unexplored channel through which unfavorable initial conditions may negatively affect workers' health status (Maclean, 2013). Moreover, our findings contribute to the literature on the relation between reporting behavior and the business cycle. Analyzing injury dynamics by their

severity reveals that worker reporting behavior, in addition to being affected by the contemporaneous economic cycle, also depends on the starting conditions.

The remainder of the paper is organized as follows. The next section reviews the economic literature on the effect of adverse conditions at entry. Section III describes the data. The econometric framework and the empirical results are presented and discussed in Section IV. Section V concludes.

II Related literature and theoretical background

The previous literature has mainly investigated the effect of high unemployment at entry on pecuniary labor market outcomes for countries characterized by greater wage flexibility than the Italian labor market. The bulk of these studies focus on entrants with at least a college education in North America (Oyer, 2006; Genda et al., 2010; Kahn, 2010; Oreopoulos et al., 2012) and detect a wage penalty for those who entered during recession that vanishes in approximately ten years. However, for a sample of Austrian low- and medium-skilled workers, Brunner and Kuhn (2014) find an increasing negative effect of the initial unemployment on wages. Genda et al. (2010) detect a negative and persistent impact of unemployment at entry on earnings for low- and medium-skilled Japanese workers but not for their US counterparts; they also argue that institutional differences (i.e., stronger employment protection legislation in Japan coupled with a school-based hiring system) may contribute to this result. Finally, Maclean (2013) shows that, for US middle-aged men, leaving school in a recession decreases mental and physical health.

With labor market rigidities, adverse conditions at entry are more likely to affect

outcomes such as employment (Raaum and Røed, 2006) or other non-pecuniary characteristics rather than wages. The Italian labor market is an interesting case to study the effect of unfavorable initial conditions since, among European countries, Italy ranks the highest in terms of employment protection legislation, wage compression and downward wage rigidity as well as in terms of centralized wage bargaining and trade union coverage (OECD, 1999,2004). Thus, adjustments to economic downturns may reasonably produce negligible effects on wages and occur through alternative channels such as job safety.

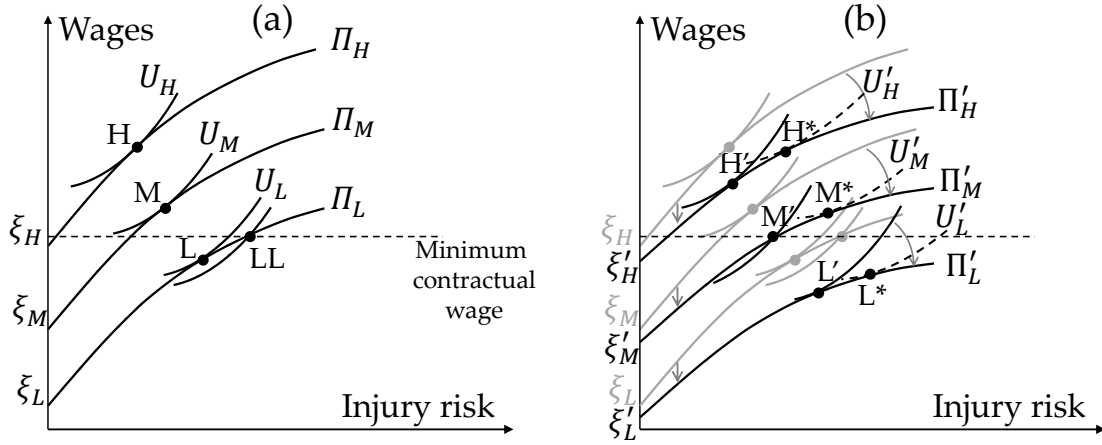


Figure 1: Optimal combinations of wages and injury risk along the business cycle

Note: The figure shows the optimal combination of wages and injury risk in a given job for heterogeneous workers as the tangency points between isoprofit curves $\Pi_P(w, inj)$ and utility curves $U_P(w, inj)$, with $P = H, M, L$. Panels (a) and (b) represent the equilibria in the good and bad state of the economy, respectively.

To develop this intuition, in Figure 1, we describe the optimal combinations of wages and injuries that may emerge in equilibrium during different states of the economy for three types of workers who differ in their level of earning potentials: high, ξ_H , medium, ξ_M and low, ξ_L . Given the presence of wage rigidities and centralized wage bargaining in the Italian labor market, we assume that each job has a minimum contractual wage (i.e., the dashed horizontal lines in the two panels of Figure 1). However, employers do

have some discretion in offering different market opportunities to workers according to their earning potentials. This heterogeneity in market opportunities reflects unobserved differences that cannot be fully captured in our empirical analysis even after controlling for observed job, employer and firm characteristics (e.g., workers' productivity). We denote the isoprofit curves as $\Pi_P(w, inj)$ and the utility curves as $U_P(w, inj)$, with $P = H, M, L$. In panel (a) we show that, even in the presence of a positive compensation for risk ($\partial\Pi/\partial inj > 0$), more productive workers (types H and M) are paid more by the firm than type L workers and can cede a portion of their salary in exchange for more workplace safety.¹ Thus, we have types H and M workers exhibiting higher wages and lower injury risk than type L workers. We assume that this situation is typical in a strong state of the economy when certain combinations (points H and M) are above the minimum contractual wage, and others are represented by a corner solution (point LL).

In panel (b), we assume that recessions may have two effects. First, the recessions reduce the earning potentials of all workers (ξ'_H , ξ'_M and ξ'_L), thus leading to a downward shift in the isoprofit curves. Second, the recessions induce a change in the slope of the isoprofit curves. The latter effect is essentially similar to the scenario proposed by Viscusi and Hersch (2001) in which segmented labor groups face market opportunities with different wage-risk trade-offs.² In other words, distressed firms may offer flatter combinations of wages and risk (i.e., the isoprofit curves, $\Pi'_P(w, inj)$ in panel b) because

¹This explains why empirical analyses display a negative correlation between wages and injuries even after controlling for observable worker, job and firm characteristics (see among others Hamermesh, 1999).

²Viscusi and Hersch (2001) study differences in workplace risk between smokers and non-smokers. They assume that market opportunities offered by employers to smokers are flatter than those offered to non-smokers (i.e., with lower premia for risk). In our scenario, segmentation is not related to an individual attribute but to labor market conditions. We are grateful to Joni Hersch for having indirectly suggested the possibility of this difference in the wage-risk trade-off.

they realize that, during downturns, entrants may accept a reduction in workplace safety (i.e., entrants' have flatter utility curves shown by the dashed curves $U_P'(w, inj)$ in panel b). Thus, new combinations can occur for high and medium productive workers at H' and M' , if only isoprofit curves flatten, and at H^* and M^* if the slope of utility curves also decreases. These changes in market opportunities are in accordance with the assumptions made by Gibbons and Waldman (2006) that, during slowdowns, employers create a higher proportion of low level positions.³ Isoprofit and utility curves may also flatten in a recession because of the strong insider-outsider dualism characterizing the Italian labor market (i.e., wage rigidity, centralized wage bargaining, high employment protection and union coverage). In this setting, trade unions are expected to exert strict control over the job contract characteristics of entrants, such that insiders could remain protected against macroeconomics shocks, and their jobs could not be threatened by wage underbidding.⁴ Entrants may be requested to bear the consequences of unfavorable macroeconomic conditions by paying a higher price in terms of workplace risk, which they may consider a fair investment to become future insiders. Nevertheless, in an insider-outsider context, the hazardous tasks assigned to young workers should continue to receive positive compensation for risk to not represent a threat to insiders.

The example of panel (b) in Figure 1 shows that, if during a recession isoprofit curves sufficiently flatten, the optimal combinations of wages and injuries for low productivity

³In the task-specific human capital model of Gibbons and Waldman (2006), wage represents the unique index of the quality of the job. In our setting, a reduction in the quality of jobs offered during a recession can be driven by an increase in the number of hazardous tasks at a given level of wage or by a decrease in the premium/remuneration of risk at any level of wage.

⁴In a typical insider-outsider dualism (Lindbeck and Snower, 2001), entrants are very unlikely to be hired on terms that oppose insiders' interest.

workers will lie below the minimum contractual wage (points L' or L^*); no amount of injury risk would compensate for their low level of productivity at the minimum wage. These workers can be profitably hired only in the shadow economy, which is characterized by wages below the minimum wage and by relatively unfavorable job safety conditions.⁵ Thus, Figure 1 illustrates that workers entering the formal sector during recessions are positively selected. To the extent that both the isoprofit and the utility curves sufficiently flatten, these workers will display, as expected, higher average wages, but they will be assigned to lower-quality jobs characterized by higher average injury rates. However, Figure 1 constitutes a static picture. These unfavorable entry outcomes may have long-lasting consequences on the career prospects of entrants. According to Gibbons and Waldman (2006), new entrants facing poor macroeconomic conditions are assigned to lower quality tasks that offer relatively fewer opportunities for accumulating the skills necessary for career progress. The lower transferability of these accumulated skills to higher-level occupations negatively affects actual workers' productivity. Moreover, including the employers' imperfect information about worker productivity could rationalize a persistent effect of the initial conditions. Prospective employers could perceive the initial low-rank job as a signal of the workers' ability, without considering the macroeconomic conditions at the time of labor market entry (Oyer, 2006). Oreopoulos et al. (2012) show that a standard job-search model, augmented with mobility costs that increase with job tenure or age, is also consistent with the persistent effects of unfavorable initial conditions. If the benefits of searching are sufficiently low (or the mobility costs increase sufficiently steeply

⁵This is consistent with the observed countercyclicality of the share of entrants in the underground economy.

with age), the catch-up of unlucky entrants may terminate before the gap is closed. Finally, a persistent effect of macroeconomic conditions at entry is also consistent with the existence of implicit/insurance contracts (e.g. Harris and Holstrom, 1982; Beaudry and DiNardo, 1991). Workers entering the labor market during recessions may tend to accept long-term contracts characterized by lower wage growth and may encounter mobility costs. All of these mechanisms of persistence may be reinforced by labor market rigidities, which may contribute to perpetuating the segmentation between lucky and unlucky generations. Indeed, Kawaguchi and Murao (2014) show that, with strict EPL and high union coverage, the persistence of the effects of recession is relatively stronger.

III Data Description

We use the WHIP-Salute database, which merges together data on work careers derived from the administrative records of the National Social Security Administration (INPS), with data on work injuries derived from the administrative records of the National Work Injuries Insurance Administration (INAIL) (Bena et al., 2012). The target population includes employees who worked in the private non-agricultural sector in Italy in the 1985-2003 period, from which a 6% random sample has been extracted. Career data provide job start and job end dates, in addition to the actual duration in weeks of each employment relationship. The data also provide information on worker characteristics (age, sex, birthplace, place of work and type of occupation), standard labor market outcomes (number of weeks worked in a year and annual earnings) and characteristics of the firms in which individuals are employed (number of employees, sector and firm age). Weekly

wages are computed as the ratio between annual deflated earnings and the number of weeks worked in a year, with both variables measured on a full-time equivalent scale. The INAIL dataset contains the date of workplace injuries (i.e., accidents that have occurred during a work task), the duration of injury-related leave at the employer-employee level and a description of the type of injury. The dataset includes all injuries, certified by physicians, leading to a leave of more than three days for the 1994-2003 period.⁶ Using the information on the diagnosis, we adopt a classification that distinguishes immediate care (IC) injuries from the non-immediate care (NIC) ones. The former identify workplace accidents that require immediate treatment at a hospital and therefore cannot be subject to reporting bias (Boone and van Ours, 2006).

We selected Italian-born men⁷ who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. We define "first-time labor market entrants" as those workers who are observed for the first time in the sample in 1994 or later.⁸ As the WHIP-Salute dataset does not adequately cover the public sector, we also exclude labor market entrants and employment spells in those industries.⁹ The resulting sample is representative of 70% of first time labor market entrants in Italy during the 1994-2003 period. Although no information on schooling is available in the

⁶Shorter healing periods do not involve INAIL but are the responsibility of the firm, according to collective contract agreements.

⁷The restriction on gender is targeted to reduce the unobserved heterogeneity that reflects the complexity of female labor supply behavior over the life cycle.

⁸We can observe the labor market history of individuals from 1985 to 2003. By considering entrants who are under 24 years old at the time of entry, we exclude the pre-1971 birth cohorts.

⁹The following ATECO 1991/ISIC rev 1.1 codes are omitted from the analysis: L, M, N, O. This barely affects the representativeness of the data. Indeed, only 4.9% of the selected labor market entrants begin their career in the public sector, and only 4.7% of individuals in the final sample have job spells in the public sector. Finally, because of its high degree of seasonality and undeclared work, we checked that our results are robust to excluding employment spells in the construction sector.

data, the restriction on age in practice excludes individuals with higher education/skills (i.e., with at least a university degree)¹⁰ and therefore reduces the potential unobserved heterogeneity problems related to this important dimension. Moreover, job safety should be less relevant for labor market entrants with higher education who tend to perform non-manual tasks. Therefore, due both to data limitations and for conceptual reasons, we concentrate on low- and medium-skilled entrants.

In accordance with the literature, we use unemployment rates to proxy for the economic cycle. In particular, we use data on regional unemployment rates for all workers over the 1985-2003 period from the Italian National Institute of Statistics (ISTAT). The slowdown of the Italian economy after 1993 resulted in an increasing trend in unemployment until 1998. A recovery occurred thereafter. Italian regions markedly differ in the level of unemployment, with the South lagging the developed North. However, to take into account the unobserved heterogeneity connected to the different entry cohorts and the different regional labor markets, our identification strategy is conditional on the region of entry and on the year of entry.

IV Effects of Macroeconomic Conditions at Entry

Estimation Strategy

We study the effect of initial unemployment rate in the region of entry, ur_{i0} , on various labor market outcomes over time, y_{it} , by adopting the following standard specification

¹⁰According to the AlmaLaurea surveys (www.almalaurea.it/en/), in 2003, only 0.7 % of students who completed their undergraduate studies were 23 years old or younger, with 28 being the average age of graduation. During the previous years included in our sample, the average age of graduation was higher.

(Oreopoulos et al., 2012):

$$y_{it} = \alpha + \left(\sum_{s=0}^S \beta_s \mathbf{1}[Exp_{it} = s] ur_{i0} \right) + \phi ur_{it} + \psi_s + \mu_b + \lambda_r + \gamma_l + \theta_t + u_{it} \quad (1)$$

In addition to introducing unrestricted fixed effects for years of potential experience, ψ_s , we interact unemployment at entry in region r with dummies specific for each year of potential experience. Thus, the effect of the unemployment at entry is allowed to be different at each year of potential experience: β_s represents the marginal effect of the initial unemployment rate s years after entry. To isolate the effect of the initial labor market conditions from subsequent macroeconomic shocks possibly correlated with initial conditions, we control for the current regional employment rate, ur_{it} . To the extent that region-cohort specific variations in unemployment rates at entry are not correlated with unobserved traits of entrants, the estimated β_s s will be exclusively driven by variations in labor demand conditions, and will deliver an unbiased estimate of the effects of recession on entrants' outcomes (Oreopoulos et al., 2012). Although we take into account several sources of unobserved heterogeneity (connected to potential experience, ψ_s , the region of birth, μ_b , the region of entry, λ_r , the year of entry cohort, γ_l , and the calendar year, θ_t), entrants encountering different demand conditions may not be fully comparable in terms of unobserved characteristics. Therefore, we also present the results obtained by augmenting the above baseline specification with additional controls related to the entry job (i.e., type of occupation such as apprentice,¹¹ blue collar, white collar, manager, as well as firm sector, size and age). Finally, we implement various robustness checks to

¹¹Apprenticeship is a form of temporary employment contract for workers under age 26.

investigate how our findings are likely to be affected by endogenous labor market entry, both from the perspective of the timing of entry and sorting into different labor markets.¹²

Main Results

We first focus our analysis on standard labor outcomes such as log weekly wages, log annual earnings and log annual weeks worked. We also use all observations in the 1994-2003 period to construct an index to measure the log mean wage in occupations in the same sector. By using this index as a dependent variable, we can detect the movement of workers in occupations receiving higher or lower salaries on average. Figure 2 shows the estimated effect of ur_0 by year of experience on the log weekly wages, the log wage index, the log annual earnings and the log of weeks worked.¹³

Panel (a) indicates that a one-point increase in the unemployment rate is associated with an increase in starting wage levels by 1.6%.¹⁴ However, during periods of high unemployment, entrants display a relatively lower wage growth. Indeed, the initial premium decreases rapidly and fades away after 7 years of experience. The results in Panel (b) focus on the log wage index and indicate that entrants during recessions are more likely to start in occupations that receive higher compensations on average. The effect of ur_0 on the log wage index is more persistent than the effect on the individual wages, thus suggesting that these cohorts of workers may have lower mobility rates from these occu-

¹²To fully exploit all the available information about the timing of the occurrence of injuries, we have also repeated the analysis within a duration framework. As shown in section A.3.4 of the Online Appendix, the results we obtained are very similar to those presented in the main text.

¹³The detailed estimation results corresponding to the Figures shown in the paper are reported in the Online Appendix.

¹⁴Using data from the Labor Force Survey we find no correlation between the local unemployment rates and the overtime hours of young workers.

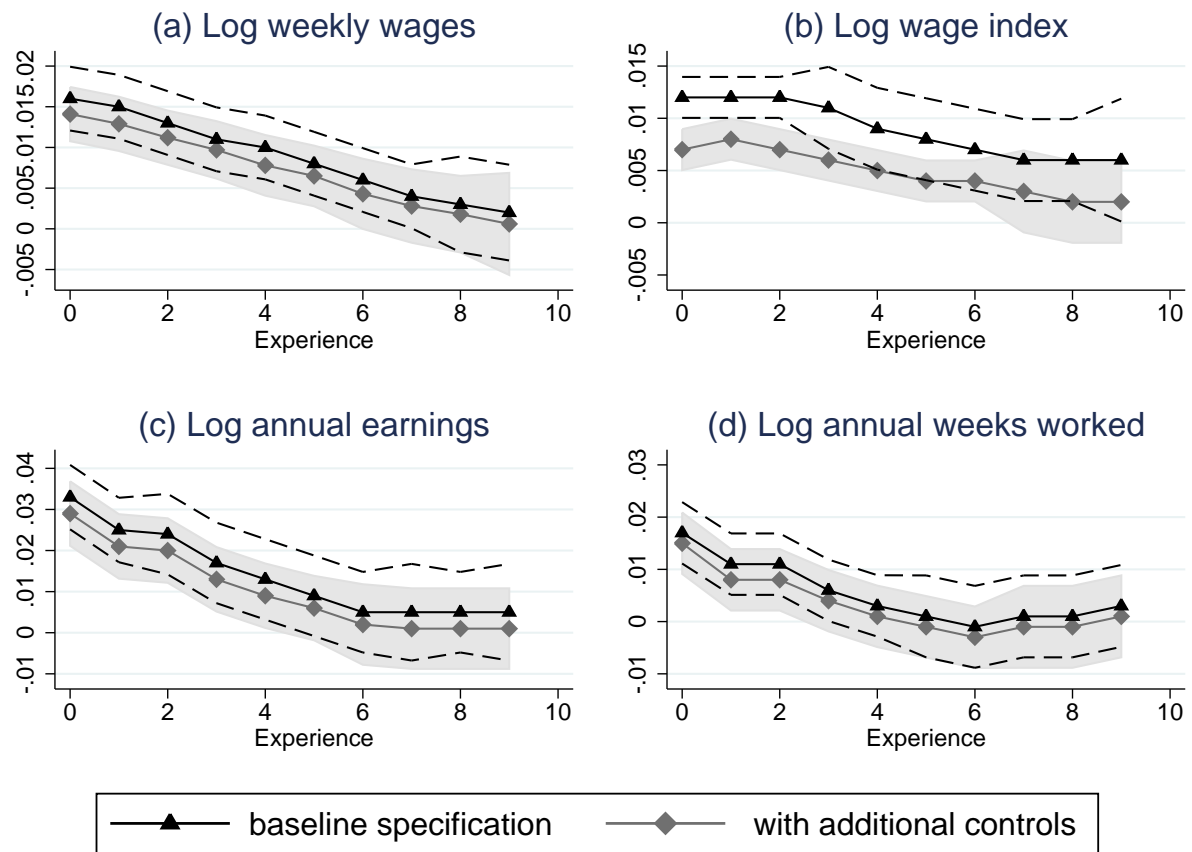


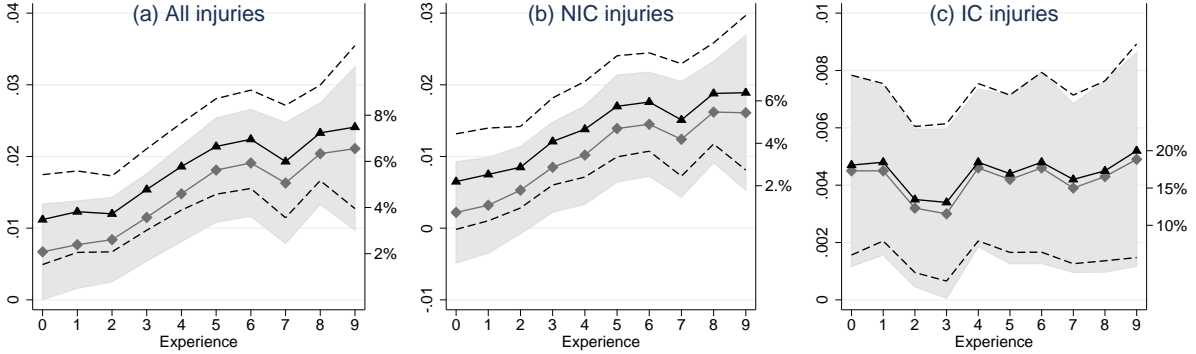
Figure 2: The effect of unemployment rate at entry on pecuniary outcomes

Note: The figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1) on the following dependent variables: log weekly wages in panel (a); log wage index in panel (b); log annual earnings in panel (c); log annual weeks worked in panel (d). The sample in the baseline specification consists of 362,682 observations of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The sample size in the regression with additional controls reduces to 349,680 due to missing values. Connected triangles represent the effect of ur_0 by year of experience in the baseline specification which includes as controls the current unemployment rate (ur_{it}) and dummy variables for: calendar year (θ_t), years of potential experience (ψ_s), region of birth (μ_b), region of entry (λ_r), year of entry cohort (γ_l). Connected diamonds represent the effect of unemployment at entry (ur_0) by year of experience when the following characteristics of the first firm and job are added to the baseline specification: dummies for sector and type of occupation (apprentice, blue collar worker and white collar worker), firms' average number of employees and age. The detailed estimation results are available in Tables A2 and A5 in the Online Appendix. Standard errors are clustered by region of entry per year of entry. The dashed lines and the gray area show the 95% confidence intervals for the baseline specification and the specification with additional controls, respectively.

pations. Panels (c) and (d) confirm the presence of a marginal premium also in terms of annual earnings and weeks worked, which become insignificant after 6 and 4 years, respectively.

