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ABSTRACT

We use a panel of survey responses linked to administrative data in Germany to measure the depreciation of skills while workers are unemployed. Both the reemployment hazard rate and reemployment earnings steadily fall with unemployment duration, and indicators of depression and loneliness rise substantially. Despite this, we find no decline in a wide range of cognitive and noncognitive skills while workers remain unemployed. We find the same pattern in a panel of American workers. The results imply that skill depreciation in general human capital is unlikely to be a major explanation for duration dependence.

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1 Introduction

As workers remain unemployed, they see their prospects for earnings and reemployment steadily fall—a tendency that economists call *duration dependence* (Van den Berg and Van Ours, 1996; Kroft, Lange and Notowidigdo, 2013). Figure 1 demonstrates this relationship using a panel of German workers. Panel (a) shows the steep decline in job finding as workers remain unemployed. The odds of finding a job are five times higher right after job loss than they are after two years of unemployment. The bottom figure shows that reemployment wages also fall over time as workers remain unemployed. The long-term unemployed earn 20 percent less than the short-term unemployed when they return to work conditional on prior earnings.

One explanation for these patterns is that human capital *depreciates* while workers are unemployed (Jarosch, 2021; Schmieder, von Wachter and Bender, 2016; Aaronson, Mazumder and Schechter, 2010). In the presence of skill depreciation, even temporary shocks causing unemployment can have long-lasting effects (Pissarides, 1992; Rothstein, 2020), which could explain chronically high unemployment in some Western European countries and so-called "scarring effects" after recessions (Acemoglu, 1995; Ljungqvist and Sargent, 2008). The serious concern about skill loss during unemployment is not only the concern of academics, but also of prominent policy makers. A great example of that is Ben Bernanke's Monetary Policy Report to the Congress in 2013:[1]

> *"One concern we do have, of course, is the fact that more than 40 percent of the unemployed have been unemployed for six months or more. Those folks are either leaving the labor force or having their skills eroded. Although we haven't seen much sign of it yet, if that situation persists for much longer then that will reduce the human capital that is part of our growth process going forward."*
>
> Ben Bernanke, Federal Reserve Chairman, 2013

Understanding the role of skills in declining outcomes clarifies which interventions are likely to be successful. Programs that attempt to maintain skills are most likely to be effective

[1] https://www.federalreserve.gov/newsevents/testimony/bernanke20130226a.htm

if skill declines actually explain the fall in reemployment prospects. If employment prospects decline for some other reason, then it is less clear that such interventions will be fruitful. We have surprisingly scarce evidence on the evolution of skills during unemployment, as pointed out by Machin and Manning (1999) in the Handbook of Labor Economics. Direct eliciations of skills are restricted to a handful of surveys with few unemployed respondents. Further, a naïve comparison of the skills of people unemployed for different periods is unlikely to reveal a causal relationship of unemployment on skills because of selection: those with weaker employable skills may take longer to find work.

To address the core challenge, we employ novel *panel* data to track the evolution of an individual's skills as he or she remains unemployed. Our data measure skills for a large sample of German workers at the onset of unemployment around 2007 and three additional times over the following three years. The panel dimension addresses traditional selection problems by making within-worker comparisons over time, implicitly controlling for unobserved factors that differ across workers.

A unique feature of our data is that it measures a wide range of cognitive and noncognitive general skills. The cognitive measurements include math skills, verbal fluency, immediate memory, and recall memory.[2] The survey also includes standard measures of so-called noncognitive skills including conscientiousness, locus-of-control, patience, reciprocity, risk tolerance, and social trust (Almlund et al., 2011; Weiss et al., 2013; Kautz et al., 2014). The cognitive and noncognitive skills measured in the survey are meaningful components of human capital. Skills measured at the onset of unemployment meaningfully predict prior wages measured in administrative data, with out-of-sample R^2 values of 5–8 percent.

We find no evidence that any of the measured skills declines during an unemployment spell. This is true when we focus on within-person changes over the unemployment spell and if we compare the skill evolution of the unemployed to those of quickly reemployed in a difference-in-differences style analysis. Cognitive skills like mathematics, verbal fluency, and

[2] The verbal fluency question comes from a Weschler Adult Intelligence score module, while memory questions come from the the Rey Auditory Verbal Learning Test (Groth-Marnat, 2003; Rey, 1964).

memory show no significant changes, and if anything, modestly improve. Noncognitive skills like locus-of-control and trust remain unaffected as workers remain unemployed. These patterns hold for workers potentially most seriously affected by unemployment: full-time workers with high labor-force attachment and those who were involuntarily unemployed. The only skills that show any evidence of decline are noncognitive skills like conscientiousness, risk tolerance, trust, patience, and reciprocity, though these skills do not appear to be earnings-relevant as they are essentially uncorrelated with earnings. We find little indication of dynamic selection based on cognitive and noncognitive skills over the unemployment spell. This is in line with previous evidence in the literature highlighting little selection based on demographic characteristics (see e.g. Schmieder, von Wachter and Bender, 2016).[3]

We provide two quantitative benchmarks to show the near-zero, statistically insignificant changes in skills among the continually unemployed which can explain only a small part of the fall in reemployment wages. First, we collapse skills into an index of predicted earnings and rule out reductions associated with larger than 3 percent (1 percent) earnings decline after 6 months (12 months). This is small relative to the 10–30 percent fall in reemployment wages among those with unemployment durations of at least 6 months. Second, focusing on the group of people who become reemployed soon after a skill survey, the point estimates suggest that skill depreciation does not explain any change in reemployment earnings, and the confidence intervals rule out explaining a share of earning declines larger than 28% after 6 months and 6% after 12 months.

We complement our analysis of newly unemployed German workers by studying a representative panel of older American workers. We use data from the Health and Retirement Study (HRS) that measures cognitive skills—including simple mathematics, memory, and fine-motor skills—for those at least 50 years old in the United States. The broad skill items

[3]The lack of dynamic selection based on skills does not rule out dynamic selection based on other factors. A recent working paper by (Mueller and Spinnewijn, 2023) demonstrates the predictability of unemployment duration based on rich and detailed information on unemployed workers. (Mueller and Spinnewijn, 2023) also show that skills like IQ cannot predict unemployment duration (see panel C in Table 3), which is consistent with our findings.

we focus on predict earnings and explain about 2 percent of overall earnings variation. While the survey provides a more limited array of skill measures relative to the German data, we observe individuals prior to unemployment and over a longer period of time. We implement an event-study framework where we study the evolution of skills before and after the unemployment onset.

Our three main findings from the American data are highly complementary to our findings from the German data. First, we confirm the core findings from the German data: skills do not appear to be affected by unemployment duration, and general measures of life satisfaction are affected. Second, we demonstrate that there are not trends in survey measurements prior to the unemployment onset. Third, we validate the plasticity of our survey measure of skills by showing that skills do respond to certain shocks. In particular, we document that there is a significant reduction in skills following retirement. While the decline of cognitive skills after retirement is established in the previous literature before (see e.g. Rohwedder and Willis, 2010), these findings highlight that the stability of skills following unemployment is not merely the artifact of the skill measures used here.

These results paint a subtle picture of unemployed workers' experiences. In multiple countries across different worker populations, general elicited skills are stable over unemployment while general life satisfaction falls. The magnitudes of the impacts on life satisfaction are quantitatively meaningful: there is a 0.2–0.3 standard deviation increase in depression, loneliness, and life dissatisfaction in both surveys.

We contribute to the examination of skill depreciation and duration dependence. Most studies focus on changes in reemployment wages without directly observing the change in skills (see e.g. Kroft, Lange and Notowidigdo, 2013; Jarosch, 2021; Schmieder, von Wachter and Bender, 2016; Centeno and Novo, 2009; Jacobson, LaLonde and Sullivan, 1993). Notable exceptions are Arellano-Bover (2022) and Dinerstein, Megalokonomou and Yannelis (2022), who document skill depreciation for young workers. Arellano-Bover (2022) shows that early-career unemployment shocks have negative effects on measured cognitive skills several decades later. Dinerstein, Megalokonomou and Yannelis (2022) exploit quasi-experimental variation in unemployment at the beginning of Greek teacher's career and show negative effects of the length of unemployment on teachers' performance measured by students' test scores. Both of these papers find clear indications of skill depreciation coming from unemployment at the beginning of individuals' careers, which underscores the concerns of policy-makers as highlighted by Ben Bernanke. Nevertheless, contrary to this evidence, we find no indication for a decline in skills over the unemployment spell in the overall population in Germany and for the older workers in the USA. This suggests that the negative consequences of unemployment might be a more relevant concern at younger ages.[4] This finding could improve the targeting of programs designed to elevate skills over the unemployment spell.

The only other paper, to our knowledge, that longitudinally measures cognitive skills following unemployment is Edin and Gustavsson (2008). They document a decrease in literacy scores using surveys of several hundred workers surveyed four years apart. We improve on this evidence by applying broader measures of skills and using more granular data with detailed information on skills evolution around unemployment onset. Other closely related work examines the plasticity of personality measures around significant life events, though the results are mixed. Some papers find these measures are stable over time (Cobb-Clark and Schurer, 2012; Cobb-Clark and Schurer, 2013; Anger, Camehl and Peter, 2017), while others find significant decreases (Preuss and Hennecke, 2018; Stillman and Velamuri, 2020). We extend previous work in three key dimensions: we link survey responses to administrative records on earnings and employment which provides more reliable measures of earnings and duration; we provide measures of a broader array of cognitive and noncognitive skills; and we use much larger samples with skill measurement at multiple points of the unemployment spell.

Finally, we align with a lengthy literature finding decreases in life satisfaction during

[4]Skills tend to grow until age 30 and then fall (Edin and Gustavsson, 2008). As a result, the previous literature's finding of a negative effect of unemployment on the young could be due to a change in the growth rate rather than the level.

unemployment. The most closely related work in this respect is Krueger and Mueller (2011), which elicits subjective well-being among a panel of newly unemployed workers at a weekly frequency. Most of other work uses lower-frequency, general population surveys (Kettlewell et al., 2020; Powdthavee, 2012; Winkelmann and Winkelmann, 1998).