Figure 3 displays the pattern of the estimated effects of initial unemployment rate on certain proxies of job safety by year of potential experience. In panels (a), (b) and (c) the dependent variables are the number of injuries (injuries of any kind, IC injuries and NIC injuries) suffered by a worker divided by the number of full-time equivalent paid weeks. With this normalization, we are able to take into account heterogeneity in the exposure to risk. In addition, these variables are expressed as the number of injuries per thousand days worked to improve the readability of the estimates (i.e., to reduce the number of decimals). However, variation in injuries at the individual level may be determined by factors other than the risk imposed by the work environment but that are otherwise connected to starting macroeconomic conditions. Indeed, a higher unemployment rate at entry may induce workers to exert greater effort and/or it may constitute a stress factor leading to less cautious behavior. Ideally, a measure of the risk imposed by the working environment may be constructed by using the number of workplace injuries incurred by the colleagues of young entrant “i” in each firm; however, this strategy is not feasible because the WHIP dataset does not contain information on all workers employed at a single firm. Therefore, at a level of greater aggregation, three injury indexes have been computed (i.e., one for each category of injuries: all, IC and NIC) as the sum of injuries in the 1994-2003 period divided by the corresponding sum of weeks worked in cells defined using occupation (blue versus white collar), sector (ATECO 1991/ISIC rev 1.1 at two

(I) Injuries at the individual level



(II) Injury incidence rates

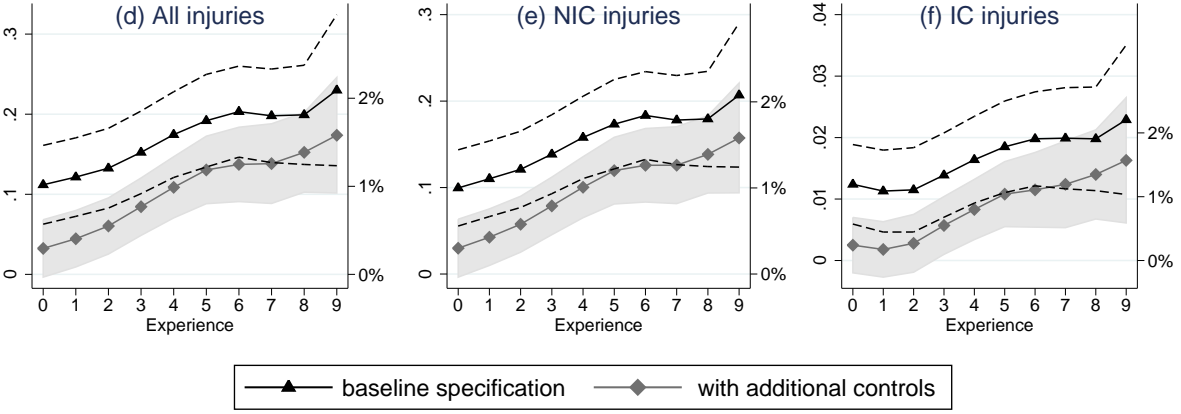


Figure 3: The effect of unemployment rate at entry on individual level injuries and injury incidence rates

Note: The figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e., the parameters β_s in equation 1) on two types of dependent variables: I) workplace accidents at the individual level (expressed as the number of injuries per thousand days worked) for all injuries, non-immediate care injuries (NIC), and immediate care injuries (IC) in panels a, b and c, respectively; II) Injury incidence rates computed as the sum of injuries in the 1994-2003 period divided the corresponding sum of weeks worked in cells defined using occupation (blue versus white collar), sector (ATECO 1991/ISIC rev 1.1 at two digits) and region. These workplace indexes have been computed using workers over 34 years old for all injuries, non-immediate care injuries (NIC), and immediate care injuries (IC) in panels d, e and f, respectively. The number of observations for individual injuries is the same as in Figure 2; due to cells missing values, for the incidence rates it decreases to 349,379 and to 342,251 in the baseline and in the additional control specification, respectively. The right vertical axis expresses these effects as a percentage of the sample mean of the corresponding dependent variable. Connected triangles and connected diamonds represent the effects of ur_0 by year of experience in the baseline specification and in the specification with additional controls, respectively (see the note to Figure 2 for information on the controls used in the two specifications). The detailed estimation results are available in Tables A3 and A6 in the Online Appendix. Standard errors are clustered by region of entry per year of entry. The dashed lines and the gray area show the 95% confidence intervals for the baseline specification and the specification with additional controls, respectively.

digits) and region. These injury incidence rates have been computed using workers over 34 years old to obtain a measure of risk totally independent of the behavior of young entrants. The value of the indexes calculated for older workers is then imputed to entrants belonging to the same cell. In panels (d), (e) and (f), we use these three injury incidence rates as dependent variables to determine the effect of ur_0 on the occupation-specific risks faced by workers along their careers. To gauge the economic relevance of the estimated effects, the right axis of each panel of Figure 3 reports the range of the estimated effects in percentage terms; these are obtained by dividing the estimated effects (reported in the left axis) by the sample average of the corresponding dependent variable.¹⁵

Panels (a), (b) and (c) in Figure 3 indicate a positive and significant effect of ur_0 on the number injuries (per thousand days worked) at the individual level, which increases over time for all injuries and NIC injuries but remains constant for IC injuries. Compared to the average number of injuries observed in the sample, the estimated effect of a one-point increase in ur_0 on the number of all injuries ranges from 3.5%, during the first year, to 7.5% when workers have potentially accumulated ten years of experience. When we restrict the analysis to NIC injuries, the estimated percentage effects are lower, but their temporal pattern increases more steeply (from 2.2% to 6.4%). Instead, for the estimated percentage losses in terms of IC injuries, which are of a greater magnitude (in the range 13%-20%), we are unable to reject that they are constant over time. The different magnitude and temporal pattern for IC and NIC injuries suggest that the reporting

¹⁵The average number of injuries per thousand days worked is 0.322. Distinguishing between NIC and IC injuries, this figure is 0.296 and 0.026, respectively. The average value of the injury incidence rate for all injuries is 10.996. Distinguishing between NIC and IC injuries, this figure is 9.958 and 1.038, respectively.

behavior may depend on initial conditions; workers beginning their career in a relatively less favorable macroeconomic scenario may have a worse bargaining position within the firm and may tend to underreport less serious injuries. This difference in reporting behavior may decrease as workers accumulate experience and their bargaining positions equalize. The absence of underreporting of IC injuries could explain why we find greater percentage losses in terms of this type of injury. It is also worth noting that, in accordance with Boone and van Ours (2006) and Boone et al. (2011), the effect of the current unemployment rate is negative and significant for all injuries and NIC injuries, but it is not statistically significant for IC injuries;¹⁶ the current economic cycle only affects less serious injuries by changing the incentives to report this type of injury. Therefore, we believe that the effect of the current unemployment rate on injuries mainly reflects the reporting behavior of workers, while the effect of ur_0 , being robust to restricting the analysis to IC injuries, truly implies a lower level of job safety.

Panels (d), (e) and (f) in Figure 3 describe the estimated effect of ur_0 on the injury incidence rates which, by construction, do not reflect the worker's behavior and effort on the job. The results are qualitatively similar to those obtained by using injuries at the individual level; entrants in recession persistently also lose in terms of injury incidence rates. Therefore, we can exclude that the effects estimated at the individual level are simply due to less cautious behaviors and/or greater effort. Comparing the estimated coefficients to the observed averages of the indexes, the estimated percentage effect of a one-point increase in ur_0 on the three injury incidence rates is very similar, ranging from

¹⁶Table A3 in the Online Appendix reports these results in columns 1, 3, and 2, respectively.

1% to 2%. The lower magnitude of these estimated percentage effects with respect to what we obtain by using individual level injuries, in addition to reflecting relatively less cautious behaviors and greater effort of entrants during recession, could also be due to the coarse nature of these proxies, which are unable to identify differences in injury risk determined by the allocation of entrants to different tasks within cells. Similarly, the absence of relevant differences between the estimates for IC and NIC indexes could be connected to the aggregate nature of these proxies of injury risk, which, by averaging across workers, eliminate differences in reporting behavior related to initial macroeconomic conditions.

To detect whether compositional effects related to observables drive our findings, in Figure 4, we report the results obtained by using workers' job and firm characteristics as dependent variables (i.e., binary indicators for being an apprentice, blue collar and white collar worker in panels a, b and c; average number of employees in panel d) in equation (1). We find that entrants during recession have a constantly higher probability of working in a blue collar occupation (panel b) and a lower probability of working in the more sheltered apprentice position (panel a). Moreover, unfavorable starting conditions negatively affect the probability of being white collar but only in the medium-long run (panel c). Panel (d) indicates that there are no differences driven by initial conditions in firms' size. As shown in Figures 2 and 3, when we introduce initial firm attributes (sector, firm size and firm age) and the type of occupation (apprentice, blue collar and white collar) as additional controls in the main regressions, the estimated effects of the initial unemployment rate on labor market outcomes are not affected. Moreover, the results are not altered by the inclusion of the initial firm's employee growth in previous years, thus suggesting that the

cyclical variation in the job-quality is not determined by different types of firms recruiting in different stages of the cycle. Similarly, the introduction of initial contractual code dummies as additional controls does not affect the main results either, thus confirming that formal contractual arrangements hide a considerable heterogeneity in job quality that, without the injury data, would not have been detected.¹⁷

¹⁷Contractual codes refer to a finer categorization of occupations (with respect to those used as additional controls in Figures 2 and 3). These occupational codes are mainly related to seniority and to automatic career progression and can be hardly used as a proxy of the skills needed in a given task (Colleoni et al., 2009). Estimates with these additional controls are shown in Tables A9 and A11 in the Online Appendix.

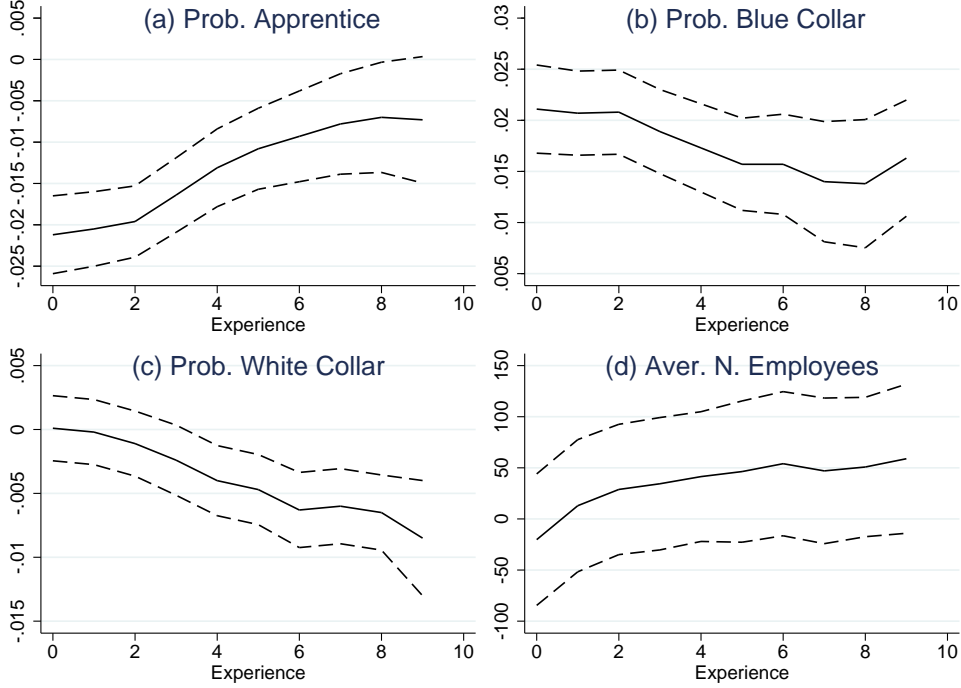


Figure 4: The effect of the unemployment rate at entry on job and firm characteristics

Note: The solid line in the figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e., the parameters β_s in equation 1) on the following dependent variables related to the worker's job or firm: binary indicators for being an apprentice, blue collar and white collar worker in panels a, b and c; average number of employees in panel d. The sample used for the estimations in panels a, b and c consists of 362,682 observations, and it decreases to 345,589 observations in panel d due to missing values. The regressions include as controls current unemployment rate (ur_{it}), calendar year effects (θ_t) and dummy variables for years of potential experience, (ψ_s), for the region of birth (μ_b), for the region of entry (λ_r), for the year of entry cohort (γ_l). All estimated coefficients are available in Table A4 in the Online Appendix. Standard errors are clustered by region of entry per year of entry. The dashed lines represent the 95% confidence intervals.

Therefore, the above evidence tends to exclude an explanation based on firm and job observable characteristics.

Entry over the business cycle

The estimated positive association between local unemployment rates and entry wages within occupations suggests that negative selection of entrants during recessions is un-

likely.¹⁸ This finding is confirmed by Figure 5, which displays the estimated effect of ur_0 on the percentiles of the log wage distribution for the year of entry and the third, sixth and ninth years of experience. After controlling for the characteristics of the first job and firm, we do not detect negative effects of ur_0 in any portion of the wage distribution.

Moreover, the observed dynamics of age at entry and educational choices along the business cycle are not consistent with the negative selection of entrants during recessions. Negative selection could occur because "high productivity" potential entrants encountering negative macroeconomic conditions could wait for better opportunities, either by accumulating additional years of education or remaining out of the labor force, or because "low productivity" entrants could be forced to anticipate the entry into the labor market if remaining in education became economically unviable. Therefore, if a process of negative selection of entrants was at work during recessions, one should observe that age at entry and the probability of being in education are negatively associated with the unemployment rate.¹⁹

¹⁸The bulk of the previous investigations examining the effect of entry conditions on wage dynamics provide evidence in favor of positive selection of entrants (or absence of negative selection) during negative macroeconomic conditions (Oyer, 2006; Genda et al., 2010; Kahn, 2010; Kwon et al., 2010; Oreopoulos et al., 2012; Brunner and Kuhn, 2014). Finally, Devereux (2002) finds that firms increase their hiring standards during a recession. This firm behavior may be more relevant in the Italian context characterized by strict employment protection and a strong insider-outsider divide.

¹⁹In addition, migration of entrants across regional labor markets may react endogenously to differences in regional unemployment rates and lead to selection mechanisms that may affect our results. In section A.3.2 in the Online Appendix, we show that migration decisions are mainly determined by permanent differences in job opportunities between regions and are not driven by the regional business cycle, and we perform robustness checks.

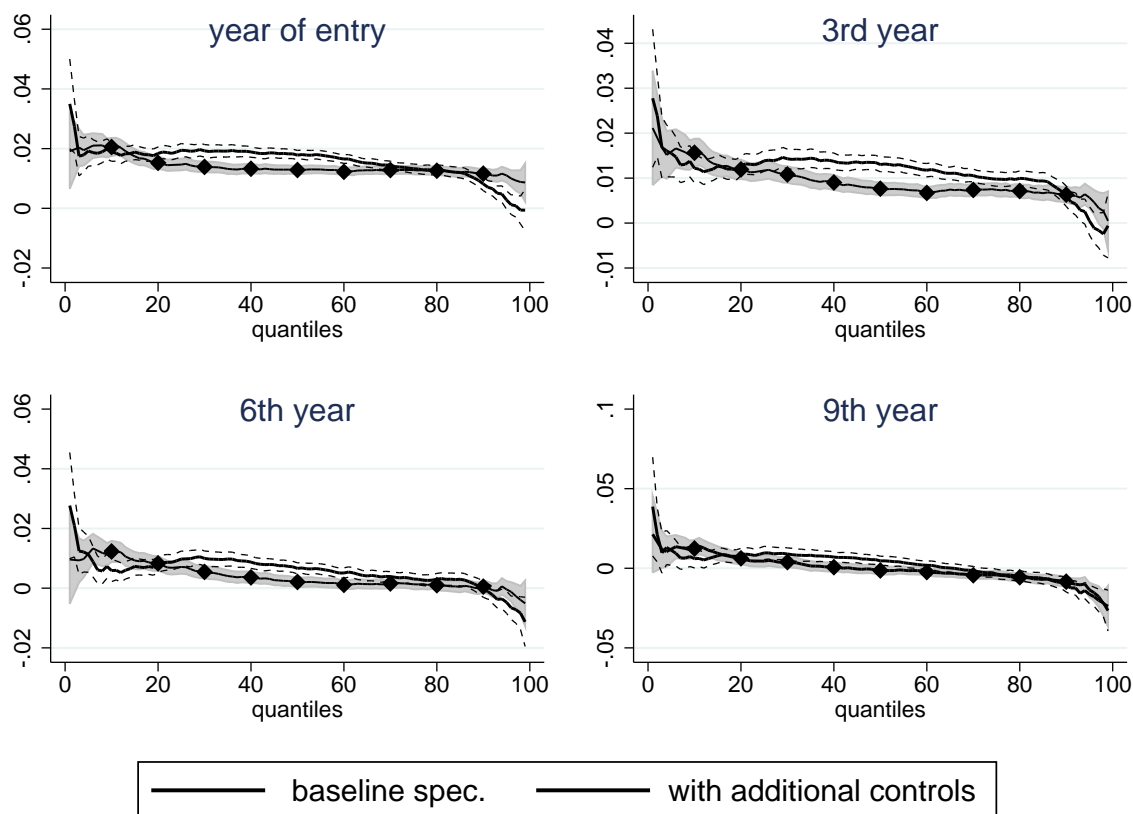


Figure 5: The effect of unemployment rate at entry on the log wage distribution

Note: The figure represents the effect of the unemployment rate at entry (ur_0) on the percentiles of the log wage distribution at the following years of experience: entry year, third year, sixth year and ninth year. The effects correspond to the β_s coefficients retrieved from the estimation with quantile regressions of specification 1. The black solid line represents the estimated effect of ur_0 in the baseline specification, which includes as controls current unemployment rate and dummies for year of entry, region of entry, region of birth, current year and experience. The connected diamonds represent the estimated effects of ur_0 after inclusion in the baseline specification of additional controls for initial firm characteristics (sector, average number of employees and age) and type of occupation (apprentice, blue collar and white collar). The sample in the baseline specification consists of 362,682 observations of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The sample size in the regressions with additional controls decreases to 349,680 due to missing values. The dashed lines and the gray area show the 95% confidence intervals for the baseline specification and the specification with additional controls, respectively.