2 Data of Newly Unemployed German Workers

This section describes the content and context of our primary data source: the IZA/IAB Linked Evaluation Dataset from Germany. It is a representative sample of newly unemployed workers around 2007 with a panel survey of elicited skills and an administrative panel of employment outcomes.

2.1 Panel Survey of Skills and Employment

The IZA Evaluation Dataset is a panel of four survey waves over three years composed of a representative sample of newly unemployed workers in Germany.[5] The German Federal Employment Agency randomly sampled prime-age individuals who filed for unemployment between June 2007 and May 2008. 17,396 individuals consented to the study (76 percent of invitees). The initial survey was completed within two months following entry into unemployment, and subsequent surveys were administered to participants who responded to all previous surveys. These occurred at twelve and thirty-six months following entry into unemployment. The initial survey screened out individuals who already had a job lined up upon entering unemployment, but subsequent waves surveyed all remaining participants regardless of labor market status. For the June, October, and February cohorts, an additional survey was administered six months after entry into unemployment. All surveys were administered by telephone.

[5] IZA maintains a complete list of publications and working papers using the Evaluation Dataset: https://ed.iza.org/files/documentation/publications.pdf. This dataset has not yet been used to study skill depreciation.

Our primary outcomes of interest are the survey's objective cognitive assessments and subjective noncognitive self-assessments, both of which we refer to as skills. All survey waves include at least some of these questions. Appendix Table A.1 details some of the individual survey skill items, Appendix Figure A.1 summarizes which of these skills were elicited from each of the survey cohorts over time, and Appendix Figure A.2 shows the number of respondents in each wave by question type.[6] Notably, we have close to 700 unemployed respondents around 6 months after onset for each question type, around 300 unemployed 12 months after, and around 150 unemployed 36 months after. This sample is an order of magnitude larger than other surveys on the skills of the unemployed. The initial survey also collects detailed demographics, and all waves include self-assessed life satisfaction and recent labor market experiences.

The personality assessments we use to measure noncognitive skills are Likert-scale responses, while the cognitive assessments measure objective performance.[7] Most questions remained the same across survey waves.

2.2 Defining Earnings and Unemployment Duration

Administrative data from Germany's Federal Employment Agency comprise our primary source of labor market outcomes. Employment data is available for the 88% of survey respondents who consented. Prior to the unemployment spell, we observe the average daily wage, hours, and separation reason for the most recent employment spell along with annual employment and earnings for the ten previous years. For each of the thirty months following entry into unemployment, we observe benefit receipt, average daily earnings, and employment contract type. Because the final survey occurred thirty-six months after unemployment onset while the administrative data continues only thirty months after unemployment onset, we

[6] See Arni et al. (2014) for a detailed discussion of the survey content, questionnaire administration, and sample composition.

[7] The cognitive questions are nontrivial. For example, Appendix Table A.3 shows that, at baseline, the three math questions are answered correctly by 97%, 60%, and 21%; of the 10 listed words, the average immediate recall amount is 6.6 and the average subsequent recall amount is 5.1; and the median number of animals listed in a minute is 23.

define labor market status at thirty-six months using the observed labor market status at thirty months. Average daily earnings during an employment spell is top-coded at 149€, and we refer to this as the wage throughout our analyses.[8]

In order to view unemployment as a discrete shock, our conception of employment focuses on relatively stable working arrangements. In this regard, a relevant feature of German labor markets is the tax-advantaged marginal employment contracts.[9] The most common arrangement is often referred to as a "mini job" (*geringfügige Beschäftigung*), which limits those without other employment to earning at most 400€ per month during our sample period. Another arrangement is often referred to as "short-term employment" (*kurzfristige Beschäftigung*), which limits participants to working at most 70 days in the position each year. These arrangements are quite common. Table A.3 shows that slightly more than one-fifth of our sample of newly unemployed workers previously had this type of arrangement as their only employment, and we do not include these individuals in our analysis sample.

Our definition of employment as non-marginal work recorded in the administrative data motivates our definitions of unemployment duration and reemployment wages. In particular, our primary definition of unemployment duration is the number of months the individual spent without any non-marginal employment following their initial entry into unemployment. The reemployment wage is then the wage in the first month that they first gained non-marginal employment.

As discussed in the Introduction, Figure 1 contains the changes in reemployment wages and hazard rates using the above definitions of employment. Panel (b) shows the change in reemployment wage relative to the prior spell. To control for macroeconomic trends, it also differences out wage growth of the quickly reemployed. We separately plot this double

[8]This comes from the limitation of the German Social Security data. Taking into account the full universe of German workers top coding affects around 10% of men and 1% of women and it is not binding for most people in our sample. Imputation methods have been developed to deal with this issue (see e.g. Card, Heining, and Kline, 2013). Nevertheless, we do not apply those to follow the existing literature on reemployment wages as close as possible (see e.g. Schmieder, von Wachter and Bender (2016)).

[9]See Ebbinghaus and Eichhorst (2009) for a comprehensive discussion of German labor market institutions around this time period.

difference for each realized duration of unemployment, which reveals a noisy but consistent fall in reemployment wages with unemployment duration. Appendix Figure A.3 confirms that the pattern is not driven by differencing out macroeconomic trends or changes in hours upon reemployment, and Appendix Figure A.4 shows that the fall in reemployment wages with duration consistently holds across all prior earnings levels.