The results of regressing the age of entry on the regional unemployment rate, region and time dummies are reported in the first column of Table 1. A one percentage point increase in the unemployment rate is associated with an increase of 0.04 years (approximately two weeks) in the average age of entry. Considering that the observed range

of variation of the unemployment rate within regions is, on average, approximately 4 percentage points, the size of the estimated effect is tiny. This positive correlation suggests that cohorts entering the labor market during unfavorable conditions tend to be marginally older and, therefore, it is not consistent with negative selection. Although small, the effect of the unemployment rate on the age at entry may be the result of strategic educational choices.²⁰ However, the effect may simply reflect delayed entry due to unemployment (which is very high in the Italian context, particularly in the South) or non-employment. Since the education level of entrants is not reported in the WHIP database, we tested the correlation between unemployment and educational choices for our specific sample and time frame by exploiting pooled data from the Italian Labor Force Survey. In the second and third columns of Table 1, we report the results of logistic regressions in which the probability of being a high school and university student is modeled as a function of the regional unemployment rate, also conditioning on age, region and year dummies. The probability of attending high school or that of being a university student are not found to be affected by the current economic cycle. This finding suggests that the slightly higher age of entrants detected during economic contractions should be imputed to episodes of unemployment/non-employment before entry rather than to further accumulation of human capital.

²⁰ Actually, high unemployment may exert opposite effects on the decision to remain in education: a higher unemployment probability decreases the opportunity cost of the educational investment; however, at the same time, it decreases the returns to education and the resources of families. The evidence is scant for Italy. Carmeci and Chies (2006), who focus on the decision of further education at the end of compulsory education for the 1993-1999 period, find that the level of unemployment rates do negatively influence the decision to invest in further education, but the annual variation in unemployment has a negligible effect.

Table 1: The effect of labor market conditions on entry decisions

	(1) age_0	(2) High School student	(3) University student
ur_0	0.044*** (0.016)		
ur_t		0.018 (0.034)	-0.006 (0.006)
N	80331	143009	196150
(Pseudo) R^2	0.082	0.103	0.070

Note: The table reports the effect of labor market conditions on the age at entry (age_0 , in column 1) measured using the WHIP-Salute dataset and on indicator variables for being a high school student (column 2) and for being a university student (column 3), measured using the Italian Labor Force Survey on a sample of young workers selected with the criteria explained in section III. All of the regressions include year fixed effects and region fixed effects. The results of column 1 are based on an OLS regression. Columns 2 and 3 report the results of logistic regressions that include age as an additional covariate. ur_0 refers to the unemployment rate of the region of entry in the year of entry. ur_t is the contemporaneous unemployment rate in the region of residence. Standard errors in parentheses are clustered by region per year. Pseudo R^2 measures are provided for logistic regressions in columns 2 and 3. *** significant at 1%, ** significant at 5%, * significant at 10%.

To further study the possibility of positive selection mechanisms, we have used the Survey on Household Income and Wealth (SHIW) from the Bank of Italy. The information available in this dataset on the payment of pension contributions allows us to identify formal and informal workers.²¹ Employment in the underground economy is a possible consequence of recessions that cannot be studied with administrative data but may be a relevant phenomenon in the Italian case. We thus replicate the analyses of section IV with the same sample restrictions explained in section III and using a specification similar to equation 1. The only difference is that, instead of interacting the initial unemployment rate with the experience dummies, here, to diminish the number of estimated parameters,

²¹The exact formulation of the question we use is: “Considering your lifetime work experience, did you ever pay, or your employer pay, pension contributions, even for a short period?” If an individual replies negatively to this question and declares to be employed, it means that she has been working in the underground economy during her entire career (Cappariello and Zizza, 2010).

we posit that the effect of the initial unemployment rate is linear in experience.²²

Table 2: The effect of labor market conditions on pecuniary outcomes. Data from SHIW

sample	log annual earnings		log months worked		log monthly wages		Probability underground
	(1)All	(2) Only formal	(3)All	(4) Only formal	(5)All	(6) Only formal	(7)All
ur_0	0.017 (0.016)	0.041** (0.021)	0.021 (0.016)	0.035** (0.016)	-0.011 (0.019)	0.005 (0.014)	0.032*** (0.012)
$ur_0 \times \text{Exper.}$	-0.003** (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002* (0.001)	-0.001 (0.001)	0.001 (0.001)
N	1278	1135	1262	1128	1262	1128	1278
R^2	0.304	0.284	0.177	0.183	0.215	0.209	0.151

Note: The table reports the effect of unemployment at entry on log annual earnings (columns 1 and 2), log months worked (columns 3 and 4), log monthly wages (columns 5 and 6) and a binary indicator variable for being an informal worker (column 7). All variables are measured from the SHIW dataset on a sample of young workers selected with the criteria explained in section III. Columns 1, 3, 5 and 7 use the entire sample of workers (i.e., formal plus informal), whereas columns 2, 4 and 6 use only the formal ones. The results are obtained from OLS regressions of the specification: $y_{it} = \alpha + \psi \text{Experience}_{it} + \delta ur_{i0} + \beta ur_{i0} \times \text{Experience}_{it} + \phi ur_{it} + \mu_b + \lambda_r + \gamma_l + \theta_t + u_{it}$. In contrast to the specification of equation 1, we use continuous experience and the effect of ur_0 is linear in experience. All remaining controls are equal to those in the baseline specification used in Figures 2 and 3. Standard errors in parentheses are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

As shown in column 7 of Table 2, where the dependent variable is an indicator variable for working in the underground economy, a percentage point increase in the unemployment rate at entry is associated with an increment of approximately 3 percentage points in the probability of being employed in an informal job. This effect is persistent over time, and it is economically relevant.²³ Restricting the analysis only to formal workers (i.e.,

²²Considering the lower number of observations and that we are using survey data, the precision of the estimates should be lower than those obtained by using the WHIP-Salute database. In the SHIW dataset, information on the number of weeks worked in a year is not available.

²³Indeed, the observed probability to hold a job in the underground economy is approximately 11 percent. This countercyclicality of the underground economy is consistent with the results of Orsi et al. (2014).

with paid pension contributions), we find a significant positive effect of unemployment at entry on log annual earnings and on log of months worked and a positive effect (although not statistically significant) on log monthly wages (see columns 2, 4 and 6 in Table 2, respectively). These results are consistent with those found in the administrative WHIP-Salute dataset.²⁴ In contrast, when retaining all workers (formal and informal jobs; in columns 1, 3 and 5) in the sample, we do not find statistically significant effects of unemployment at entry on log of weeks worked and log of annual earnings, and the estimated effect on log of monthly wages becomes negative (although not statistically significant). In the segmented labor market theory, workers enter the informal sector because they are rationed out of the formal sector as a result of an overly regulated labor market. In the formal sector, wages are relatively higher because they are set above market-clearing prices due to minimum wages. According to the SHIW dataset, (after controlling for experience, region of entry, year of entry into the labor market, current year and current unemployment rate) the monthly wage of workers employed in the underground economy is approximately 24% lower with respect to that of formal workers.²⁵ Hence, the positive effect of the unemployment rate at entry on pecuniary outcomes detected in the WHIP-Salute dataset could be due, at least in part, to this countercyclical pattern of the underground economy.

If positive selection based on unobserved ability was the only explanation behind our results, the observed increase in average wages for entrants during a recession would be

²⁴The size and the statistical significance of the estimated effects decrease as workers accumulate labor market experience.

²⁵All of the estimated effects remain stable once we also control for all the available firm (size and the sector) and worker (level of education, age at entry, type of occupation and family wealth) characteristics.

most likely accompanied by a corresponding decrease in average injury risk. However, the observed increase in workplace accidents, together with the anticyclical pattern of selection into the underground economy, may be explained by the endogenous changes in wage offers curves and in entrants' attitudes toward risk outlined in Figure 1. Unfortunately, the coexistence of several sources of unobserved firms' and entrants' heterogeneity do not allow us to disentangle the compositional effects due to the positive selection from changes in market opportunities and preferences (Rosen, 1974).

Effect on workers' mobility and tenure

Workers' mobility may help explain what drives the increase in injuries and whether such dynamics are consistent with existing theoretical models. We investigate whether entrants during recessions search more intensively (consistent with job-search models) and accumulate lower experience or tenure. Figure 6 displays the estimated effect of unemployment at entry on entrants' mobility (i.e., binary indicators for being in the entry firm, panel a; being in a firm different from that of the previous year, panel b; being out of the WHIP-Salute sample, panel d; and years of tenure in the current firm, panel c) using the same specification of equation (1) and using data from the second year of potential experience onward.²⁶ Entrants do not exhibit a higher probability of leaving the initial firm (panel a) and are not more likely to change firms as time goes by (panel b).²⁷

²⁶During the year of entry, the analyzed outcomes are the same for all workers.

²⁷Given the nature of the data, the non-employment status may hide a transition to jobs in the public administration or to self-employment, which are not entirely covered by INPS administrative archives. However, for a young low- and medium-skilled male, these outcomes were negligible in those years.



Figure 6: The effect of unemployment rate at entry on labor market transitions

Note: The solid line in the figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e. the parameters β_s in equation 1) on the following dependent variables: binary indicators for being in the entry firm (panel a) and being in a firm different from that of the previous year (panel b), tenure measured as the number of years in the current firm (panel c), and non-employment status (i.e., a binary indicator for being out from the WHIP-Salute sample during the current post-entry year) (panel d). The sample uses data from the second year of potential experience onward for our sample of entrants (282,351 observations for panels a, b and c; 373,847 observations for panel d, as the dependent variable is defined also for years in which the workers are not observed in the sample). These OLS regressions include as controls the current unemployment rate (ur_{it}), calendar year effects (θ_t) and dummy variables for years of potential experience, (ψ_s), for the region of birth (μ_b), for the region of entry (λ_r), and for the year of entry cohort (γ_l). All estimated coefficients are available in Table A7 in the Online Appendix. Robust standard errors in parentheses are clustered by region of entry per year of entry. The dashed lines represent the 95% confidence intervals.

These findings are in sharp contrast with the evidence for less rigid labor markets where between-firm mobility is a key ingredient for the catch-up process, particularly in the short-medium run (see for example Oreopoulos et al., 2012). Indeed, the dynamics shown in panel (c) display very tiny negative effects on tenure (lower for entrants in recessions) only in the long run. Panel (d) shows that entrants during a recession have a lower probability of being non-employed. This higher attachment to the labor market,

coupled with the estimated initial wage premium and the evidence of the previous section, opposes an explanation of the losses based on the lower productivity of workers entering during a recession.

Given that we do not detect a lower accumulation of tenure or experience for entrants during recessions, our findings could, at least in part, be rationalized with the human capital mechanisms proposed by Gibbons and Waldman (2006) who suggest that, if entrants are assigned to low-quality tasks, initial conditions may have persistent effects by decreasing worker productivity. Moreover, as suggested by Oreopoulos et al. (2012), the recovery from unfavorable initial conditions may be hampered by the accumulation of specific human capital, which increases the opportunity cost to change jobs. In the Italian context, these mechanisms may be reinforced, as accumulating human capital is not merely accumulating knowledge for labor market entrants but is also an investment to become insiders. This could explain why, in contrast to other countries, during unfavorable conditions, entrants do not display a higher search intensity and do not catch-up as time passes. With respect to labor markets that are characterized by less rigid institutional settings, entrants' incentives to search for "better" jobs may be comparatively lower.

This interpretation is also supported by the estimates from a specification where the effects of experience and of initial conditions are allowed to vary for employees working in a firm that is different from the entry firm, defined as movers, with respect to stayers.²⁸

²⁸We use the same specification of equation 1 plus the following interactions for $s > 0$: $\mathbf{1}[Exp_{it} = s] \times ur_{i0} \times mover_{it}$, $\mathbf{1}[Exp_{it} = s] \times mover_{it}$, where $mover_{it}$ is an indicator variable for working in a firm that is different from the entry firm.

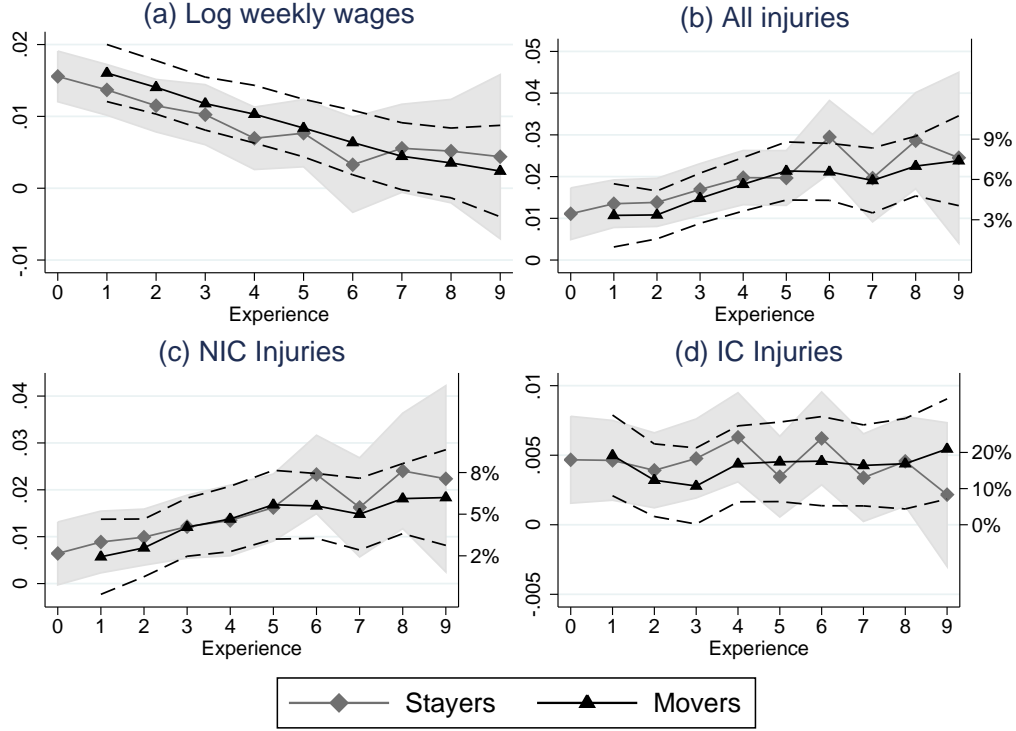


Figure 7: The effect of unemployment at entry for stayers and movers

Note: The figure reports the estimated effect of unemployment at entry (ur_0) for stayers and movers on log weekly wages (panel a), all injuries (panel b), non-immediate care injuries (NIC in panel c), and immediate care injuries (IC in panel d). Stayers are the individuals who remain with the first employer. Movers are those individuals working in a firm that is different from the first employer. The right vertical axis expresses these effects as a percentage of the sample mean of the corresponding dependent variable. Connected diamonds represent the estimated effects of ur_0 by year of experience for stayers (i.e., the parameters β_s in equation 1 where stayers are the omitted category). Connected triangles represent the estimated effects for movers. The latter are estimated as the effect of unemployment at entry (i.e., the estimated effect, β_s , for the omitted category, stayers) plus the coefficient of an additional interaction term, $\mathbf{1}[Exp_{it} = s] \times ur_{i0} \times mover_{it}$, included in equation 1. By construction, an individual can be a mover only after the year of entry (i.e., from year 1 onward). The regressions use the same sample of the baseline specification of Figure 2 and include the following as controls: the current unemployment rate; dummy variables for calendar year, years of potential experience, region of birth, the region of entry and year of entry cohort; and the interactions $\mathbf{1}[Exp_{it} = s] \times mover_{it}$, for $s > 0$. The gray area and the dashed lines represent the 95% confidence intervals for stayers and movers, respectively. Robust standard errors are clustered by region of entry per year of entry. All estimated coefficients are available in Table A8 in the Online Appendix.

We find that movers have a relatively lower wage growth and a lower decrease in injuries with experience.²⁹ The worst evolution of movers' careers could, at least in part, be explained by lay-offs of less productive workers. Nevertheless, further considering

²⁹The detailed estimation results can be found in Table A8 in the Online Appendix.

that the estimated effect of initial labor market conditions is the same for movers and for stayers (as shown in Figure 7), our findings indicate that, on average, changes in employer are not associated with better labor market outcomes also for workers who begin with unfavorable conditions. To explain these patterns alone, job-search models and human capital models should feature prohibitive mobility costs and/or no benefits associated with job search.

V Conclusions

Our results clearly identify a category of workers at higher risk of injuries during recessions. Moreover, similar to what was found by other studies analyzing differences in injuries between temporary and permanent workers (Guadalupe, 2003, Picchio and Van Ours, 2017), the observed different reporting behavior for severe and less severe accidents suggests that entrants during unfavorable macroeconomic conditions have a weak bargaining position that may lead them to underreport injuries. Therefore, authorities could improve injury prevention effectiveness by directing more controls to entrants and calibrating audits according to the business cycle. Our findings also indicate that the negative and persistent effects of unemployment at entry on job safety may depend on the institutional setting and on the rigidities of the Italian labor market. A centralized wage setting system, although decreasing differences in monetary remunerations among different cohorts of workers, cannot prevent the transmission of shocks to other job characteristics, particularly if these amenities are less easily measured and are less subject to

bargaining and monitoring than pecuniary outcomes.

Transitions to more hazardous tasks during recessions do not necessarily entail the creation of new risks; however, they may induce a more unequal distribution of risk between different cohorts of entrants and, generally, between incumbent workers and young outsiders. A redistribution of hazardous tasks towards young workers implies that injuries will be more likely to occur at earlier stages of a career, thus exerting their negative effect over a longer period. This non-pecuniary adjustment mechanism, although enhancing flexibility at entry, may entail sizeable indirect/uninsured and human costs associated with permanent reductions in entrant's health, human capital accumulation and productivity (De Greef et al., 2011). Thus, labor market reforms that target diminishing the dualism between incumbent workers and new entrants (such as the recent changes introduced by the so-called Job Act of the Italian government, Legislative Decree No. 23/2015) and the rigidities in the wage-setting mechanisms may contribute to reducing long-lasting disparities among different cohorts of workers.

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A Online Appendix for “ Macroeconomic Conditions at Entry and Injury Risk at the Workplace” (not intended for publication)

Roberto Leombruni

University of Turin, IT-10136, Torino, Italy

roberto.leombruni@unito.it

Tiziano Razzolini

University of Siena, IT-53100, Siena, Italy

tiziano.razzolini@unisi.it

Francesco Serti

IMT School of Advances Studies, IT-55100, Lucca and University of Alicante, ES-03690

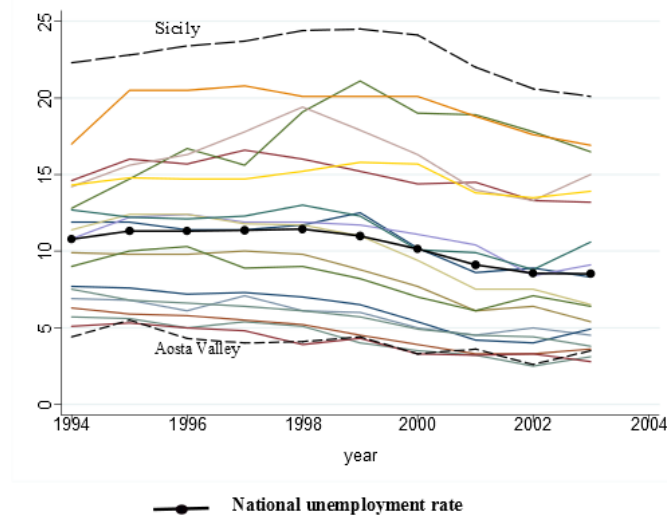
francesco.serti@gmail.com

This appendix contains descriptive statistics, tables reporting the estimated parameters corresponding to the results shown only graphically in the paper and additional robustness checks. The data used in the analyses, unless otherwise stated, comes from the WHIP-Salute database.

A.1 Descriptive Statistics

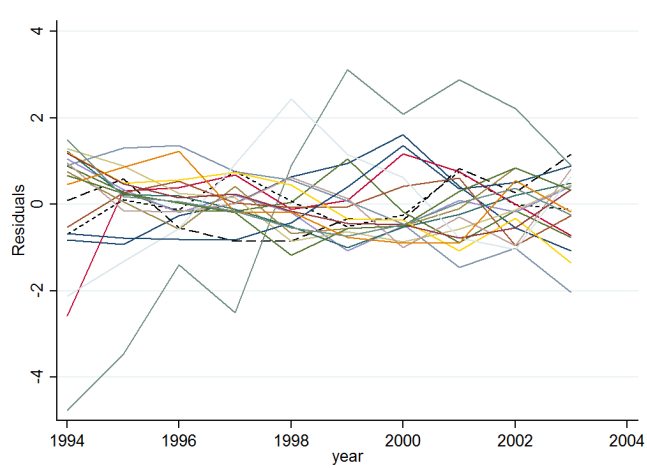
Figure A1 below depicts the national and regional unemployment rates over the 1994-2003 period. Figure A2 demonstrates that after washing out the national trend and the time-constant regional heterogeneity, significant cyclical differences across regions persist: this source of variation is used to identify the effects of local business cycle fluctuations.

Figure A1: National and regional unemployment rates, 1994-2003.



Source: ISTAT.

Figure A2: Residual unemployment rates, 1994-2003.



Note: The lines represent the region-specific residuals from a regression of regional unemployment rate on year and region dummies. Source: ISTAT.

Table A1 includes some descriptive statistics for our sample of workers by year of entry. The mean age at entry exhibits a slight increasing trend. The percentage of new entrants' manufacturing jobs follows a negative trend which is accompanied by a stable

increase of the proportion of entrants in the service sector.

The share of workers starting their careers as apprentices³⁰ and blue collar workers is quite stable at around 88%. However, the categorization of blue versus white collars is likely to conceal a significant amount of heterogeneity in terms of task assignment. The proportion of entrants born in the North of Italy exhibits a negative trend, whereas the percentage of workers born in the South and in the islands increases over time. However, more jobs for new entrants are created in the North, consistent with the historical economic duality between the richer North and the less developed Southern part of the country. It is also interesting to note that the proportion of entrants in the Northern regions is higher during the years of increasing unemployment and decreases during the post-1998 recovery period when the proportion of jobs created in the Southern regions increases. Moreover, the difference between the proportion of entrants in the Southern/(Northern) labor markets and the proportion of entrants born in the South/(North) is always negative/(positive). This evidence points to the relevance of mobility from the disadvantaged Southern regions toward the richer Northern part of the country. Table A1 also describes the means of the main labor outcomes analyzed in the paper. The number of injuries has been divided by the number of full time equivalent paid weeks in order to take into account the exposure to risk. We report these variables as the number of injuries per thousand days worked to improve the readability of the estimates (i.e., to reduce the number of decimals). Interestingly, there is a clear increase of both IC and

³⁰Apprenticeship is a form of temporary employment contract for workers under age 26 (i.e., the maximum duration is three years). The firm is obliged to provide certified training and is compensated by incurring lower social security contributions.

NIC injuries in those years characterized by higher unemployment rates. Entry wages seem to follow a similar dynamics, as they are positively correlated with unemployment rates.

Table A1: Descriptive statistics for entrants in the year of entry

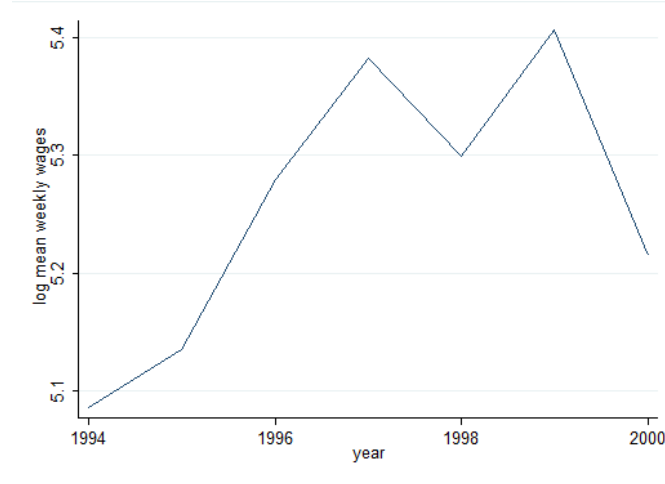
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Total
age	18.95	19.12	19.36	19.42	19.50	19.59	19.66	19.57	19.49	19.50	19.41
enter in manufact.	0.613	0.630	0.583	0.519	0.527	0.480	0.452	0.408	0.386	0.367	0.502
enter in services	0.387	0.370	0.417	0.481	0.473	0.520	0.548	0.592	0.614	0.633	0.498
blue collar & apprent.	0.885	0.887	0.875	0.885	0.889	0.891	0.883	0.869	0.879	0.878	0.882
born in North	0.479	0.477	0.443	0.435	0.432	0.397	0.378	0.352	0.356	0.343	0.412
enter in North	0.491	0.510	0.476	0.476	0.480	0.439	0.425	0.394	0.394	0.376	0.449
born in Center	0.251	0.235	0.228	0.234	0.237	0.224	0.227	0.228	0.218	0.218	0.230
enter in Center	0.274	0.267	0.270	0.271	0.272	0.265	0.271	0.275	0.262	0.258	0.269
born in South and Isl.	0.270	0.288	0.329	0.331	0.331	0.379	0.395	0.420	0.426	0.439	0.358
enter in South and Isl.	0.235	0.222	0.254	0.252	0.248	0.295	0.304	0.331	0.344	0.366	0.282
All injuries	0.372	0.445	0.365	0.428	0.469	0.416	0.351	0.310	0.280	0.246	0.372
NIC injuries	0.334	0.390	0.315	0.379	0.427	0.374	0.333	0.284	0.259	0.239	0.337
IC injuries	0.0375	0.0542	0.0505	0.0487	0.0416	0.0421	0.0184	0.0256	0.0207	0.00691	0.0355
log wage	5.301	5.295	5.303	5.316	5.317	5.323	5.303	5.295	5.288	5.270	5.302
number of entrants	7907	9397	8050	8089	8018	8298	8792	7864	7238	6678	80331

Note: The table reports the average values for the year of entry of the following variables: age, log wage, injuries at the individual level, dummy indicators for individuals born (or entering the labor market) in North, Center and South and Islands, dummy indicators for entering in manufacturing and in services, and a dummy indicator for being an apprentice or a blue-collar. The last row contains the number of entrants during each year. All injuries refers to the number of injuries per thousands days worked for any type of workplace accidents. IC and NIC injuries refer to the same measure for Immediate Care injuries and Non-Immediate Care injuries, respectively. The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003 and were under 24 years old at the time of entry.

A similar trend in entry wages is also evident for a comparable sample of workers selected from the European Consumption Household Panel (ECHP) in the 1994-2000 period (see Figure A3). However, workers entered during the last years of recession (i.e., 1997-99) seem to experience slower wage growth rates than the other cohorts even though

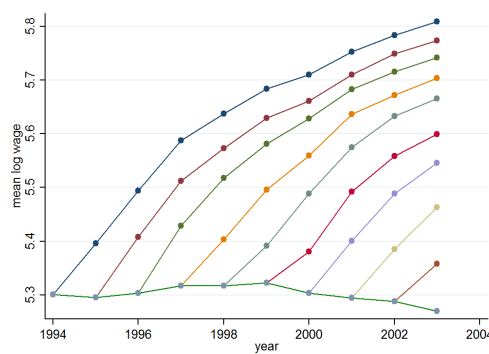
they started at the highest levels of entry wages (see Figure A4 based on WHIP data).

Figure A3: Mean log entry wages, ECHP



Note: This figure shows the mean log wages in the year of entry for different cohorts in the period 1994-2000. The sample includes entrants who respect the selection criteria described in the note of Table A1. The weekly wages are computed dividing the real gross monthly salary earnings by the notional number of weeks in a month. The weekly wages are reported on a full time equivalent scale using the information about the amount of hours worked in a week. Source: Authors' computation from European Community Household Panel (ECHP) data.

Figure A4: Log mean wage by year of experience for different cohorts of entrants

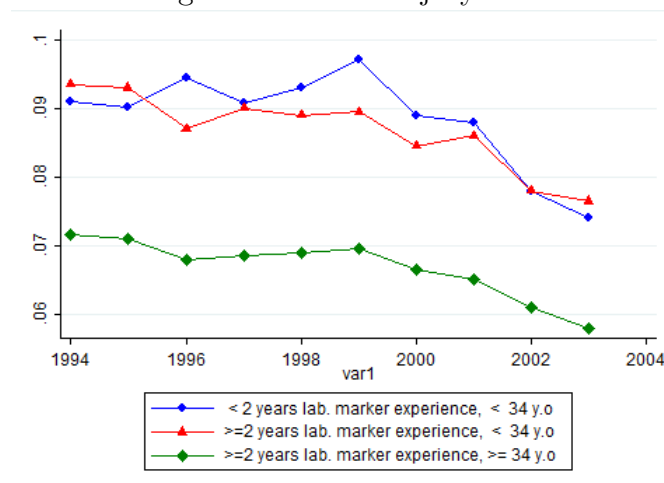


Note: This figure shows the mean log wages by year of experience for cohorts or workers entered in different years. The bottom green line represents mean log wage in the year of entry. The sample follows the selection criteria described in the note of Table A1

To provide descriptive evidence on the relation between workplace safety and unemployment rates we have computed the mean injury risk computed as the number of all injuries divided by the aggregate number of weeks worked in a year, for three categories of workers in the 1994-2003 period. Figure A5 shows that workers younger than 34 years

with less than 2 years of labor market experience exhibit an increase in injury risk during the years characterized by higher unemployment rates. The mean injury risk of workers with more than two years of labor market experience either above or below than 34 years seems not to react to movements of the unemployment rate and decreases over time. This evidence is consistent with the dualism between entrants and incumbents characterizing the Italian institutional setting (described in the main paper), as it suggests that insiders are relatively more sheltered against macroeconomic shocks and the burden of adjustment is borne by entrants.

Figure A5: Mean injury risk



Note: The lines represent the year-specific mean injury risk for three categories of workers. The blue line represents the mean injury risk for workers with less than 2 years of labor market experience and less than 34 years old. The red line represents the mean injury risk for worker with two or more years of labor market experience and less than 34 years old. The green line represents the mean injury risk for worker with two or more years of labor market experience and more than 34 years old.

A.2 Detailed Estimation Results

This section displays the detailed estimates of the effects of the initial unemployment rate (ur_{i0}) shown graphically in sections IV - IV, together with the estimated parameters associated with the current unemployment rate (ur_{it}) and the experience dummies.

Table A2: The effect of experience and unemployment rates on pecuniary outcomes

	(1)	(2)	(3)	(4)
	ln(wage)	ln(wage index)	ln(earnings)	ln(weeks worked)
$\mathbf{1}[Exp_{it} = 1]$	0.106*** (0.008)	0.005 (0.006)	0.860*** (0.016)	0.754*** (0.012)
$\mathbf{1}[Exp_{it} = 2]$	0.222*** (0.013)	0.030*** (0.010)	1.038*** (0.027)	0.816*** (0.018)
$\mathbf{1}[Exp_{it} = 3]$	0.316*** (0.018)	0.080*** (0.014)	1.256*** (0.039)	0.939*** (0.026)
$\mathbf{1}[Exp_{it} = 4]$	0.401*** (0.024)	0.131*** (0.019)	1.409*** (0.053)	1.008*** (0.036)
$\mathbf{1}[Exp_{it} = 5]$	0.468*** (0.029)	0.170*** (0.023)	1.558*** (0.066)	1.090*** (0.044)
$\mathbf{1}[Exp_{it} = 6]$	0.536*** (0.035)	0.196*** (0.028)	1.687*** (0.081)	1.152*** (0.053)
$\mathbf{1}[Exp_{it} = 7]$	0.592*** (0.039)	0.217*** (0.033)	1.761*** (0.091)	1.169*** (0.059)
$\mathbf{1}[Exp_{it} = 8]$	0.644*** (0.046)	0.239*** (0.039)	1.824*** (0.106)	1.180*** (0.068)
$\mathbf{1}[Exp_{it} = 9]$	0.697*** (0.055)	0.252*** (0.047)	1.863*** (0.122)	1.167*** (0.074)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.016*** (0.002)	0.012*** (0.001)	0.033*** (0.004)	0.017*** (0.003)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.015*** (0.002)	0.012*** (0.001)	0.025*** (0.004)	0.011*** (0.003)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.013*** (0.002)	0.012*** (0.001)	0.024*** (0.005)	0.011*** (0.003)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.011*** (0.002)	0.011*** (0.002)	0.017*** (0.005)	0.006* (0.003)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.010*** (0.002)	0.009*** (0.002)	0.013*** (0.005)	0.003 (0.003)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.008*** (0.002)	0.008*** (0.002)	0.009* (0.005)	0.001 (0.004)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.006** (0.002)	0.007*** (0.002)	0.005 (0.005)	-0.001 (0.004)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.004* (0.002)	0.006*** (0.002)	0.005 (0.006)	0.001 (0.004)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.003 (0.003)	0.006** (0.002)	0.005 (0.005)	0.001 (0.004)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.002 (0.003)	0.006** (0.003)	0.005 (0.006)	0.003 (0.004)
ur_{it}	-0.008*** (0.001)	-0.007*** (0.000)	-0.008*** (0.002)	0.000 (0.002)
N	362682	362682	362682	362682
R^2	0.163	0.159	0.290	0.236

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 2 of the paper) on the following dependent variables: log weekly wages (column 1); log wage index (column 2); log annual earnings (column 3); log annual weeks worked (column 4). The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry and the year of entry cohort. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A3: The effect of experience and unemployment rates on injuries

	Individual Injuries			Injury incidence rates		
	(1) All Injuries	(2) IC injuries	(3) NIC Injuries	(4) All injuries	(5) IC injuries	(6) NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	-0.0481* (0.0256)	-0.0210** (0.0100)	-0.0271 (0.0240)	-0.1493* (0.0873)	0.0264** (0.0121)	-0.1757** (0.0776)
$\mathbf{1}[Exp_{it} = 2]$	-0.0722*** (0.0271)	-0.0174 (0.0108)	-0.0548** (0.0242)	-0.4190** (0.1721)	0.0217 (0.0218)	-0.4406*** (0.1540)
$\mathbf{1}[Exp_{it} = 3]$	-0.1112*** (0.0397)	-0.0219 (0.0133)	-0.0893** (0.0352)	-0.8575*** (0.2470)	-0.0210 (0.0311)	-0.8366*** (0.2213)
$\mathbf{1}[Exp_{it} = 4]$	-0.1682*** (0.0459)	-0.0491*** (0.0151)	-0.1191*** (0.0411)	-1.2912*** (0.3263)	-0.0667* (0.0402)	-1.2246*** (0.2928)
$\mathbf{1}[Exp_{it} = 5]$	-0.1808*** (0.0540)	-0.0507*** (0.0180)	-0.1301*** (0.0474)	-1.6352*** (0.4126)	-0.1018** (0.0508)	-1.5334*** (0.3701)
$\mathbf{1}[Exp_{it} = 6]$	-0.1938*** (0.0605)	-0.0613*** (0.0207)	-0.1325** (0.0522)	-1.9416*** (0.4785)	-0.1370** (0.0588)	-1.8046*** (0.4293)
$\mathbf{1}[Exp_{it} = 7]$	-0.1996*** (0.0728)	-0.0661*** (0.0230)	-0.1335** (0.0645)	-2.0381*** (0.5532)	-0.1525** (0.0695)	-1.8855*** (0.4947)
$\mathbf{1}[Exp_{it} = 8]$	-0.2434*** (0.0799)	-0.0721*** (0.0265)	-0.1713** (0.0699)	-2.2935*** (0.6209)	-0.1834** (0.0805)	-2.1101*** (0.5544)
$\mathbf{1}[Exp_{it} = 9]$	-0.2514*** (0.0906)	-0.0857*** (0.0253)	-0.1657** (0.0821)	-2.7056*** (0.7722)	-0.2239** (0.0933)	-2.4817*** (0.6907)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0112*** (0.0032)	0.0047*** (0.0016)	0.0065* (0.0034)	0.1119*** (0.0251)	0.0124*** (0.0033)	0.0996*** (0.0225)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0123*** (0.0029)	0.0048*** (0.0014)	0.0075** (0.0033)	0.1215*** (0.0250)	0.0113*** (0.0034)	0.1102*** (0.0223)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0120*** (0.0027)	0.0035*** (0.0013)	0.0085*** (0.0029)	0.1326*** (0.0254)	0.0115*** (0.0035)	0.1211*** (0.0225)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0154*** (0.0029)	0.0034** (0.0014)	0.0121*** (0.0031)	0.1524*** (0.0263)	0.0139*** (0.0035)	0.1386*** (0.0233)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0186*** (0.0031)	0.0048*** (0.0014)	0.0138*** (0.0034)	0.1745*** (0.0273)	0.0164*** (0.0036)	0.1580*** (0.0243)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0214*** (0.0034)	0.0044*** (0.0014)	0.0170*** (0.0036)	0.1919*** (0.0295)	0.0185*** (0.0038)	0.1733*** (0.0264)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.0224*** (0.0035)	0.0048*** (0.0016)	0.0176*** (0.0035)	0.2032*** (0.0290)	0.0198*** (0.0039)	0.1834*** (0.0259)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.0193*** (0.0040)	0.0042*** (0.0015)	0.0151*** (0.0040)	0.1980*** (0.0298)	0.0199*** (0.0042)	0.1781*** (0.0263)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.0233*** (0.0034)	0.0045*** (0.0016)	0.0188*** (0.0036)	0.1992*** (0.0316)	0.0198*** (0.0043)	0.1794*** (0.0281)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.0241*** (0.0058)	0.0052*** (0.0019)	0.0189*** (0.0055)	0.2300*** (0.0481)	0.0229*** (0.0062)	0.2070*** (0.0425)
ur_{it}	-0.0166*** (0.0018)	-0.0006 (0.0004)	-0.0160*** (0.0018)	-0.2823*** (0.0155)	-0.0044*** (0.0016)	-0.2780*** (0.0141)
N	362682	362682	362682	349379	349379	349379
R^2	0.003	0.000	0.003	0.146	0.083	0.157

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 3 of the paper) on two types of dependent variables calculated for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC): I) injuries measured at the individual level (as the number of injuries per thousand days worked); II) Injury incidence rates (computed using workers over 34 years old in cells defined using occupation, sector and region). The sample used and the additional regressors included as controls are the same of Table A2. Due to cells missing values the number of observations used for incidence rates is lower. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A4: The effect of experience and unemployment rates on job and firm characteristics

	(1)	(2)	(3)	(4)	(5)
	Apprentice	Blue collar	White collar	Aver. numb. of employees	Year of firm birth
$\mathbf{1}[Exp_{it} = 1]$	-0.0103 (0.0103)	-0.0072 (0.0096)	0.0180*** (0.0057)	-491.1111*** (122.0646)	-0.6851*** (0.1772)
$\mathbf{1}[Exp_{it} = 2]$	-0.0598*** (0.0203)	0.0140 (0.0185)	0.0467*** (0.0114)	-652.4799*** (212.3137)	-1.2554*** (0.3439)
$\mathbf{1}[Exp_{it} = 3]$	-0.1767*** (0.0294)	0.0950*** (0.0272)	0.0830*** (0.0165)	-627.2470** (282.5111)	-1.8567*** (0.4954)
$\mathbf{1}[Exp_{it} = 4]$	-0.2939*** (0.0392)	0.1788*** (0.0368)	0.1165*** (0.0217)	-601.0239 (368.5376)	-2.3321*** (0.6595)
$\mathbf{1}[Exp_{it} = 5]$	-0.3787*** (0.0479)	0.2430*** (0.0449)	0.1366*** (0.0273)	-636.5541 (458.9337)	-2.9501*** (0.8189)
$\mathbf{1}[Exp_{it} = 6]$	-0.4311*** (0.0572)	0.2686*** (0.0535)	0.1636*** (0.0322)	-689.9521 (546.7727)	-3.7899*** (0.9621)
$\mathbf{1}[Exp_{it} = 7]$	-0.4765*** (0.0664)	0.3051*** (0.0621)	0.1712*** (0.0383)	-627.2085 (653.4127)	-4.1091*** (1.1817)
$\mathbf{1}[Exp_{it} = 8]$	-0.5166*** (0.0800)	0.3273*** (0.0725)	0.1880*** (0.0443)	-561.3404 (758.3805)	-4.3434*** (1.3470)
$\mathbf{1}[Exp_{it} = 9]$	-0.5382*** (0.1060)	0.3158*** (0.0805)	0.2187*** (0.0575)	-371.1938 (824.4677)	-4.6681*** (1.5256)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	-0.0212*** (0.0024)	0.0211*** (0.0022)	0.0001 (0.0013)	-20.2449 (32.8142)	-0.0274 (0.0507)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	-0.0205*** (0.0023)	0.0207*** (0.0021)	-0.0002 (0.0013)	12.9736 (32.9913)	-0.0277 (0.0500)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	-0.0196*** (0.0022)	0.0208*** (0.0021)	-0.0011 (0.0013)	28.8675 (32.5239)	-0.0379 (0.0499)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	-0.0164*** (0.0023)	0.0189*** (0.0021)	-0.0024* (0.0014)	34.4513 (33.0310)	-0.0266 (0.0488)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	-0.0131*** (0.0024)	0.0173*** (0.0022)	-0.0040*** (0.0014)	41.4381 (32.3806)	-0.0217 (0.0506)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	-0.0108*** (0.0025)	0.0157*** (0.0023)	-0.0047*** (0.0014)	46.3484 (35.2471)	-0.0046 (0.0524)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	-0.0093*** (0.0028)	0.0157*** (0.0025)	-0.0063*** (0.0015)	54.0599 (35.9684)	0.0389 (0.0515)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	-0.0078** (0.0031)	0.0140*** (0.0030)	-0.0060*** (0.0015)	47.0341 (36.3415)	0.0342 (0.0546)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	-0.0070** (0.0034)	0.0138*** (0.0032)	-0.0065*** (0.0015)	50.8119 (34.7873)	0.0302 (0.0576)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	-0.0073* (0.0039)	0.0163*** (0.0029)	-0.0085*** (0.0023)	58.9073 (37.2060)	0.0384 (0.0667)
ur_{it}	-0.0006 (0.0008)	-0.0014 (0.0009)	0.0020*** (0.0005)	-40.4455*** (12.1242)	0.1726*** (0.0221)
N	362682	362682	362682	345849	346105
R^2	0.125	0.069	0.034	0.013	0.056