A unique feature of our linked administrative-survey data is that the survey includes typically unobserved labor market activities, such as self-employment or informal arrangements. This is particularly relevant for probing the robustness of our main result that skills do not change during unemployment. A potential concern is that the null result is driven by measurement error, as those who lack employment in the administrative data for long stretches are actually employed through alternative means. However, we find no indication that such type of mismeasurement can explain our findings. Appendix B details the relationship between administrative and survey-based measures of unemployment and shows that our results are robust to a narrower definition of unemployment based on the absence of any survey-based or administrative record of employment or training.

2.3 Defining Skill Indices

Because many skills are measured using multiple items, we reduce the questions for each skill group to a standardized unidimensional index. For each survey item, we construct a question-specific z-score, where we standardize using the mean and standard deviation of initial wave responses. We construct a skill-specific index by taking an equal-weighted average of the questions pertaining to that skill[10]. Finally, we standardize these indices—again using the initial survey's mean and standard deviation—to aid comparison across skills.

Recent work has highlighted potential limitations of interpreting psychometric responses cardinally (Bond and Lang, 2019; Nielsen, 2023), so we also follow Nielsen (2019) and index

[10] This aggregation also increases statistical power for detecting effects that operate in the same direction for a given skill (Kling, Liebman and Katz, 2007).

elicited skills to an economic outcome with a clear cardinal interpretation: earnings. In particular, we define summary skill indices for groups of skills. For each skill group—cognitive skills (math, verbal fluency, and memory); one set of noncognitive skills (the Big-5 and locus of control, which were elicited from all respondents); another set of noncognitive skills (risk tolerance, trust, patience, and reciprocity); and all skills together—we predict wages immediately prior to the unemployment spell with the baseline elicitations. In accordance with our primary definitions of employment and unemployment, we do so only for those with non-marginal employment immediately prior to the spell who have not yet been reemployed in non-marginal employment by the first survey. To avoid measurement error due to differences in hours worked, we also restrict the prediction exercise to those whose previous job was full-time. With each mapping of a group of skills to predicted earnings, we define summary skill indices in subsequent survey waves.

2.4 Predictive Content of Skills

The summary indices mapping skill groups to earnings are useful only insofar as the skills are predictive of earnings. We validate this in two ways. We first show that baseline skills are meaningfully correlated with prior earnings. Given this correlation and the variation in baseline skills, we then show that the elicited general skills explain a nontrivial amount of the variation in prior earnings.

For the first part—that baseline skills are predictive of prior earnings—Figure A.5 displays coefficients on each skill from separate univariate regressions with prior earnings as the dependent variable. We restrict to those in non-marginal employment for comparability with our analysis sample, and we restrict to those in full-time employment to avoid measurement error stemming from hours differences. As shown in panel (a), math has the most statistically and economically significant relationship with prior earnings; a 1 standard deviation increase in math performance is correlated with approximately 12% higher earnings. Locus of control and each of the Big-5 also have statistically significant relationships with prior earnings; a 1 standard deviation increase for each one is correlated with approximately 3% higher earnings. We confirm in panel (b) that these correlations hold even conditional on detailed demographics.

For the second part—that variation in baseline skills explains a meaningful portion of the variation in prior earnings—Appendix Table A.2 shows that the composite skill index explains 5–8% of the *out-of-sample* variation in baseline earnings.[11]

Due to its interpretability and usefulness in subsequent decompositions, our preferred index is based on an OLS prediction whose inputs are z-scores of the individual skill groups. This implicitly treats ordinal responses as cardinal, so we also explore more flexible prediction methods that accommodate nonlinearities. Out-of-sample R^2 slightly increases when we use fully saturated levels of the cumulative distribution function for Likert-scale responses as inputs into a regularized prediction procedure. We show our results are robust when using these more flexible indices (see Appendix Figure A.7).

Another benefit of a linear mapping from skill z-scores to predicted earnings is that we can easily demonstrate predicted earnings losses for decreases in skills. Appendix Figure A.6 plots the earnings changes implied by our baseline indices mapping. A "loss" in a skill is defined as a decrease (increase) in the survey item z-score for an item with a positive (negative) coefficient in the multivariate regression of prior earnings on survey items at baseline. With this definition, a 0.5 standard deviation decrease in *all* skills is correlated with 30% lower predicted earnings. We view this as additional evidence that our earnings-based skill indices are well-powered to detect changes in skills.

2.5 Summary Statistics at Baseline

Table 1 presents demographics and baseline survey responses by eventual unemployment duration. Column 1 describes our analysis sample that limits the employment to those

[11]For model evaluation, we use the out-of-sample R^2 with 10-fold cross-validation. This randomly splits the baseline data into 10 groups, trains the given model on 9 groups of the 10 groups, evaluates that model fit on the 1 hold-out group, and averages over the 10 possible iterations.

whose prior employment spell was a non-marginal job.[12] Workers earned on average 58€ each day before job loss, which is approximately the average wage in Social Security data among all employed workers over this time period (Card, Heining and Kline, 2013). They are relatively high-attachment workers, as over four-fifths were previously full-time and the average duration of the previous employment spell is almost 10 years.

One potential concern with our main result showing no skill depreciation during unemployment is that skill depreciation for the long-term unemployed already occurred by the first survey, which was administered in the first two months of unemployment. The baseline survey levels provide suggestive evidence against that explanation. In particular, the baseline skill elicitations are, if anything, higher for those with eventually long unemployment durations. This is not dispositive, though, as those with longer eventual unemployment durations also differ along other dimensions: they are older, more educated, more likely to be female, and less likely to have involuntarily lost their job.[13]

While skills elicited in the first survey are not differentiated by reemployment status, self-reported life satisfaction clearly is. There is an approximately 0.3 standard deviation gap between those who are reemployed and all others who are not yet reemployed.

3 Evolution of Skills among Unemployed German Workers

This section discusses the evolution of skills over the unemployment spell for German workers. We show that skills do not decline during unemployment. Our upper bound on the contribution of changes in skills to falling reemployment wages observed in the data rules out

[12] Table A.3 shows the difference between the analysis sample and all respondents. The primary difference between these two groups is that almost by definition, our analysis sample is less likely to have any marginal employment (and thus more likely to have a full-time with higher earnings). Still, the demographic characteristics and the measured skills in the two samples are very similar, which provides evidence in favor of our finding's generalizability.

[13] One concern is that the workers who never become reemployed appear observably different. Our results in the 6-month and 12-month survey waves are robust to excluding those who never become reemployed.

contributions of more than 28%. These results are robust to various measurement concerns.

3.1 Empirical Measurement of Skill Evolution

We begin showing the evolution of skills over the unemployment spell. In our benchmark specification, we assess the skills of the unemployed in comparison to those who have been employed within 2 months of job loss and stayed employed afterward. We apply this comparison to control for potential elicitation bias of skills, as similar questions are used to measure skills at each subsequent wave.

By choosing workers who are employed within 2 months as a reference group, we implicitly assume that the elicitation error is the same for them and for the unemployed. If anything, this biases toward finding skill depreciation among the unemployed. Specifically, to the extent there is additionally skill *appreciation* during employment, we would overestimate the extent of skill *depreciation* among the unemployed.[14]

To assess the change in skill over the unemployment spell, we run the following regression:

$$Skill_{it} = \sum_{\tau \in 2,6,12,30} \left(\alpha_\tau \mathbb{I}[t=\tau] + \beta_\tau unemp_{it} \times \mathbb{I}[t=\tau]\right) + \epsilon_{it} \tag{1}$$

where $Skill_{it}$ measures the individual i skill measured in wave t, and $unemp_{it}$ measures if someone is unemployed through wave t (vs. reemployed before wave 2 and continuously employed through wave t)[15]. The panel has waves $t \in \{2, 6, 12, 36\}$, and the corresponding β_τ coefficients reflect the average skills of the unemployed relative to the reference group. Notice that in this regression we do not control for individual effects, so β_τ reflects both the selection (i.e. the long-term unemployed might have different skills at the baseline) and the

[14]The choice of the reference group does not drive the lack of skill depreciation among the unemployed. Online Appendix Figures A.8 and A.9 show that measured skills in the reference group are close to zero in each wave, while the measured skills of the unemployed slightly increase over time.

[15]As of each follow-up survey, approximately two-thirds of those who were reemployed before the wave 2 were not continuously employed through wave t. Including these individuals in the reference group does not affect our results.

depreciation of skills over the unemployment spell.

We report the β_τ coefficients in panel (a) of Figure 2 using various skill measures as an outcome.[16] The figure shows the average change in the composite skill index (black dots) for the unemployed at 2, 6, 12, and 36 months after unemployment onset. This skill index is the log of the predicted daily wage based on all available skills. To contextualize the confidence interval magnitudes, we set the absolute value of the upper and lower bounds of the y-axis to correspond to 1 standard deviation in the composite skill index at baseline.

Average skills among the still unemployed are only slightly lower than those for the reemployed 2 months after unemployment. The marginally significant point estimate indicates that earnings predicted by all skills are 4 percentage points lower for the unemployed. Separating by cognitive and noncognitive skills, we find smaller differences that are not statistically significant. The fact that the unemployed and those who found a job within two months are very similar in the baseline survey justifies our choice of using the latter as a reference group.

Panel (a) of Figure 2 also highlights that the average unemployed's skills do not fall over the unemployment spell. If anything, there is a slight increase in the measured skill of the unemployed, though any differences are generally statistically insignificant. The lack of change in average unemployed's skills could reflect the combination of two things: 1) the long-term unemployed are not negatively selected; 2) the skills of the unemployed are not depreciated over the unemployment spell.

We isolate the contribution of skill depreciation by looking at the within-person evolution of skills. In particular, we estimate the following regression:

$$Skill_{it} = \gamma_i + \sum_{\tau \in 6,12,30} (\alpha_\tau \mathbb{I}[t=\tau] + \beta_\tau unemp_{it} \times \mathbb{I}[t=\tau]) + \epsilon_{it} \tag{2}$$

[16]We report α_τ in the Online Appendix Figures A.8 (blue diamonds), which correspond to the evolution of the skills for the reference group of those who found a job within 2 months and remained continuously employed. For the reference group, the change in cognitive skills is generally positive and the change in noncognitive skills is generally zero.