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 4 of the paper) on the following dependent variables related to the first job or employer: binary indicators for apprentice(column 1), blue collar (column 2) and a white collar workers (column 3); average number of employees in panel d (column 4), year of firm birth (column 5). The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry and the year of entry cohort. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A5: The effect of experience and unemployment rates on pecuniary outcomes; with additional controls (sector, type of occupation, and firms' size and age)

	(1) ln(wage)	(2) ln(wage index)	(3) ln(earnings)	(4) ln(weeks worked)
$\mathbf{1} [Exp_{it} = 1]$	0.104*** (0.011)	0.010* (0.005)	0.858*** (0.020)	0.755*** (0.014)
$\mathbf{1} [Exp_{it} = 2]$	0.221*** (0.021)	0.041*** (0.009)	1.041*** (0.036)	0.820*** (0.024)
$\mathbf{1} [Exp_{it} = 3]$	0.313*** (0.031)	0.096*** (0.013)	1.262*** (0.054)	0.948*** (0.036)
$\mathbf{1} [Exp_{it} = 4]$	0.400*** (0.041)	0.152*** (0.018)	1.423*** (0.072)	1.023*** (0.049)
$\mathbf{1} [Exp_{it} = 5]$	0.466*** (0.051)	0.195*** (0.022)	1.575*** (0.091)	1.109*** (0.059)
$\mathbf{1} [Exp_{it} = 6]$	0.533*** (0.062)	0.224*** (0.026)	1.713*** (0.109)	1.180*** (0.073)
$\mathbf{1} [Exp_{it} = 7]$	0.589*** (0.070)	0.252*** (0.030)	1.796*** (0.123)	1.207*** (0.084)
$\mathbf{1} [Exp_{it} = 8]$	0.642*** (0.082)	0.281*** (0.034)	1.865*** (0.141)	1.223*** (0.096)
$\mathbf{1} [Exp_{it} = 9]$	0.693*** (0.094)	0.300*** (0.040)	1.908*** (0.164)	1.215*** (0.106)
$\mathbf{1} [Exp_{it} = 0] \times ur_{i0}$	0.014*** (0.002)	0.007*** (0.001)	0.029*** (0.004)	0.015*** (0.003)
$\mathbf{1} [Exp_{it} = 1] \times ur_{i0}$	0.013*** (0.002)	0.008*** (0.001)	0.021*** (0.004)	0.008*** (0.003)
$\mathbf{1} [Exp_{it} = 2] \times ur_{i0}$	0.011*** (0.002)	0.007*** (0.001)	0.020*** (0.004)	0.008*** (0.003)
$\mathbf{1} [Exp_{it} = 3] \times ur_{i0}$	0.010*** (0.002)	0.006*** (0.001)	0.013*** (0.004)	0.004 (0.003)
$\mathbf{1} [Exp_{it} = 4] \times ur_{i0}$	0.008*** (0.002)	0.005*** (0.001)	0.009** (0.004)	0.001 (0.003)
$\mathbf{1} [Exp_{it} = 5] \times ur_{i0}$	0.007*** (0.002)	0.004*** (0.001)	0.006 (0.004)	-0.001 (0.003)
$\mathbf{1} [Exp_{it} = 6] \times ur_{i0}$	0.004* (0.002)	0.004** (0.001)	0.002 (0.005)	-0.003 (0.003)
$\mathbf{1} [Exp_{it} = 7] \times ur_{i0}$	0.003 (0.002)	0.003* (0.002)	0.001 (0.005)	-0.001 (0.004)
$\mathbf{1} [Exp_{it} = 8] \times ur_{i0}$	0.002 (0.002)	0.002 (0.002)	0.001 (0.005)	-0.001 (0.004)
$\mathbf{1} [Exp_{it} = 0] \times ur_{i0}$	0.001 (0.003)	0.002 (0.002)	0.001 (0.005)	0.001 (0.004)
ur_{it}	-0.009*** (0.000)	-0.008*** (0.000)	-0.010*** (0.002)	-0.001 (0.002)
N	349680	349680	349680	349680
R^2	0.271	0.520	0.343	0.263

Note: The Table reports the estimated effects of experience ($\mathbf{1} [Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1} [Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 2 of the paper) on the following dependent variables: log weekly wages (column 1); log wage index (column 2); log annual earnings (column 3); log annual weeks worked (column 4). The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. Besides including the controls of the baseline specification (dummy variables for calendar year, the region of birth, the region of entry, the year of entry cohort), the regressions also control for the following initial firm and job characteristics: sector, type of occupation (apprentice, blue collar worker and white collar worker), and firms' size (average number of employees) and age. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A6: The effect of experience and unemployment rates on injuries; with additional controls (sector, type of occupation, and firms' size and age)

	Individual Injuries			Injury incidence rates		
	(1) All Injuries	(2) IC injuries	(3) NIC Injuries	(4) All injuries	(5) IC injuries	(6) NIC injuries
$1[Exp_{it} = 1]$	-0.0563* (0.0297)	-0.0227** (0.0091)	-0.0337 (0.0282)	0.0499 (0.1238)	0.0475*** (0.0147)	0.0025 (0.1114)
$1[Exp_{it} = 2]$	-0.0955** (0.0407)	-0.0188* (0.0107)	-0.0767* (0.0396)	-0.0458 (0.2510)	0.0648** (0.0294)	-0.1106 (0.2254)
$1[Exp_{it} = 3]$	-0.1348** (0.0584)	-0.0236* (0.0136)	-0.1112** (0.0551)	-0.2689 (0.3671)	0.0503 (0.0436)	-0.3193 (0.3289)
$1[Exp_{it} = 4]$	-0.2002*** (0.0764)	-0.0530*** (0.0173)	-0.1472** (0.0739)	-0.4654 (0.4856)	0.0382 (0.0575)	-0.5036 (0.4351)
$1[Exp_{it} = 5]$	-0.2176** (0.0910)	-0.0547** (0.0210)	-0.1629* (0.0876)	-0.5912 (0.6037)	0.0325 (0.0720)	-0.6237 (0.5405)
$1[Exp_{it} = 6]$	-0.2358** (0.1055)	-0.0667** (0.0259)	-0.1692* (0.1008)	-0.6073 (0.7276)	0.0355 (0.0866)	-0.6428 (0.6516)
$1[Exp_{it} = 7]$	-0.2501** (0.1260)	-0.0714** (0.0293)	-0.1787 (0.1227)	-0.5110 (0.8424)	0.0463 (0.1021)	-0.5573 (0.7529)
$1[Exp_{it} = 8]$	-0.3017** (0.1435)	-0.0786** (0.0334)	-0.2231 (0.1356)	-0.6371 (0.9776)	0.0323 (0.1152)	-0.6694 (0.8787)
$1[Exp_{it} = 9]$	-0.3132** (0.1564)	-0.0920*** (0.0347)	-0.2211 (0.1540)	-0.6977 (1.0463)	0.0334 (0.1257)	-0.7311 (0.9375)
$1[Exp_{it} = 0] \times ur_{i0}$	0.0067* (0.0034)	0.0045*** (0.0017)	0.0022 (0.0036)	0.0324* (0.0183)	0.0025 (0.0023)	0.0299* (0.0171)
$1[Exp_{it} = 1] \times ur_{i0}$	0.0077** (0.0031)	0.0045*** (0.0015)	0.0032 (0.0034)	0.0445** (0.0180)	0.0018 (0.0023)	0.0426** (0.0167)
$1[Exp_{it} = 2] \times ur_{i0}$	0.0084*** (0.0030)	0.0032** (0.0014)	0.0053* (0.0031)	0.0604*** (0.0179)	0.0028 (0.0024)	0.0576*** (0.0165)
$1[Exp_{it} = 3] \times ur_{i0}$	0.0115*** (0.0031)	0.0030** (0.0015)	0.0085*** (0.0032)	0.0845*** (0.0183)	0.0057** (0.0024)	0.0788*** (0.0170)
$1[Exp_{it} = 4] \times ur_{i0}$	0.0148*** (0.0034)	0.0046*** (0.0014)	0.0102*** (0.0035)	0.1087*** (0.0195)	0.0083*** (0.0025)	0.1004*** (0.0180)
$1[Exp_{it} = 5] \times ur_{i0}$	0.0181*** (0.0037)	0.0042*** (0.0015)	0.0139*** (0.0038)	0.1304*** (0.0215)	0.0108*** (0.0027)	0.1196*** (0.0197)
$1[Exp_{it} = 6] \times ur_{i0}$	0.0191*** (0.0038)	0.0046*** (0.0017)	0.0145*** (0.0037)	0.1373*** (0.0237)	0.0115*** (0.0031)	0.1258*** (0.0217)
$1[Exp_{it} = 7] \times ur_{i0}$	0.0163*** (0.0043)	0.0039** (0.0015)	0.0124*** (0.0041)	0.1383*** (0.0254)	0.0124*** (0.0036)	0.1259*** (0.0227)
$1[Exp_{it} = 8] \times ur_{i0}$	0.0204*** (0.0036)	0.0043** (0.0017)	0.0162*** (0.0036)	0.1524*** (0.0254)	0.0140*** (0.0037)	0.1384*** (0.0228)
$1[Exp_{it} = 9] \times ur_{i0}$	0.0211*** (0.0058)	0.0049** (0.0019)	0.0161*** (0.0055)	0.1737*** (0.0368)	0.0163*** (0.0052)	0.1574*** (0.0324)
ur_{it}	-0.0161*** (0.0018)	-0.0005 (0.0005)	-0.0156*** (0.0018)	-0.2606*** (0.0160)	-0.0021 (0.0016)	-0.2584*** (0.0145)
N	349680	349680	349680	342251	342251	342251
R^2	0.006	0.001	0.006	0.481	0.406	0.481

Note: The Table reports the estimated effects of experience ($1[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $1[Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 3 of the paper) on two types of dependent variables calculated for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC): I) injuries measured at the individual level (as the number of injuries per thousand days worked); II) Injury incidence rates (computed using workers over 34 years old in cells defined using occupation, sector and region). The additional regressors included as controls are the same of Table A5. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A7: The effect of experience and unemployment rates on labor market transitions

	(1) Entry firm	(2) Change firm	(3) Tenure	(4) Non-Employed
$\mathbf{1} [Exp_{it} = 2]$	-0.2107*** (0.0161)	0.0611*** (0.0060)	0.4812*** (0.0199)	0.0000 (0.0065)
$\mathbf{1} [Exp_{it} = 3]$	-0.2631*** (0.0202)	-0.0081 (0.0097)	0.9921*** (0.0409)	-0.0255** (0.0120)
$\mathbf{1} [Exp_{it} = 4]$	-0.2746*** (0.0202)	-0.0494*** (0.0132)	1.5302*** (0.0623)	-0.0338** (0.0168)
$\mathbf{1} [Exp_{it} = 5]$	-0.2532*** (0.0247)	-0.0897*** (0.0162)	2.0817*** (0.0770)	-0.0307 (0.0226)
$\mathbf{1} [Exp_{it} = 6]$	-0.2646*** (0.0234)	-0.1120*** (0.0193)	2.6116*** (0.1012)	-0.0250 (0.0284)
$\mathbf{1} [Exp_{it} = 7]$	-0.2526*** (0.0367)	-0.1200*** (0.0238)	3.0923*** (0.1297)	-0.0188 (0.0343)
$\mathbf{1} [Exp_{it} = 8]$	-0.2472*** (0.0333)	-0.1409*** (0.0278)	3.6124*** (0.1471)	-0.0004 (0.0389)
$\mathbf{1} [Exp_{it} = 9]$	-0.2127*** (0.0333)	-0.1570*** (0.0388)	4.2220*** (0.2066)	0.0032 (0.0389)
$\mathbf{1} [Exp_{it} = 1] \times ur_{i0}$	0.0011 (0.0036)	-0.0059*** (0.0014)	0.0093 (0.0085)	-0.0303*** (0.0025)
$\mathbf{1} [Exp_{it} = 2] \times ur_{i0}$	0.0003 (0.0036)	-0.0046*** (0.0014)	0.0173** (0.0082)	-0.0240*** (0.0024)
$\mathbf{1} [Exp_{it} = 3] \times ur_{i0}$	-0.0016 (0.0036)	-0.0003 (0.0015)	0.0153* (0.0083)	-0.0210*** (0.0025)
$\mathbf{1} [Exp_{it} = 4] \times ur_{i0}$	-0.0021 (0.0038)	0.0015 (0.0015)	0.0094 (0.0088)	-0.0200*** (0.0026)
$\mathbf{1} [Exp_{it} = 5] \times ur_{i0}$	-0.0037 (0.0037)	0.0031** (0.0015)	-0.0014 (0.0084)	-0.0200*** (0.0027)
$\mathbf{1} [Exp_{it} = 6] \times ur_{i0}$	-0.0034 (0.0038)	0.0037** (0.0016)	-0.0113 (0.0088)	-0.0209*** (0.0028)
$\mathbf{1} [Exp_{it} = 7] \times ur_{i0}$	-0.0030 (0.0045)	0.0022 (0.0017)	-0.0141 (0.0100)	-0.0210*** (0.0028)
$\mathbf{1} [Exp_{it} = 8] \times ur_{i0}$	-0.0030 (0.0045)	0.0029* (0.0017)	-0.0221* (0.0114)	-0.0227*** (0.0027)
$\mathbf{1} [Exp_{it} = 9] \times ur_{i0}$	-0.0034 (0.0045)	0.0034** (0.0017)	-0.0369*** (0.0133)	-0.0227*** (0.0029)
ur_{it}	0.0039** (0.0019)	-0.0040** (0.0019)	0.0296*** (0.0104)	0.0347*** (0.0025)
N	282351	282351	282351	373847
R^2	0.196	0.017	0.253	0.075

Note: The Table reports the estimated effects of experience ($\mathbf{1} [Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1} [Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure 6 of the paper) on the following variables: binary indicators for being in the entry firm (Column 1) and for being in a firm different from that of the previous year (Column 2), tenure (Column 3) and a binary indicator for being absent from the WHIP-Salute database (Column 4). These OLS regressions use data from the second year of potential experience onward for our sample of entrants. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry and the year of entry cohort. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A8: The effect of experience and unemployment rates for stayers in the entry firm and movers on the main outcomes

	(1) ln(wage)	(2) All injuries	(3) IC injuries	(4) NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	0.1162*** (0.0090)	-0.0873*** (0.0299)	-0.0205* (0.0106)	-0.0667** (0.0275)
$\mathbf{1}[Exp_{it} = 2]$	0.2592*** (0.0154)	-0.1198*** (0.0336)	-0.0243** (0.0118)	-0.0955*** (0.0312)
$\mathbf{1}[Exp_{it} = 3]$	0.3799*** (0.0202)	-0.1788*** (0.0381)	-0.0424*** (0.0125)	-0.1364*** (0.0341)
$\mathbf{1}[Exp_{it} = 4]$	0.4794*** (0.0251)	-0.2288*** (0.0469)	-0.0658*** (0.0171)	-0.1630*** (0.0437)
$\mathbf{1}[Exp_{it} = 5]$	0.5332*** (0.0323)	-0.2299*** (0.0554)	-0.0431** (0.0180)	-0.1869*** (0.0492)
$\mathbf{1}[Exp_{it} = 6]$	0.6214*** (0.0421)	-0.3158*** (0.0682)	-0.0800*** (0.0208)	-0.2359*** (0.0597)
$\mathbf{1}[Exp_{it} = 7]$	0.6424*** (0.0420)	-0.2510*** (0.0776)	-0.0534** (0.0206)	-0.1975*** (0.0730)
$\mathbf{1}[Exp_{it} = 8]$	0.6898*** (0.0500)	-0.3063*** (0.0917)	-0.0818*** (0.0263)	-0.2245*** (0.0794)
$\mathbf{1}[Exp_{it} = 9]$	0.7213*** (0.0621)	-0.3113*** (0.1108)	-0.0566* (0.0311)	-0.2547** (0.1008)
$\mathbf{1}[Exp_{it} = 1] \times mover_{it}$	-0.0337*** (0.0104)	0.1085*** (0.0341)	-0.0009 (0.0069)	0.1095*** (0.0337)
$\mathbf{1}[Exp_{it} = 2] \times mover_{it}$	-0.0694*** (0.0099)	0.0856*** (0.0299)	0.0120* (0.0062)	0.0736** (0.0290)
$\mathbf{1}[Exp_{it} = 3] \times mover_{it}$	-0.0984*** (0.0110)	0.1055*** (0.0276)	0.0290*** (0.0086)	0.0766*** (0.0262)
$\mathbf{1}[Exp_{it} = 4] \times mover_{it}$	-0.1156*** (0.0114)	0.0946*** (0.0267)	0.0228** (0.0088)	0.0718** (0.0278)
$\mathbf{1}[Exp_{it} = 5] \times mover_{it}$	-0.0989*** (0.0118)	0.0831*** (0.0270)	-0.0074 (0.0071)	0.0905*** (0.0267)
$\mathbf{1}[Exp_{it} = 6] \times mover_{it}$	-0.1232*** (0.0178)	0.1666*** (0.0279)	0.0235** (0.0099)	0.1431*** (0.0281)
$\mathbf{1}[Exp_{it} = 7] \times mover_{it}$	-0.0837*** (0.0128)	0.0866** (0.0335)	-0.0125 (0.0123)	0.0992*** (0.0327)
$\mathbf{1}[Exp_{it} = 8] \times mover_{it}$	-0.0795*** (0.0175)	0.0991 (0.0619)	0.0133 (0.0105)	0.0858 (0.0621)
$\mathbf{1}[Exp_{it} = 9] \times mover$	-0.0582** (0.0291)	0.1015** (0.0510)	-0.0298 (0.0230)	0.1313** (0.0515)