Notice that this is the same regression as before (equation 1) but with individual fixed effects γ_i and excluding wave 1 (month 2) from the summation index τ. The coefficient of interest is again β_τ, which now shows the average within-person change relative to the baseline skill measured two months after onset.

We plot the estimated β_τ in Panel (b) of Figure 2. We do not find any indication of average earnings-relevant skills falling within-person over the unemployment spell. The confidence intervals include 0, and the point estimates, if anything, are positive. For every skill group at every point in time, we can rule out relative decreases larger than only a few points in log predicted earnings. This is in stark contrast to the observed changes in wages upon reemployment relative to prior wages shown in Figure 1 and Appendix Figure A.4, where the change in earnings for longer unemployment spells is approximately 20 log points.

Appendix Figure A.10 shows that the lack of relative changes in skills mostly holds for each of the individual skill items. None of the point estimates is significant. For the cognitive skills that have the greatest association with prior earnings, the relative changes are, if anything, positive.

To the extent that any skills depreciate during unemployment, they are noncognitive skills. Conscientiousness, risk tolerance, trust, patience, and reciprocity all decline by 0.2-0.6 standard deviations. While these point estimates are all negative, they do not drive the earnings-based skill indices because these self-assessed personality traits have much weaker associations with prior earnings. Moreover, noncognitive skills that have stronger associations with prior earnings—like locus of control and stability—do not decrease with longer unemployment durations.

It is also worth highlighting that Panel (a)—showing the average change of the unemployed's skill—and Panel (b)—showing the within-person skill change—of Figure 2 are very similar. Therefore, the change of skills over the unemployment spell primarily reflects the within-person change in skills, while the dynamic selection of individuals based on their baseline skills plays little role. The lack of dynamic selection might not be surprising given the limited dynamic selection observed in past wages (see the row labeled "prior wage" in Table 1). Still, we are not aware of any paper documenting this fact by directly assessing the overall evolution of skills over unemployment durations.

3.2 Quantifying the Contribution of Skill Changes to the Fall in Reemployment Wages

We have so far demonstrated that reemployment wages fall considerably during unemployment (see Figure 1) while earnings-relevant skills do not (see Panel (b) of Figure 2). One complication in interpreting the relative magnitudes of these findings is that they apply to slightly different samples: reemployment wages are by definition observed only for those who find a job within our survey panel.

To quantify the contribution of skill changes to the fall in reemployment wages, we study subsamples of survey respondents whose reemployment we observe. We compare the change in skills to the change in log wages—the log reemployment wage minus the log wage in the job prior to unemployment onset—for those respondents who are continually unemployed through a given survey wave but become reemployed soon afterward. In particular, we take respondents whose unemployment spell lasts more than 6 (12) months but fewer than 12 (30) months. We compare these respondents' change in log wages to the within-person skill change measured at months 6 (12).

We estimate the within-person change in skills by applying the same regression specification as before, shown in equation 2, except that we restrict the sample to respondents who find a job between 6 (12) and 12 (30) months and to those who are in the reference group. For the change in log earnings, we calculate the log wage change relative to the wage change in the reference group. We apply the comparison to the reference group to control for macroeconomic trends and to make the empirical designs estimating wage changes and skill changes comparable.

Formally, we estimate the change in log wages by applying the following regression specification on the same sample of workers (reemployed between a certain period and the reference group):

$$\log(wage_{it}) - \log(wage_{i0}) = \theta_t + \beta reemp_{it} + \epsilon_{it} \tag{3}$$

where $\log(wage_{it}) - \log(wage_{i0})$ is the difference in log wages at time t and the log wages at the previous job and $reemp_{it}$ equals to one if the individuals are reemployed between 6 (12) and 12 (30) months. We include each reemployed individual only once in the sample (in the month when the individual is reemployed), while the reference group is included in all months. Therefore, θ_t shows the change in log wage between time t and in the previous job for the reference group (reemployed within 2 months and stayed employed afterward), while β shows the wage changes for those reemployed in month t relative to the reference group wage change.

Table 2 shows the main decomposition results. Panel A corresponds to the unemployed who were reemployed between 6 and 12 months after job loss. The first row shows substantial wage losses (16.8%, s.e. 4.5%) in line with existing estimates in the literature (see e.g. Schmieder, von Wachter and Bender (2016)). The remaining rows show within-person skill changes in terms of log predicted wages. These skill indices remained the same between months 2 (wave 1) and months 6 (wave 2). The wage change that can be attributed to the within-person skill change (0.2%, s.e. 2.5%) is small, statistically insignificant, and has a sign opposite to the one implied by skill depreciation. The confidence intervals in column (2) suggest that we can rule out a larger than 5% fall in wages due to skill depreciation at the conventional significance levels. In columns (3) and (4) we also calculate the potential contribution of skill changes to the fall in reemployment wages by taking the ratio of the change in skill to the change in wages. The point estimate suggests that the contribution is negative and close to zero (0.8%). The 95th percentile confidence intervals reported in column (4) suggest that at most 28% of the fall in wage can be attributed to the change in skills.

We see a similar pattern if we look separately at different components of the skill measure. The change in the cognitive index can explain wage changes between -4% and 3%. Therefore, at the conventional significance level, it can explain at most 21% of the wage fall upon reemployment. The change in noncognitive skills alone explains even less. We can rule out a contribution that is larger than 6% (5%) for the primary (secondary) noncognitive skill index.

Panel B of Table 2 focuses on those reemployed between months 12 and 30 months.[17] The long-term unemployed experience an even larger wage loss (28.1%, s.e. 3%) than those who found a job between 6 and 12 months. At the same time, the within-person change in skills between months 2 (wave 1) and 12 (wave 3) is again small, statistically insignificant, and "wrong-signed". The point estimates indicate that skills increase for the unemployed (relative to the reference group). Even with modest sample sizes, the 95% confidence intervals rule out skill changes contributing to more than 6% of the fall in reemployment wages.

3.3 Interpretation and Alternative Explanations

Our finding that many skills do not depreciate during unemployment leverages a unique panel survey including a wide range of skills for a large sample of long-term unemployed individuals. In this section, we discuss some of our data's limitations and how to interpret our results in light of these limitations.

Included skills. The survey elicits cognitive and noncognitive skills that are significantly predictive of earnings. We interpret these as general skills, and they do not measure every dimension of earnings-relevant skills. Nevertheless, they are used extensively in the academic literature, and they are also very similar to those used by policymakers for understanding skills specifically for the unemployed. Unemployment insurance agencies administer these types of survey-based general skills assessments to identify appropriate job-search plans

[17] The relatively small share of respondents is due to earlier reemployment, survey attrition, and limited question elicitation. See Appendix Figure A.2 for further details on the first two reasons and Appendix Figure A.1 for further details on the third reason.

and training programs. For example, Florida used to mandate all unemployment insurance claimants complete a general skills review at the onset of unemployment[18]. In a recent review of American Job Centers across the United States, Fortson et al. (2017) find that all surveyed centers offer these types of assessments—usually, the Test of Adult Basic Education (TABE)—for these purposes, and almost one-third deem them as core to their training targeting.

Elicitation bias. One set of concerns relates to the fact that the skills are elicited through a survey. First, like most measures of noncognitive skills, ours are self-assessed. Reassuringly, respondents have no incentive to dissemble, and the self-assessments used in the survey are standard procedures used in the psychology literature.

Second, even for objective skills like answering math questions correctly, the skill elicitation is a function of both ability and effort. The effect of continued unemployment on survey effort is theoretically ambiguous: the opportunity cost of effort may be lower while unemployed due to greater free time, but the psychological costs may be higher while unemployed from discouragement. We view measuring the net effect of skills and effort as a feature rather than a bug, as "marshalling effort" is plausibly related to job search efficiency and employee productivity.

Third, the questions are repeated across waves. The effect of this on our results is hard to characterize: survey learning would generate positive drift in measured skill changes while survey fatigue would generate negative drift. We account for these effects, whatever they may be, by using a group of workers who are reemployed by the baseline survey and who remain continually employed thereafter. This comparison group differences out common influences of learning or fatigue specific to the survey. To the extent that skills are accumulated during employment, this differencing would bias us towards finding skill depreciation. Therefore, if anything, that would lead to attributing a bigger role of skill changes explaining the fall in reemployment wages.

[18] This applied from 2011 through 2013. Chapter 443 of the Florida Statutes outlines this requirement.

In addition to that, we do not find evidence of differential elicitation bias driving our main findings. If elicitation bias increases over time, then both the standard deviation of skills and their predictive power for explaining reemployment wages should fall over time. Appendix Table A.4 shows that the standard deviation of the different skills is relatively stable across the waves, while Appendix Table A.5 documents that the predictive power of skills for explaining reemployment wage differences is similar to the baseline explanatory power of skills. These findings underscore that elicitation bias does not play a major role in our context.

Survey timing. Another set of concerns relates to the survey's timing. First, the initial survey is administered up to two months *after* the onset of unemployment. It is possible that skill depreciation takes place immediately upon unemployment onset. However, those who are quickly reemployed do not experience any decline in reemployment wages, which suggests that their skills were not deteriorated significantly. Furthermore, there is no meaningful differences in baseline skills between those quickly reemployed and those remaining unemployed, suggesting that the skills of the long-term unemployed also did not depreciate considerably in the first two months.[19]

Selective Attrition. While we do not find evidence of skill depreciation in the sample we observe, one concern is that we fail to observe the evolution of skills for those who cease responding to the survey. To test for this, we compare prior trends for those who keep responding to the survey in the future with those who stop responding to the survey.

We find essentially no evidence of negative differential attrition. Appendix Table A.6 displays coefficients from separate regressions of the change since baseline as of survey wave t on an indicator for failing to respond to the following survey wave t', an indicator for remaining continually unemployed through survey, and interaction term between the two, and a constant. The sample includes only those who are continually unemployed through t' or

[19]We find no indication of depreciation for the unemployed before the unemployment onset among older Americans (see Section 4).

reemployed by month 2 and continually employed through t', so the constant represents the average change by t for the continually reemployed who also respond at t'. The primary coefficients of interest correspond to the interaction terms, indicating whether the unemployed who attrit are on different trends. Without correcting for multiple hypothesis testing, nearly all of the interaction term coefficients are statistically insignificant and positive. This implies that the unemployed who attrit are, if anything, on *upward* skill trajectories. The only statistically significant trend is for the secondary noncognitive index for those who attrit by month 12, though we can rule out negative trends greater than 1.2 log points of prior wages.