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Table A8 continued

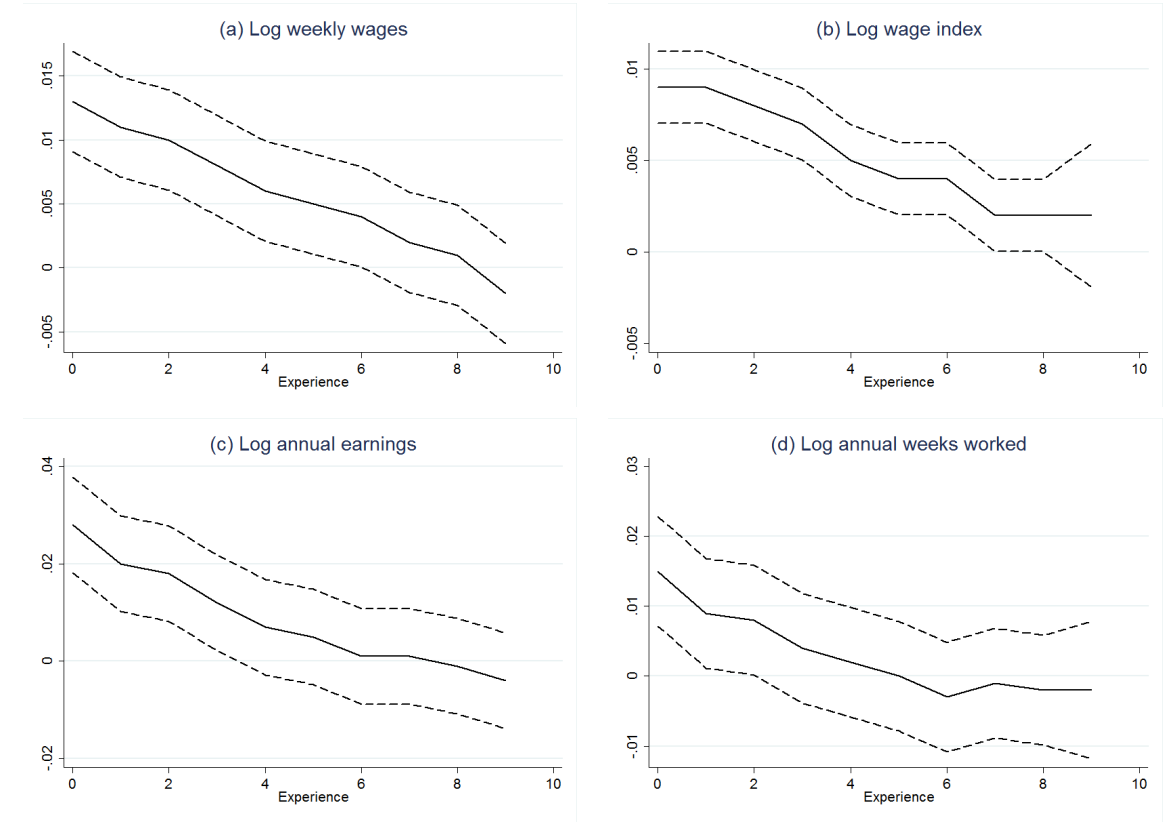
	(1) ln(wage)	(2) All injuries	(3) IC injuries	(4) NIC injuries
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0156*** (0.0018)	0.0111*** (0.0032)	0.0047*** (0.0016)	0.0064* (0.0034)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0137*** (0.0018)	0.0135*** (0.0029)	0.0046*** (0.0015)	0.0089*** (0.0034)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0115*** (0.0019)	0.0138*** (0.0029)	0.0039*** (0.0014)	0.0099*** (0.0031)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0102*** (0.0021)	0.0169*** (0.0032)	0.0048*** (0.0014)	0.0121*** (0.0034)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0069*** (0.0022)	0.0198*** (0.0033)	0.0063*** (0.0016)	0.0135*** (0.0038)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0077*** (0.0024)	0.0197*** (0.0033)	0.0035** (0.0015)	0.0162*** (0.0036)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.0033 (0.0034)	0.0295*** (0.0045)	0.0062*** (0.0017)	0.0233*** (0.0043)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.0056* (0.0031)	0.0196*** (0.0053)	0.0034** (0.0016)	0.0162*** (0.0054)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.0052 (0.0037)	0.0286*** (0.0059)	0.0046*** (0.0016)	0.0240*** (0.0063)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.0044 (0.0058)	0.0245** (0.0104)	0.0022 (0.0026)	0.0224** (0.0101)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0} \times mover_{it}$	0.0023** (0.0010)	-0.0028 (0.0030)	0.0004 (0.0008)	-0.0032 (0.0029)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0} \times mover_{it}$	0.0026*** (0.0008)	-0.0030 (0.0022)	-0.0007 (0.0005)	-0.0023 (0.0021)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0} \times mover_{it}$	0.0015 (0.0010)	-0.0021 (0.0023)	-0.0020*** (0.0006)	-0.0001 (0.0022)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0} \times mover_{it}$	0.0034*** (0.0010)	-0.0016 (0.0024)	-0.0019* (0.0010)	0.0003 (0.0027)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0} \times mover_{it}$	0.0007 (0.0013)	0.0017 (0.0029)	0.0011* (0.0006)	0.0006 (0.0028)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0} \times mover_{it}$	0.0031 (0.0021)	-0.0083*** (0.0030)	-0.0016 (0.0011)	-0.0067** (0.0028)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0} \times mover_{it}$	-0.0011 (0.0015)	-0.0006 (0.0036)	0.0009 (0.0010)	-0.0014 (0.0034)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0} \times mover_{it}$	-0.0016 (0.0021)	-0.0061 (0.0068)	-0.0002 (0.0008)	-0.0059 (0.0068)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0} \times mover_{it}$	-0.0020 (0.0036)	-0.0007 (0.0067)	0.0033* (0.0018)	-0.0040 (0.0065)
ur_{it}	-0.0078*** (0.0005)	-0.0166*** (0.0018)	-0.0007 (0.0004)	-0.0159*** (0.0017)
N	362682	362682	362682	362682
R^2	0.167	0.003	0.000	0.003

Note: The Table reports: the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$) for stayers and its differential effects for movers (the coefficients of $\mathbf{1}[Exp_{it} = s] \times mover_{it}$); the estimated effects of unemployment rate at entry by year of experience for stayers (i.e., the parameters of $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ which are shown in the Figure 7 of the paper) and the coefficients of the triple interactions $\mathbf{1}[Exp_{it} = 8] \times ur_{i0} \times mover_{it}$ (i.e., the differential effect of unemployment rate at entry by year of experience for movers); the estimated effect of current unemployment rate (ur_{it}). Stayers are the individuals still working for the first employer. The dummy $mover_{it}$ is equal to one when the individual is working in a firm different from the first employer. The outcome variables are log weekly wages, all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC) at the individual level (in columns 1, 2, 3 and 4, respectively). The regressions control for year of entry, region of entry, region of birth and current year. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%

A.3 Robustness checks

A.3.1 Controlling for the full set of initial firm and job characteristics

Figure A6: The effect of unemployment rate at entry on pecuniary outcomes; with the full set of controls (sector, type of occupation and contractual code, and firms' age, size, and growth)



Note: The figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e. the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the main text) on the following dependent variables: log weekly wages in panel (a); log wage index in panel (b); log annual earnings in panel (c); log annual weeks worked in panel (d). The sample includes Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include the controls used in the baseline specification (see note of Table A2) plus all the available controls related the initial job and firm: sector, type of occupation (apprentice, blue collar worker and white collar worker), firms' size and age, average growth of the number of employees in the previous three years, and fixed effects for the code identifying contractual arrangements. The inclusion of the last two regressors reduces the sample size to 233,069 observations. Detailed estimation results are available in Table A9. Standard errors are clustered by region of entry per year of entry. The dashed lines show the 95% confidence intervals

Table A9: The effect of experience and unemployment rates on pecuniary outcomes; with the full set of controls (sector, type of occupation and contractual code, and firms' age, size, and growth)

	(1)	(2)	(3)	(4)
	ln(wage)	ln(wage index)	ln(earnings)	ln(weeks worked)
$\mathbf{1} [Exp_{it} = 1]$	0.116*** (0.009)	0.018*** (0.004)	0.873*** (0.018)	0.757*** (0.013)
$\mathbf{1} [Exp_{it} = 2]$	0.237*** (0.014)	0.050*** (0.008)	1.070*** (0.028)	0.833*** (0.018)
$\mathbf{1} [Exp_{it} = 3]$	0.342*** (0.020)	0.106*** (0.011)	1.308*** (0.041)	0.966*** (0.026)
$\mathbf{1} [Exp_{it} = 4]$	0.445*** (0.026)	0.164*** (0.015)	1.474*** (0.055)	1.030*** (0.036)
$\mathbf{1} [Exp_{it} = 5]$	0.512*** (0.034)	0.204*** (0.019)	1.614*** (0.069)	1.102*** (0.043)
$\mathbf{1} [Exp_{it} = 6]$	0.588*** (0.039)	0.232*** (0.022)	1.757*** (0.083)	1.170*** (0.052)
$\mathbf{1} [Exp_{it} = 7]$	0.664*** (0.043)	0.264*** (0.026)	1.842*** (0.091)	1.178*** (0.055)
$\mathbf{1} [Exp_{it} = 8]$	0.725*** (0.052)	0.291*** (0.031)	1.925*** (0.111)	1.200*** (0.066)
$\mathbf{1} [Exp_{it} = 9]$	0.802*** (0.067)	0.306*** (0.039)	2.012*** (0.141)	1.210*** (0.083)
$\mathbf{1} [Exp_{it} = 0] \times ur_{i0}$	0.013*** (0.002)	0.009*** (0.001)	0.028*** (0.005)	0.015*** (0.004)
$\mathbf{1} [Exp_{it} = 1] \times ur_{i0}$	0.011*** (0.002)	0.009*** (0.001)	0.020*** (0.005)	0.009** (0.004)
$\mathbf{1} [Exp_{it} = 2] \times ur_{i0}$	0.010*** (0.002)	0.008*** (0.001)	0.018*** (0.005)	0.008** (0.004)
$\mathbf{1} [Exp_{it} = 3] \times ur_{i0}$	0.008*** (0.002)	0.007*** (0.001)	0.012*** (0.005)	0.004 (0.004)
$\mathbf{1} [Exp_{it} = 4] \times ur_{i0}$	0.006*** (0.002)	0.005*** (0.001)	0.007 (0.005)	0.002 (0.004)
$\mathbf{1} [Exp_{it} = 5] \times ur_{i0}$	0.005*** (0.002)	0.004*** (0.001)	0.005 (0.005)	-0.000 (0.004)
$\mathbf{1} [Exp_{it} = 6] \times ur_{i0}$	0.004 (0.002)	0.004*** (0.001)	0.001 (0.005)	-0.003 (0.004)
$\mathbf{1} [Exp_{it} = 7] \times ur_{i0}$	0.002 (0.002)	0.002* (0.001)	0.001 (0.005)	-0.001 (0.004)
$\mathbf{1} [Exp_{it} = 8] \times ur_{i0}$	0.001 (0.002)	0.002 (0.001)	-0.001 (0.005)	-0.002 (0.004)
$\mathbf{1} [Exp_{it} = 9] \times ur_{i0}$	-0.002 (0.002)	0.002 (0.002)	-0.004 (0.005)	-0.002 (0.005)
ur_{it}	-0.009*** (0.001)	-0.008*** (0.000)	-0.012*** (0.002)	-0.003 (0.002)
N	233069	233069	233069	233069
R^2	0.345	0.544	0.381	0.290

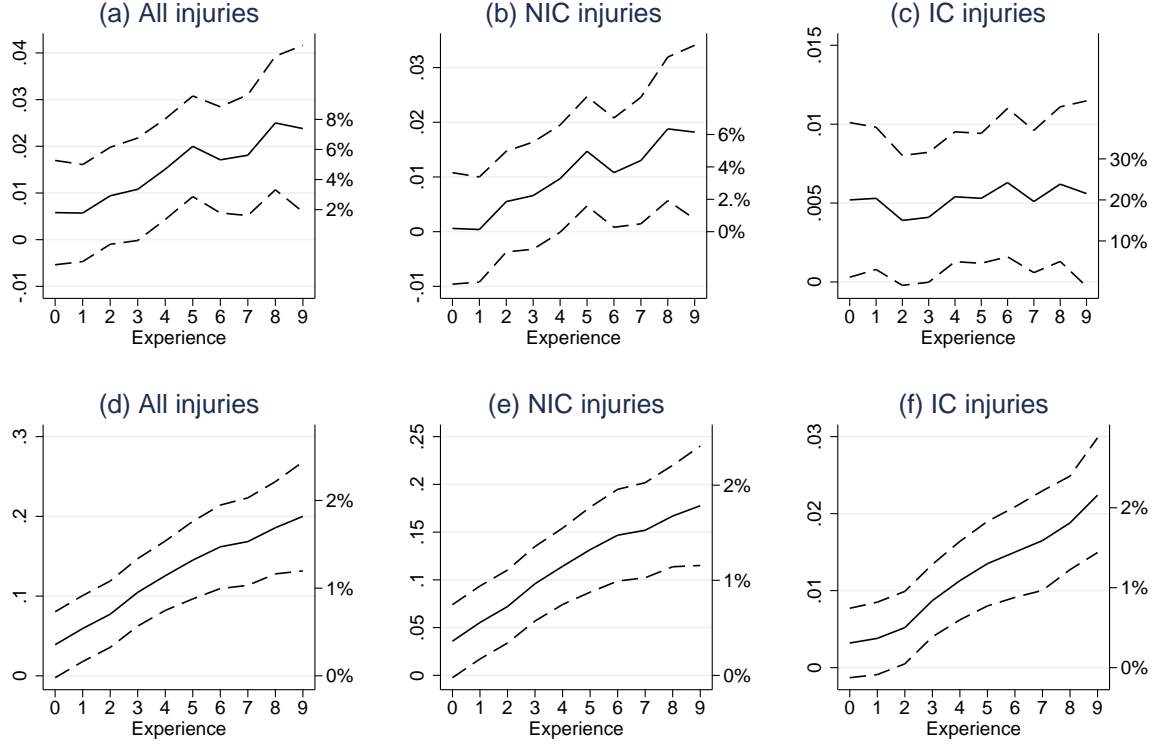
Note: The Table reports the estimated effects of experience ($\mathbf{1} [Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1} [Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure A6) on the following variables: log weekly wages in column (1); log wage index in column (2); log annual earnings in column (3); log annual weeks worked in column (4). The sample includes Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include the controls used in the baseline specification (see note of Table A2) plus all the available controls related the initial job and firm: sector, type of occupation (apprentice, blue collar worker and white collar worker), firms' size and age, average growth of the number of employees in the previous three years, and fixed effects for the code identifying contractual arrangements. The inclusion of the last two regressors reduces the sample size to 233,069 observations. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A10: The effect of experience and unemployment rates on pecuniary outcomes; baseline specification, using the restricted sample of Table A9

	(1)	(2)	(3)	(4)
	ln(wage)	ln(wage index)	ln(earnings)	ln(weeks worked)
$\mathbf{1}[Exp_{it} = 1]$	0.105*** (0.008)	0.011** (0.005)	0.866*** (0.017)	0.760*** (0.012)
$\mathbf{1}[Exp_{it} = 2]$	0.213*** (0.013)	0.033*** (0.010)	1.044*** (0.025)	0.831*** (0.016)
$\mathbf{1}[Exp_{it} = 3]$	0.302*** (0.019)	0.080*** (0.015)	1.260*** (0.037)	0.958*** (0.024)
$\mathbf{1}[Exp_{it} = 4]$	0.390*** (0.024)	0.129*** (0.020)	1.406*** (0.050)	1.016*** (0.031)
$\mathbf{1}[Exp_{it} = 5]$	0.445*** (0.031)	0.161*** (0.025)	1.528*** (0.062)	1.083*** (0.038)
$\mathbf{1}[Exp_{it} = 6]$	0.509*** (0.036)	0.182*** (0.029)	1.653*** (0.076)	1.145*** (0.046)
$\mathbf{1}[Exp_{it} = 7]$	0.566*** (0.039)	0.202*** (0.035)	1.707*** (0.083)	1.141*** (0.051)
$\mathbf{1}[Exp_{it} = 8]$	0.614*** (0.048)	0.218*** (0.041)	1.772*** (0.102)	1.158*** (0.061)
$\mathbf{1}[Exp_{it} = 9]$	0.688*** (0.060)	0.231*** (0.050)	1.856*** (0.123)	1.168*** (0.070)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.014*** (0.002)	0.011*** (0.001)	0.030*** (0.005)	0.017*** (0.004)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.012*** (0.002)	0.011*** (0.001)	0.022*** (0.005)	0.010*** (0.004)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.012*** (0.002)	0.011*** (0.001)	0.021*** (0.005)	0.010*** (0.004)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.010*** (0.002)	0.009*** (0.001)	0.015*** (0.005)	0.005 (0.004)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.008*** (0.002)	0.008*** (0.002)	0.010* (0.005)	0.003 (0.004)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.007*** (0.002)	0.007*** (0.002)	0.008 (0.005)	0.001 (0.004)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.005** (0.002)	0.006*** (0.002)	0.003 (0.006)	-0.002 (0.004)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.004 (0.003)	0.005*** (0.002)	0.004 (0.006)	0.001 (0.004)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.003 (0.003)	0.005** (0.002)	0.003 (0.006)	-0.001 (0.004)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	-0.000 (0.003)	0.004** (0.002)	-0.002 (0.006)	-0.002 (0.005)
ur_{it}	-0.008*** (0.001)	-0.007*** (0.000)	-0.011*** (0.002)	-0.003 (0.002)
N	233069	233069	233069	233069
R^2	0.170	0.161	0.305	0.253

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the paper) on the following dependent variables: log weekly wages in column (1); log wage index in column (2); log annual earnings in column (3); log annual weeks worked in column (4). The regressions include the controls used in the baseline specification (see note of Table A2) and is run on the 233,069 observations used by the regression with the full set of controls shown in Table A9. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%

Figure A7: The effect of unemployment rate at entry on injuries; with the full set of controls (sector, type of occupation and contractual code, and firms' age, size, and growth)



Note: The figure shows the effect of unemployment at entry (ur_0) by year of experience (i.e. the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the paper) on two types of dependent variables: I) workplace accidents measured at the individual (injuries per thousand days worked) level for all injuries, non-immediate care injuries (NIC), and immediate care injuries in panels a, b and c, respectively; II) Injury incidence rates - computed using workers over 34 years old in cells defined using occupation, sector and region - measured for all injuries, non-immediate care injuries (NIC), and immediate care injuries in panels d, e and f, respectively. The right vertical axis expresses these effects as a percentage of the sample mean of the corresponding dependent variable. The sample includes Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include the controls used in the baseline specification (see note of Table A3) plus all the available controls related the initial job and firm: sector, type of occupation (apprentice, blue collar worker and white collar worker), firms' size and age, average growth of the number of employees in the previous three years, and fixed effects for the code identifying contractual arrangements. The inclusion of the last two regressors reduces the sample size. Detailed estimation results are available in Table A11. Standard errors are clustered by region of entry per year of entry. The dashed lines show the 95% confidence intervals

Table A11: The effect of experience and unemployment rates on injuries; with the full set of controls (sector, type of occupation and contractual code, and firms' age, size, and growth)

	Individual Injuries			Injury incidence rates		
	(1) All Injuries	(2) IC injuries	(3) NIC Injuries	(4) All injuries	(5) IC injuries	(6) NIC injuries
$1[Exp_{it} = 1]$	-0.0362 (0.0325)	-0.0142 (0.0104)	-0.0220 (0.0310)	-0.2557*** (0.0792)	0.0044 (0.0074)	-0.2601*** (0.0732)
$1[Exp_{it} = 2]$	-0.1152*** (0.0361)	-0.0096 (0.0110)	-0.1056*** (0.0355)	-0.6246*** (0.1560)	-0.0201 (0.0147)	-0.6044*** (0.1437)
$1[Exp_{it} = 3]$	-0.1324*** (0.0482)	-0.0137 (0.0148)	-0.1188*** (0.0433)	-1.0908*** (0.2362)	-0.0714*** (0.0218)	-1.0195*** (0.2177)
$1[Exp_{it} = 4]$	-0.1927*** (0.0519)	-0.0347** (0.0165)	-0.1581*** (0.0478)	-1.4535*** (0.3164)	-0.1149*** (0.0296)	-1.3386*** (0.2909)
$1[Exp_{it} = 5]$	-0.2083*** (0.0609)	-0.0349* (0.0195)	-0.1734*** (0.0538)	-1.7488*** (0.3981)	-0.1451*** (0.0366)	-1.6036*** (0.3660)
$1[Exp_{it} = 6]$	-0.1822** (0.0709)	-0.0464** (0.0215)	-0.1358** (0.0632)	-2.0472*** (0.4816)	-0.1774*** (0.0436)	-1.8698*** (0.4430)
$1[Exp_{it} = 7]$	-0.2117** (0.0832)	-0.0395 (0.0248)	-0.1722** (0.0772)	-2.1663*** (0.5857)	-0.2017*** (0.0534)	-1.9646*** (0.5375)
$1[Exp_{it} = 8]$	-0.2607*** (0.0896)	-0.0511 (0.0316)	-0.2096*** (0.0795)	-2.4613*** (0.6698)	-0.2470*** (0.0589)	-2.2144*** (0.6166)
$1[Exp_{it} = 9]$	-0.2500** (0.1194)	-0.0530** (0.0252)	-0.1970* (0.1098)	-2.6592*** (0.7745)	-0.2877*** (0.0707)	-2.3715*** (0.7105)
$1[Exp_{it} = 0] \times ur_{i0}$	0.0058 (0.0057)	0.0052** (0.0025)	0.0006 (0.0052)	0.0390* (0.0211)	0.0032 (0.0023)	0.0358* (0.0195)
$1[Exp_{it} = 1] \times ur_{i0}$	0.0057 (0.0053)	0.0053** (0.0023)	0.0004 (0.0049)	0.0593*** (0.0211)	0.0038 (0.0024)	0.0554*** (0.0195)
$1[Exp_{it} = 2] \times ur_{i0}$	0.0094* (0.0053)	0.0039* (0.0021)	0.0055 (0.0047)	0.0773*** (0.0212)	0.0052** (0.0024)	0.0721*** (0.0195)
$1[Exp_{it} = 3] \times ur_{i0}$	0.0108* (0.0056)	0.0041* (0.0021)	0.0066 (0.0050)	0.1047*** (0.0216)	0.0087*** (0.0024)	0.0960*** (0.0199)
$1[Exp_{it} = 4] \times ur_{i0}$	0.0151*** (0.0055)	0.0054** (0.0021)	0.0097* (0.0050)	0.1255*** (0.0222)	0.0113*** (0.0026)	0.1142*** (0.0204)
$1[Exp_{it} = 5] \times ur_{i0}$	0.0200*** (0.0055)	0.0053** (0.0021)	0.0147*** (0.0051)	0.1451*** (0.0248)	0.0135*** (0.0028)	0.1316*** (0.0227)
$1[Exp_{it} = 6] \times ur_{i0}$	0.0171*** (0.0058)	0.0063** (0.0024)	0.0108** (0.0051)	0.1618*** (0.0267)	0.0150*** (0.0030)	0.1468*** (0.0245)
$1[Exp_{it} = 7] \times ur_{i0}$	0.0181*** (0.0066)	0.0051** (0.0023)	0.0130** (0.0059)	0.1684*** (0.0280)	0.0165*** (0.0033)	0.1520*** (0.0254)
$1[Exp_{it} = 8] \times ur_{i0}$	0.0250*** (0.0073)	0.0062** (0.0025)	0.0188*** (0.0067)	0.1857*** (0.0295)	0.0188*** (0.0031)	0.1669*** (0.0271)
$1[Exp_{it} = 9] \times ur_{i0}$	0.0238*** (0.0091)	0.0056* (0.0030)	0.0182** (0.0081)	0.2000*** (0.0349)	0.0224*** (0.0038)	0.1776*** (0.0319)
ur_{it}	-0.0159*** (0.0024)	0.0000 (0.0006)	-0.0160*** (0.0022)	-0.2625*** (0.0192)	-0.0025 (0.0020)	-0.2600*** (0.0175)
N	233069	233069	233069	228198	228198	228198
R^2	0.013	0.005	0.012	0.506	0.437	0.506

Note: The Table reports the estimated effects of experience ($1[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $1[Exp_{it} = s] \times ur_{i0}$ in equation 1 which are shown in the Figure A7) on two types of dependent variables: I) workplace accidents measured at the individual level for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC) in columns 1, 2 and 3 respectively; II) Injury incidence rates - computed using workers over 34 years old in cells defined using occupation, sector and region - measured for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC) in columns 4, 5 and 6 respectively. The sample includes Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include the controls used in the baseline specification (see note of Table A3) plus all the available controls related the initial job and firm: sector, type of occupation (apprentice, blue collar worker and white collar worker), firms' size and age, average growth of the number of employees in the previous three years, and fixed effects for the code identifying contractual arrangements. The inclusion of the last two regressors reduces the sample size. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A12: The effect of experience and unemployment rates on injuries; baseline specification, using the restricted sample of Table A11

	Individual Injuries			Injury incidence rates		
	(1) All Injuries	(2) IC injuries	(3) NIC Injuries	(4) All injuries	(5) IC injuries	(6) NIC injuries
$1[Exp_{it} = 1]$	-0.0337 (0.0322)	-0.0151 (0.0102)	-0.0187 (0.0307)	-0.3031*** (0.0869)	0.0009 (0.0101)	-0.3040*** (0.0788)
$1[Exp_{it} = 2]$	-0.1063*** (0.0365)	-0.0104 (0.0108)	-0.0959*** (0.0354)	-0.5923*** (0.1730)	-0.0161 (0.0197)	-0.5762*** (0.1567)
$1[Exp_{it} = 3]$	-0.1176** (0.0487)	-0.0148 (0.0145)	-0.1028** (0.0437)	-1.0398*** (0.2504)	-0.0673** (0.0284)	-0.9724*** (0.2271)
$1[Exp_{it} = 4]$	-0.1728*** (0.0522)	-0.0361** (0.0160)	-0.1366*** (0.0475)	-1.3767*** (0.3325)	-0.1126*** (0.0367)	-1.2641*** (0.3019)
$1[Exp_{it} = 5]$	-0.1861*** (0.0611)	-0.0365* (0.0189)	-0.1497*** (0.0532)	-1.6285*** (0.4206)	-0.1409*** (0.0479)	-1.4876*** (0.3800)
$1[Exp_{it} = 6]$	-0.1555** (0.0732)	-0.0485** (0.0209)	-0.1070 (0.0648)	-1.9855*** (0.4823)	-0.1820*** (0.0542)	-1.8035*** (0.4370)
$1[Exp_{it} = 7]$	-0.1799** (0.0850)	-0.0423* (0.0240)	-0.1376* (0.0780)	-1.9849*** (0.5623)	-0.1980*** (0.0646)	-1.7869*** (0.5082)
$1[Exp_{it} = 8]$	-0.2203** (0.0959)	-0.0542* (0.0307)	-0.1662* (0.0844)	-2.1221*** (0.6269)	-0.2264*** (0.0729)	-1.8957*** (0.5667)
$1[Exp_{it} = 9]$	-0.2118* (0.1234)	-0.0565** (0.0248)	-0.1553 (0.1114)	-2.4761*** (0.7554)	-0.2883*** (0.0847)	-2.1878*** (0.6819)
$1[Exp_{it} = 0] \times ur_{i0}$	0.0093* (0.0053)	0.0055** (0.0025)	0.0037 (0.0048)	0.1564*** (0.0335)	0.0176*** (0.0042)	0.1389*** (0.0299)
$1[Exp_{it} = 1] \times ur_{i0}$	0.0091* (0.0049)	0.0057** (0.0022)	0.0034 (0.0045)	0.1782*** (0.0336)	0.0181*** (0.0042)	0.1600*** (0.0300)
$1[Exp_{it} = 2] \times ur_{i0}$	0.0125** (0.0049)	0.0042** (0.0020)	0.0083* (0.0044)	0.1900*** (0.0333)	0.0186*** (0.0042)	0.1714*** (0.0296)
$1[Exp_{it} = 3] \times ur_{i0}$	0.0136*** (0.0051)	0.0044** (0.0021)	0.0092** (0.0046)	0.2161*** (0.0344)	0.0218*** (0.0043)	0.1943*** (0.0306)
$1[Exp_{it} = 4] \times ur_{i0}$	0.0177*** (0.0051)	0.0057*** (0.0021)	0.0120** (0.0047)	0.2334*** (0.0346)	0.0241*** (0.0044)	0.2094*** (0.0308)
$1[Exp_{it} = 5] \times ur_{i0}$	0.0228*** (0.0053)	0.0056*** (0.0021)	0.0172*** (0.0049)	0.2480*** (0.0380)	0.0256*** (0.0047)	0.2224*** (0.0338)
$1[Exp_{it} = 6] \times ur_{i0}$	0.0197*** (0.0055)	0.0065*** (0.0024)	0.0132*** (0.0048)	0.2700*** (0.0380)	0.0275*** (0.0047)	0.2425*** (0.0339)
$1[Exp_{it} = 7] \times ur_{i0}$	0.0205*** (0.0063)	0.0053** (0.0023)	0.0151*** (0.0056)	0.2629*** (0.0386)	0.0277*** (0.0049)	0.2352*** (0.0343)
$1[Exp_{it} = 8] \times ur_{i0}$	0.0269*** (0.0068)	0.0065** (0.0025)	0.0204*** (0.0063)	0.2625*** (0.0388)	0.0277*** (0.0047)	0.2348*** (0.0349)
$1[Exp_{it} = 9] \times ur_{i0}$	0.0262*** (0.0091)	0.0058** (0.0029)	0.0204** (0.0081)	0.2908*** (0.0483)	0.0330*** (0.0055)	0.2578*** (0.0434)
ur_{it}	-0.0169*** (0.0023)	-0.0000 (0.0006)	-0.0169*** (0.0022)	-0.2732*** (0.0185)	-0.0034* (0.0019)	-0.2697*** (0.0169)
N	233069	233069	233069	228198	228198	228198
R^2	0.003	0.001	0.003	0.142	0.084	0.151

Note: The Table reports the estimated effects of experience ($1[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $1[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the main text) on two types of dependent variables: I) workplace accidents measured at the individual level for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC) in columns 1, 2 and 3 respectively; II) Injury incidence rates - computed using workers over 34 years old in cells defined using occupation, sector and region - measured for all injuries, immediate care injuries (IC), and non-immediate care injuries (NIC) in columns 4, 5 and 6 respectively. The regression includes the controls used in the baseline specification (see note of Table A3) and is run on the observations used by the regressions with the full set of controls shown in Table A11. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%

A.3.2 Regional Mobility

Mobility of entrants across regional labor markets could be endogenous with respect to the local business cycle. As shown in Table A13, this threat to identification is more relevant for entrants born in the South of Italy, where 27% of entrants start working in a region different from the region of birth. The message of these descriptive statistics is confirmed by using a logistic regression to model a dichotomous variable for entering the labor market in a region different from the region of birth as a function of the unemployment rate of the region of birth in the year of entry and year dummies. Indeed, as shown in the first column of Table A14, for a one-point increase in the unemployment rate in the region of birth, the odds of entering in a region different from the region of birth increases approximately by a factor of 1.11. However, as shown in the second column of Table A14, once we introduce region of birth dummies, the economic cycle in the region of birth loses both statistical and economic significance. These results suggest that in our sample migration decisions are related to permanent differences in job opportunities between regions, but they are not determined by the regional business cycle. Nevertheless, we also replicated the baseline analyses to check the robustness of our results, by: 1) excluding entrants in regions different from the region of birth (see Table A15); 2) using all the possible interactions between the region of entry dummies and the region of birth dummies as controls (see Table A16); 3) running regressions separately for entrants born in the North-Center regions and for those born in the South of Italy (see Tables A17 and A18, respectively). All these robustness checks confirm the basic findings obtained in the baseline regressions. We have also tried to instrument the initial unemployment rate

with the unemployment rate at the end of compulsory schooling (14 y.o.) in the place of birth. The results, which are available upon request, are qualitatively similar. However, as argued by Brunner and Kuhn (2014), it is very unlikely that this kind of instrument does not have a direct effect on our dependent variables. Indeed, we have found evidence that, after controlling for the entry unemployment rate, unemployment rate at the end of compulsory schooling increases the age of entry, and therefore it seems to have also a direct effect on entrants' outcomes.

Table A13: Distribution of entrants by macro-region of birth and macro-region of entry

Region of birth	% of entr. in North	% of entr. in Center	% of entr. in South and Islands	% of entrants in region different from reg. of birth
North	96.4	2.2	1.4	7.6
Center	3.0	94.8	2.2	8.4
South and Isl.	12.6	11.5	75.9	27.0

Note: The first three columns report the percentage of entrants by macro-regions (i.e., North, Center and South and Islands) for each macro-region of birth. The last column represents the % of entrants in a region different from the region of birth (i.e., taking into account also mobility within the same macro-region). The sample used is made up by the observations of the entry year for the workers analyzed in the main sample (i.e., see the note of Table A1).

Table A14: The effect of labor market conditions on probability of starting working in a region different from the region of birth

	(1)	(2)
ur_N	0.106*** (0.019)	0.005 (0.096)
region of birth fixed effects	no	yes
year fixed effects	no	yes
N	80331	80331
Pseudo R^2	0.074	0.095

Note: The table reports the parameters (estimated by logistic regressions) associated with the unemployment rate of the region of birth in the year of entry, ur_N . The dependent variable of the two regressions is an indicator variable for starting working in a region different from the region of birth. In column 2 we also control for region of birth and year fixed effects. The sample used is made up by the observations of the entry year for the workers analyzed in the main sample (i.e., see the note of Table A1). Standard errors in parentheses are clustered by region of birth per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A15: Robustness to regional mobility: excluding entrants in a region different from the region of birth

	(1)	(2)	(3)	(4)
	ln(wage)	All injuries	IC injuries	NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	0.1136*** (0.0084)	-0.0744*** (0.0268)	-0.0270** (0.0111)	-0.0474* (0.0242)
$\mathbf{1}[Exp_{it} = 2]$	0.2330*** (0.0133)	-0.0830*** (0.0290)	-0.0230** (0.0114)	-0.0600** (0.0255)
$\mathbf{1}[Exp_{it} = 3]$	0.3348*** (0.0191)	-0.1226*** (0.0401)	-0.0288** (0.0144)	-0.0939*** (0.0345)
$\mathbf{1}[Exp_{it} = 4]$	0.4226*** (0.0249)	-0.1641*** (0.0437)	-0.0560*** (0.0166)	-0.1081*** (0.0389)
$\mathbf{1}[Exp_{it} = 5]$	0.4897*** (0.0304)	-0.1725*** (0.0545)	-0.0566*** (0.0193)	-0.1159** (0.0474)
$\mathbf{1}[Exp_{it} = 6]$	0.5585*** (0.0373)	-0.1871*** (0.0621)	-0.0672*** (0.0227)	-0.1198** (0.0541)
$\mathbf{1}[Exp_{it} = 7]$	0.6152*** (0.0422)	-0.1830** (0.0723)	-0.0704*** (0.0250)	-0.1126* (0.0629)
$\mathbf{1}[Exp_{it} = 8]$	0.6716*** (0.0494)	-0.2424*** (0.0810)	-0.0779*** (0.0282)	-0.1646** (0.0702)
$\mathbf{1}[Exp_{it} = 9]$	0.7175*** (0.0573)	-0.2585*** (0.0932)	-0.0959*** (0.0271)	-0.1626* (0.0834)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0174*** (0.0019)	0.0120*** (0.0034)	0.0042** (0.0016)	0.0077** (0.0038)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0160*** (0.0019)	0.0146*** (0.0033)	0.0047*** (0.0015)	0.0099*** (0.0037)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0144*** (0.0020)	0.0138*** (0.0029)	0.0034** (0.0014)	0.0104*** (0.0032)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0122*** (0.0020)	0.0175*** (0.0030)	0.0033** (0.0014)	0.0143*** (0.0033)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0102*** (0.0022)	0.0190*** (0.0033)	0.0047*** (0.0014)	0.0142*** (0.0037)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0088*** (0.0022)	0.0227*** (0.0037)	0.0043*** (0.0015)	0.0185*** (0.0040)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.0063** (0.0025)	0.0237*** (0.0039)	0.0047*** (0.0016)	0.0190*** (0.0040)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.0049* (0.0027)	0.0203*** (0.0042)	0.0039** (0.0015)	0.0164*** (0.0042)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.0037 (0.0027)	0.0253*** (0.0037)	0.0043** (0.0017)	0.0210*** (0.0040)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.0030 (0.0037)	0.0264*** (0.0065)	0.0053*** (0.0019)	0.0211*** (0.0063)
ur_{it}	-0.0077*** (0.0006)	-0.0194*** (0.0025)	-0.0006 (0.0006)	-0.0188*** (0.0024)
N	313697	313697	313697	313697
R^2	0.172	0.002	0.000	0.002

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the main text) on the on following dependent variables: log weekly wage (column 1), all injuries (column 2), immediate care injuries (IC in column 3), and non-immediate care injuries (NIC in column 3). The injuries variables are the number of injuries per thousand days worked at the individual level. The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003, who were under 24 years old at the time of entry. The sample does not include entrants in a region different from the region of birth. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry and the year of entry cohort. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%

Table A16: Robustness to regional mobility: controlling for all possible interactions between the region of entry dummies and the region of birth dummies

	(1) ln(wage)	(2) All injuries	(3) IC injuries	(4) NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	0.1070*** (0.0077)	-0.0477* (0.0256)	-0.0209** (0.0100)	-0.0268 (0.0240)
$\mathbf{1}[Exp_{it} = 2]$	0.2229*** (0.0128)	-0.0709*** (0.0271)	-0.0171 (0.0108)	-0.0539** (0.0241)
$\mathbf{1}[Exp_{it} = 3]$	0.3182*** (0.0180)	-0.1084*** (0.0403)	-0.0215 (0.0134)	-0.0869** (0.0355)
$\mathbf{1}[Exp_{it} = 4]$	0.4042*** (0.0238)	-0.1646*** (0.0462)	-0.0484*** (0.0152)	-0.1162*** (0.0413)
$\mathbf{1}[Exp_{it} = 5]$	0.4720*** (0.0291)	-0.1754*** (0.0548)	-0.0497*** (0.0182)	-0.1257*** (0.0480)
$\mathbf{1}[Exp_{it} = 6]$	0.5396*** (0.0358)	-0.1873*** (0.0608)	-0.0600*** (0.0211)	-0.1273** (0.0521)
$\mathbf{1}[Exp_{it} = 7]$	0.5962*** (0.0398)	-0.1927*** (0.0729)	-0.0645*** (0.0234)	-0.1282** (0.0642)
$\mathbf{1}[Exp_{it} = 8]$	0.6487*** (0.0468)	-0.2353*** (0.0802)	-0.0702*** (0.0269)	-0.1651** (0.0698)
$\mathbf{1}[Exp_{it} = 9]$	0.7017*** (0.0557)	-0.2425*** (0.0900)	-0.0834*** (0.0258)	-0.1591* (0.0812)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0154*** (0.0018)	0.0112*** (0.0031)	0.0046*** (0.0016)	0.0066* (0.0034)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0144*** (0.0018)	0.0124*** (0.0030)	0.0047*** (0.0014)	0.0077** (0.0034)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0129*** (0.0019)	0.0120*** (0.0027)	0.0034*** (0.0013)	0.0086*** (0.0030)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0112*** (0.0019)	0.0155*** (0.0029)	0.0033** (0.0014)	0.0122*** (0.0031)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0093*** (0.0021)	0.0187*** (0.0031)	0.0048*** (0.0014)	0.0139*** (0.0035)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0078*** (0.0021)	0.0214*** (0.0034)	0.0043*** (0.0014)	0.0170*** (0.0037)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.0056** (0.0024)	0.0224*** (0.0035)	0.0048*** (0.0016)	0.0177*** (0.0036)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.0042* (0.0024)	0.0194*** (0.0040)	0.0041*** (0.0015)	0.0153*** (0.0040)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.0034 (0.0026)	0.0234*** (0.0034)	0.0044*** (0.0016)	0.0190*** (0.0037)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.0022 (0.0034)	0.0243*** (0.0058)	0.0051*** (0.0018)	0.0192*** (0.0056)
ur_{it}	-0.0078*** (0.0005)	-0.0163*** (0.0018)	-0.0006 (0.0004)	-0.0157*** (0.0018)
N	362682	362682	362682	362682
R^2	0.167	0.004	0.001	0.004

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the main text) on the on following dependent variables: log weekly wage (column 1), all injuries (column 2), immediate care injuries (IC in column 3), and non-immediate care injuries (NIC in column 4). The injuries variables are the number of injuries per thousand days worked at the individual level. The sample is representative of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry, the year of entry cohort, and all the possible interactions between region of entry dummies and region of birth dummies. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%

Table A17: Robustness to regional mobility: estimates for entrants born in the North-Center regions

	(1)	(2)	(3)	(4)
	ln(wage)	All injuries	IC injuries	NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	0.0997*** (0.0086)	-0.0408 (0.0408)	-0.0146 (0.0128)	-0.0262 (0.0380)
$\mathbf{1}[Exp_{it} = 2]$	0.2227*** (0.0141)	-0.0708* (0.0419)	-0.0263** (0.0131)	-0.0444 (0.0396)
$\mathbf{1}[Exp_{it} = 3]$	0.3216*** (0.0186)	-0.1358*** (0.0519)	-0.0304* (0.0160)	-0.1054** (0.0496)
$\mathbf{1}[Exp_{it} = 4]$	0.4125*** (0.0242)	-0.2085*** (0.0580)	-0.0597*** (0.0167)	-0.1489*** (0.0556)
$\mathbf{1}[Exp_{it} = 5]$	0.4839*** (0.0292)	-0.2082*** (0.0635)	-0.0735*** (0.0208)	-0.1347** (0.0582)
$\mathbf{1}[Exp_{it} = 6]$	0.5461*** (0.0343)	-0.2874*** (0.0837)	-0.0801*** (0.0238)	-0.2073** (0.0809)
$\mathbf{1}[Exp_{it} = 7]$	0.6137*** (0.0394)	-0.2368*** (0.0887)	-0.0807*** (0.0256)	-0.1561* (0.0853)
$\mathbf{1}[Exp_{it} = 8]$	0.6579*** (0.0475)	-0.3584*** (0.1029)	-0.1169*** (0.0298)	-0.2415** (0.0956)
$\mathbf{1}[Exp_{it} = 9]$	0.7054*** (0.0585)	-0.2806** (0.1199)	-0.1173*** (0.0306)	-0.1634 (0.1147)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0101*** (0.0031)	-0.0006 (0.0109)	0.0052** (0.0023)	-0.0058 (0.0103)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0104*** (0.0032)	-0.0038 (0.0091)	0.0033** (0.0016)	-0.0071 (0.0087)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0079** (0.0031)	-0.0016 (0.0097)	0.0041** (0.0018)	-0.0057 (0.0092)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0056* (0.0030)	0.0051 (0.0104)	0.0031* (0.0017)	0.0020 (0.0097)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0028 (0.0030)	0.0096 (0.0097)	0.0044** (0.0018)	0.0052 (0.0092)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0007 (0.0031)	0.0104 (0.0098)	0.0052*** (0.0020)	0.0052 (0.0094)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	-0.0007 (0.0032)	0.0210* (0.0122)	0.0044** (0.0022)	0.0166 (0.0116)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	-0.0037 (0.0034)	0.0092 (0.0113)	0.0030 (0.0020)	0.0062 (0.0108)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	-0.0033 (0.0037)	0.0226* (0.0119)	0.0070*** (0.0026)	0.0156 (0.0113)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	-0.0042 (0.0048)	0.0105 (0.0144)	0.0052 (0.0032)	0.0053 (0.0132)
ur_{it}	-0.0055*** (0.0017)	-0.0122*** (0.0038)	-0.0001 (0.0007)	-0.0121*** (0.0036)
N	251783	251783	251783	251783
R^2	0.193	0.002	0.000	0.002

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1 of the main text) on the on following dependent variables: log weekly wage (column 1), all injuries (column 2), immediate care injuries (IC in column 3), and non-immediate care injuries (NIC in column 4). The injuries variables are the number of injuries per thousand days worked at the individual level. The sample is representative of entrants born in the North-Center regions who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry, the year of entry cohort, and all the possible interactions between region of entry dummies and region of birth dummies. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A18: Robustness to regional mobility: estimates for entrants born in the South and Islands

	(1)	(2)	(3)	(4)
	ln(wage)	All injuries	IC injuries	NIC injuries
$\mathbf{1}[Exp_{it} = 1]$	0.0801*** (0.0149)	0.0759 (0.0627)	0.0119 (0.0171)	0.0639 (0.0637)
$\mathbf{1}[Exp_{it} = 2]$	0.1568*** (0.0243)	-0.0323 (0.0634)	0.0194 (0.0209)	-0.0517 (0.0604)
$\mathbf{1}[Exp_{it} = 3]$	0.2192*** (0.0343)	-0.0552 (0.0844)	0.0352 (0.0256)	-0.0903 (0.0809)
$\mathbf{1}[Exp_{it} = 4]$	0.2789*** (0.0432)	-0.0528 (0.0910)	0.0173 (0.0288)	-0.0701 (0.0870)
$\mathbf{1}[Exp_{it} = 5]$	0.3338*** (0.0530)	-0.0470 (0.1172)	0.0283 (0.0319)	-0.0753 (0.1160)
$\mathbf{1}[Exp_{it} = 6]$	0.3732*** (0.0656)	-0.0502 (0.1272)	0.0397 (0.0353)	-0.0899 (0.1223)
$\mathbf{1}[Exp_{it} = 7]$	0.3998*** (0.0745)	-0.0610 (0.1393)	0.0220 (0.0416)	-0.0830 (0.1303)
$\mathbf{1}[Exp_{it} = 8]$	0.4202*** (0.0838)	-0.0438 (0.1630)	0.0278 (0.0473)	-0.0716 (0.1537)
$\mathbf{1}[Exp_{it} = 9]$	0.4776*** (0.1090)	-0.0133 (0.1993)	0.0632 (0.0488)	-0.0765 (0.1955)
$\mathbf{1}[Exp_{it} = 0] \times ur_{i0}$	0.0060*** (0.0018)	0.0143** (0.0057)	0.0062*** (0.0023)	0.0082 (0.0057)
$\mathbf{1}[Exp_{it} = 1] \times ur_{i0}$	0.0060*** (0.0017)	0.0105* (0.0054)	0.0054** (0.0023)	0.0051 (0.0053)
$\mathbf{1}[Exp_{it} = 2] \times ur_{i0}$	0.0065*** (0.0018)	0.0149*** (0.0055)	0.0044** (0.0022)	0.0105** (0.0052)
$\mathbf{1}[Exp_{it} = 3] \times ur_{i0}$	0.0064*** (0.0017)	0.0182*** (0.0058)	0.0041* (0.0022)	0.0141** (0.0054)
$\mathbf{1}[Exp_{it} = 4] \times ur_{i0}$	0.0058*** (0.0019)	0.0189*** (0.0058)	0.0058** (0.0023)	0.0131** (0.0055)
$\mathbf{1}[Exp_{it} = 5] \times ur_{i0}$	0.0049** (0.0019)	0.0212*** (0.0061)	0.0053** (0.0023)	0.0159*** (0.0059)
$\mathbf{1}[Exp_{it} = 6] \times ur_{i0}$	0.0038* (0.0020)	0.0213*** (0.0062)	0.0054** (0.0026)	0.0158*** (0.0056)
$\mathbf{1}[Exp_{it} = 7] \times ur_{i0}$	0.0039* (0.0021)	0.0204*** (0.0062)	0.0061** (0.0024)	0.0143** (0.0057)
$\mathbf{1}[Exp_{it} = 8] \times ur_{i0}$	0.0044** (0.0022)	0.0216*** (0.0067)	0.0063** (0.0025)	0.0153** (0.0066)
$\mathbf{1}[Exp_{it} = 9] \times ur_{i0}$	0.0029 (0.0024)	0.0224*** (0.0085)	0.0049 (0.0034)	0.0175** (0.0078)
ur_{it}	-0.0073*** (0.0005)	-0.0174*** (0.0021)	-0.0008 (0.0005)	-0.0166*** (0.0020)
N	110899	110899	110899	110899
R^2	0.095	0.005	0.001	0.005

Note: The Table reports the estimated effects of experience ($\mathbf{1}[Exp_{it} = s]$), current unemployment rate (ur_{it}) and unemployment rate at entry by year of experience (i.e., the parameters β_s of elements $\mathbf{1}[Exp_{it} = s] \times ur_{i0}$ in equation 1) on the on following dependent variables: log weekly wage (column 1), all injuries (column 2), immediate care injuries (IC in column 3), and non-immediate care injuries (NIC in column 4). The injuries variables are the number of injuries per thousand days worked at the individual level. The sample is representative of entrants born in the South and Islands who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as controls also dummy variables for calendar year, the region of birth, the region of entry, the year of entry cohort, and all the possible interactions between region of entry dummies and region of birth dummies. Standard errors are clustered by region of entry per year of entry. *** significant at 1%, ** significant at 5%, * significant at 10%.

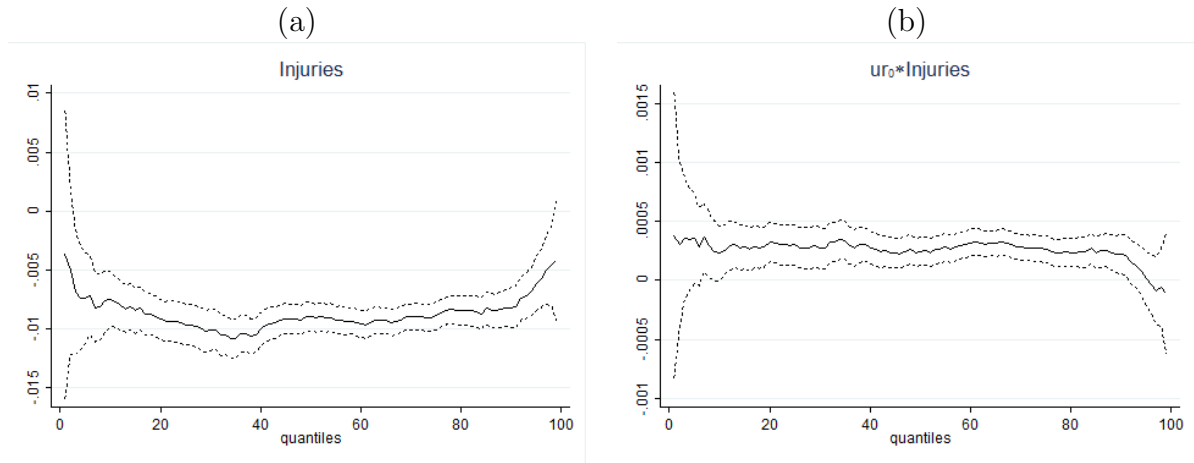
A.3.3 Quantile Regressions

It is worth investigating whether the correlation between the two proxies of job quality at our disposal (wages and injuries) is affected by the macroeconomic conditions at entry. We expect that wages and injuries are negatively correlated, reflecting the fact that workers with more risky jobs tend to have lower unobserved ability. If negative selection takes place during recession, the decrease in unobserved ability of entrants should simultaneously lead to a reduction in wages and workplace safety. Hence, the interaction term between injuries and unemployment at entry should help predicting reductions in the percentiles of the wage distribution, especially in its lowest part. We estimate quantile regressions following the specification of equation (1) in the paper using as dependent variable log wages and adding among the regressors also individual injuries (all injuries) and the interaction of the latter with ur_0 .³¹ As expected, the estimated coefficient for injuries - reported in panel (a) of Figure A8 - is negative. More interestingly, the estimated coefficient for the interaction between injuries and unemployment at entry - shown in panel (b) - is positive and significant between the 10th and 90th percentiles.³² The fact that injuries, when unemployment is high, are not associated with reductions of the wage quantiles is not consistent with negative selection. Our findings might be consistent with positive selection or other changes in market opportunities and in preferences that during recessions place, in equilibrium, workers in more hazardous jobs.

³¹The coefficients of ur_0 interacted with experience remain qualitatively similar to those shown in Figure 5 of the main text.

³²Similar results apply if we consider only IC injuries or if we use the injury indexes computed considering IC or NIC injuries. The inclusion of additional controls such as initial firm attributes (sector, average number of employees, age) and type of occupation yields qualitatively similar results.

Figure A8: Quantile regressions over the log wage distribution: estimated coefficients of All injuries at the individual level (Injuries) and of the interaction between unemployment rate at entry (ur_0) and All injuries at the individual level



Note: The figure shows the estimated effects of All injuries at the individual level, in panel (a), and of the interaction between All injuries and the unemployment rate at entry, in panel (b), on the percentiles of the log wage distribution. They are obtained from quantile regressions following the same specification of equation (1) in the paper augmented by introducing All injuries at the individual level and the interaction between All injuries and the unemployment rate at entry as additional covariates. The sample consists of 363,682 observations of Italian-born men who had their first labor market experience between 1994 and 2003 and who were under 24 years old at the time of entry. The regressions include as additional explanatory variables the current unemployment rate, the unemployment rate at entry and dummies for: year of entry, region of entry, region of birth, current year and experience. The dotted lines show the 95% confidence intervals.

A.3.4 Survival Analysis: results

In this subsection the information on the exact starting day of each job spell and the exact day of an injury is used to estimate duration models. This methodology allows us to construct a precise measure of risk exposure, to analyze the evolution of injury hazard rates and, by using frailty models, to take into account the role of unobserved heterogeneity among different cohorts of entrants. To incorporate current unemployment rate as a time-varying covariates, employment spells have been split in year-specific records. In our survival analysis, the dataset and log likelihood function are set to account for interval truncations (Cleves, 2010), that is periods in which some workers are not observed because they are not employed in the sectors under analysis.³³ The comparison of the values of the Akaike Information Criterion (AIC) selects the log-logistic regression model as the best parametric model.

The log-logistic regression model in the accelerated failure time (AFT) metric has the following parametrization: $\varepsilon_j = \exp(-x_j\beta)t_j$

where t_j is failure time and ε_j is distributed as a log-logistic. In this specification a negative coefficient β accelerates failure time, that is, injuries occur earlier. We use the same regressors of the linear specification (1) presented in the main text with the exception of experience and current year dummies. The latter, in presence of year of entry dummies, would implicitly capture time since entry.

In this specification we introduce frailties following a gamma distribution to control

³³See Table A21 for details. In a robustness check we have assumed that the exposure to risk is zero during periods of non-employment. The time elapsed in non-employment status is thus ignored and all employment spells are considered as contiguous. The main results are qualitatively similar.

for unobserved heterogeneity shared by workers entering in the same year. We thus deal with unobserved heterogeneity adopting a random effect approach instead of the fixed cohort of entry effect used in linear models. In this specification year of entry dummies are used to define shared frailties and are not included as regressors.

Table A19 displays the estimated coefficients from the log-logistic regressions and the hazard ratios from the Cox proportional hazards models for all, NIC and IC injuries respectively. Columns 1, 4 and 7 show the estimates from the baseline log-logistic specification using the following explanatory variables: initial and current unemployment rates, region of entry and region of birth. For all and NIC injuries (columns 1 and 4) the exponentiated coefficients of ur_0 (i.e. $\exp(-0.046)$) imply that a one percentage point increase in initial unemployment rate decreases the time up to the first injury by a factor approximately equal to 0.96. The exponentiated coefficient of unemployment at entry for IC injuries in Column 7 (i.e. $\exp(-0.089)$) indicates a greater reduction in survival time, by a factor equal to 0.91. The specifications including shared frailties in Columns 3, 6 and 9 yield larger coefficients for ur_0 than the ones estimated in the baseline specification. These coefficients imply that a percentage point increase in ur_0 reduces survival time by a factor of 0.87 and 0.86 for all (and NIC) injuries and for IC injuries, respectively. Although the (log of) theta coefficients and the likelihood ratio tests show that shared frailties are significantly different from zero, the AIC indicates that the baseline specifications, using year of entry dummies simply as regressors, are to be preferred. Hence, unobserved heterogeneity among different cohorts of entrants seems not to play a dominant role in determining the increase in hazard rates.

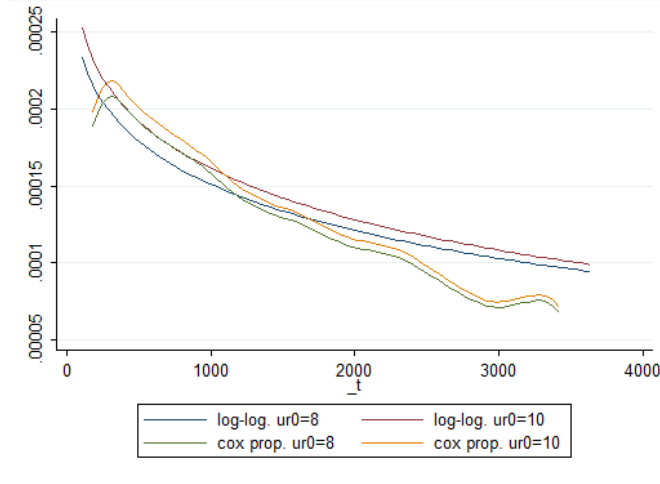
Table A19: Estimates from log-logistic duration models and from Cox proportional hazard model

	All injuries			NIC injuries			IC injuries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log-log.	Log-log.	Cox propr. Haz.	Log-logistic	Log-logistic	Cox propr. Haz.	Log-logistic	Log-logistic	Cox propr. Haz.
		with frailties			with frailties			with frailties	
u_0	-0.046*** (0.016)	-0.144*** (0.013)	1.024** (0.012)	-0.040** (0.016)	-0.141*** (0.013)	1.020* (0.012)	-0.089* (0.046)	-0.151*** (0.034)	1.073* (0.040)
u_t	0.069*** (0.006)	0.060*** (0.006)	0.944*** (0.004)	0.072*** (0.007)	0.062*** (0.006)	0.941*** (0.005)	0.039*** (0.014)	0.030*** (0.014)	0.970*** (0.011)
Region of birth dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Region of entry dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year of entry dummies	yes	no	yes	yes	no	yes	yes	no	yes
cons	8.996*** (0.236)	10.035*** (0.197)		8.965*** (0.243)	10.082*** (0.205)		14.272*** (0.861)	13.613*** (0.582)	
ln gamma	0.134*** (0.007)	0.120*** (0.007)		0.135*** (0.008)	0.121*** (0.008)		0.198*** (0.026)	0.172*** (0.024)	
ln theta		-5.815*** (0.762)			-5.634*** (0.724)			-21.140 (190.098)	
LR test theta		2.598 [0.054]			3.021 [0.041]			0.000 [1.000]	
Global test			164.62 [0.000]			166.46 [0.000]			40.35 [0.8059]
Schoenfeld residuals									
Log likelihood	-47423.479	-47474.771	-145520.6	-45267.127	-45316.430	-136799.2	-7701.9192	-7714.6232	-14025.259
AIC	94948.96	95035.54	291139.2	90636.25	90718.86	273696.4	15505.84	15515.25	28148.52
N	348521	348521	348521	351515	351515	351515	393243	393243	393243

Note: *** significant at 1%, ** significant at 5%, * significant at 10%. For log-logistic regressions the estimated coefficients are reported. In columns 1, 4 and 7 standard errors are clustered at the individual level. Columns 3, 6, and 9 report hazard ratios from Cox proportional hazard models and the standard errors of the original coefficients in parentheses. P-values of the global test based on Schoenfeld residuals and Likelihood ratio test on theta are reported in square brackets. Frailties in columns 2, 5 and 8 follow a gamma distribution.

Results from the Cox proportional hazard model in Columns 3, 6 and 9 indicate a similar story. A percentage point increase in the unemployment at entry increases the hazard rate of all injuries and NIC injuries by 2 % (Columns 3 and 6). Figure A9 plots the hazard rates for all injuries estimated by using the baseline log-logistic regression and the Cox Proportional hazard model at $ur_0=8$ and $ur_0=10$. The coefficient of ur_0 in Column 9 shows that a percentage point increase in initial unemployment rates raises the hazard rate of IC injuries by 7.3%. Interestingly for all injuries and NIC injuries, the use of Cox proportional hazard models, although providing qualitatively the same effect as the log-logistic regression, is rejected by the data. Tests based on Schoenfeld residuals indicate a violation of the proportionality assumption. In particular, the variable-by-variable tests reveal that the Schoenfeld residuals for the initial unemployment rate, as well as year of entry dummies, vary with time. Conversely the proportionality assumption holds for immediate care injuries indicating that unemployment at entry induces a permanent shift in the hazard function. It is worth noting again that current unemployment rate has a much smaller effect for IC than for NIC injuries.

Figure A9: Estimated hazards by log-logistic and Cox PH model, all injuries



Note: The figure shows the estimated hazards by log-logistic and Cox Proportional hazard model for all injuries, at two different level of initial unemployment rate ($ur_0 = 8$, $ur_0 = 10$)

A.3.5 Survival Analysis: log likelihood specification

In our preferred specification we use a loglogistic hazard function. As shown in Table A20 we have split the episodes in year-specific records to incorporate time-varying covariates.

The contribution of each record to the loglikelihood function for individual i is as follows:

$$\text{Log}L_i = c_i \log[\theta(T_i)] + \log[S(T_i)]$$

where $c_i = 1$ if the spell ends with an injury and 0 if the individual i is censored.

$\theta(T_i)$ is the hazard rate and is equal to $f(T_i)/S(T_i)$. Given the structure of our dataset

we consider the individuals to be at risk of injury only during episodes of employment.

Since some individuals experience periods of unemployment, we have interval truncation.

More precisely, we observe each worker at the time of first entry; thus, we know the spell

start date and the time at which the individual is first at risk. However, if a spell of

unemployment occurs, we observe subsequent year specific records with delayed entry.

For example, if individual i is employed for t_1 days in his first job but experiences unemployment between t_1 and t_2 , the hazard function and survivor function computed at the first year-specific record at reemployment should be conditional on the survival function computed at time t_2 .

Table A21 summarizes the contributions to the log-likelihood of each year-specific record for individuals, censored and not censored, with and without interval truncations.

Table A20: Structure of the dataset

individuals	Working spell		year	injury	t0	t1	initial	current
	spell start	spell stop					unemployment	unemployment
[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]
881	14137	14244	1998	0	0	107	5.8	5.8
881	14244	14609	1999	0	107	472	5.8	4.7
881	14609	14975	2000	0	472	838	5.8	4.4
881	14975	15340	2001	0	838	1203	5.8	3.7
881	15340	15705	2002	0	1203	1568	5.8	3.8
881	15705	16070	2003	0	1568	1933	5.8	3.6
[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]
1808	13163	13514	1996	0	0	351	6.2	6.2
1808	13514	13879	1997	0	351	716	6.2	5.9
1808	13879	14106	1998	0	716	943	6.2	5.8
1808	14167	14244	1998	0	1004	1081	6.2	5
1808	14244	14593	1999	0	1081	1430	6.2	4.7
1808	14868	14873	2000	1	1705	1710	6.2	3.7
[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]	[..]

Table A21: Loglikelihood contributions

Individual	Record	Year	Censoring Indicator	Survival Time	Entry Time	Time Var. Covariates	Contribution to the log likelihood
Multiple data records after episode splitting in year specific records and interval truncation							
3	1	1994	0	t_1	0	ur_{1994}	$\log(S(t_1))$
3	2	1995	0	t_3	t_2	ur_{1995}	$\log(S(t_3)/S(t_2))$
3	3	[..]	[..]	[..]	[..]	[..]	[..]
4	1	1994	0	t_1	0	ur_{1994}	$\log(S(t_1))$
4	2	1995	1	t_3	t_2	ur_{1995}	$\log(f(t_3)/S(t_2))$
Multiple data records after episode splitting in year specific records and no interval truncation							
1	1	1994	0	t_1	0	ur_{1994}	$\log(S(t_1))$
1	2	1995	0	t_2	t_1	ur_{1995}	$\log(S(t_2)/S(t_1))$
1	3	[..]	[..]	[..]	[..]	[..]	[..]
2	1	1994	0	t_1	0	ur_{1994}	$\log(S(t_1))$
2	2	1995	1	t_2	t_1	ur_{1995}	$\log(f(t_2)/S(t_1))$

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