We also find little evidence that survey attrition is correlated with employment status. Our population of interest is those who remain continually unemployed, and our analysis sample compares their skill trajectories to trajectories for those who are reemployed by the baseline survey and remain continually employed. Appendix Table A.7 shows that the attrition probability for the continually reemployed is not statistically significantly different as of month 6 and month 30, while the continually reemployed are 4 percentage points likelier to attrit by the month 12 survey.

Measurement error in unemployment. While our main result defines unemployment as the absence of non-marginal employment in administrative records, we also explore a more granular definition of unemployment that additionally restricts to those without any marginal employment in administrative records and without any self-reported employment in survey records. Using the survey data we can also exclude unemployed workers with training in the analysis. Appendix Figure B.2 and Appendix Figure B.3 show that the same patterns hold in this more limited sample. While the decreased sample size widens the confidence intervals, it is still the case that the composite skill index change point estimate is positive and statistically insignificant.

Alternative skill indices Our baseline specifications treat any ordinal skill items as cardinal, but we show that more flexible, high-dimensional specifications produce similar results.

We apply the prediction model using fully saturated ordinal responses as described in Appendix Table A.2. The LASSO prediction has much higher out-of-sample predictive power than OLS, but its shrinkage properties bias us against finding skill changes. On the other hand, the poor out-of-sample predictive power of OLS is due to being on the other side of the bias-variance tradeoff. Figure A.7 shows that the main results hold for both alternative indices. All the point estimates of within-person changes are positive, and we reject any decrease in skill indices greater than 5 percentage points despite the increased noise.

Floor effects. The lack of decrease in skills could be explained by having many respondents near the lowest values of skill elicitations at baseline. In Appendix Table A.3 we demonstrate that this is not the case in our survey by showing the raw values of the skill elicitations. None of the skill item averages are near their minimum levels.

Involuntary job loss. We confirm our null results hold within subgroups that are more plausibly susceptible to skill depreciation: those who were previously employed full-time but involuntarily lost their job. Appendix Figure A.12 and A.13 shows that the point estimates remain largely unchanged but the confidence intervals are modestly larger if we restrict the analysis to that subgroup of workers.

3.4 Change in Life Satisfaction

The survey item that exhibits the clearest divergence over the unemployment spell is not skill-based. We study the change in self-assessed life satisfaction in Appendix Figure A.11. The figure shows that there is a meaningful selection in baseline levels and falls since baseline for the unemployed. Panel (a) shows life satisfaction at baseline is almost half a standard deviation lower for the unemployed relative to the reemployed and Panel (b) shows this falls by approximately 0.1 standard deviations for the continually unemployed and rises by approximately 0.1 standard deviations for the reemployed. As a result, we see a 0.2-0.3 standard deviation decline in life satisfaction for the unemployed relative to the control group.

4 Evolution of Skills for Older American Unemployed

To explore the generalizability of these results, we examine a panel of older American workers. A key advantage of the survey data used here is that we can measure skills *before* the unemployment onset. The primary deficiencies relative to the German data are that skill elicitations are less detailed and that the skills are measured less frequently.

4.1 Data and Methodology

We use survey responses from the Health and Retirement Study (HRS), which is a panel of approximately 20,000 Americans over the age of 50 each year spanning 1992 through 2018. The survey includes questions on employment status—allowing us to identify unemployment spells for each respondent that has one—and asks questions that measure a variety of cognitive skills.

Upon unemployment, we document a similar decline in re-employment hazards and re-employment earnings as in Germany (see Figure A.14). Reemployment hazards fall from 23 percent two years after we initially observe unemployment to 7 percent two years later. Reemployment earnings two years after we initially observe unemployment are almost 40 percent lower than they were before unemployment, which fall to nearly 60 percent lower four years after unemployment.

To study skill depreciation, we use the full panel of available surveys and elicited skills. The skills are summary measures that aggregate information across many different survey items. The primary measures that have significant coverage are the Telephone Interview for Cognitive Status (TICS), a Cognitive Score (COGTOT), Mental Status Summary Score (MSTOT), and Fine Motor Skills (FINEA).[20]

[20]Some skills, like vocabulary, are measured more sparingly. We include estimates of the effect of unemployment on these outcomes in Appendix Table A.8.

We form event studies of skills around job-loss events. For workers reporting unemployment at some point, we identify the first observed unemployment spell and treat that as the event of interest. The data included in the event-study figures and corresponding regression estimates use all the pre-unemployment data in which the respondent was employed up to ten years before their event, and all the post-unemployment data in which the respondent was unemployed up to ten years after their event. Our panels, therefore, are not balanced, but they maximize the available data for each event study. We use an event-study specification to measure changes in outcomes each year around layoffs:

$$Skill_{it} = \alpha_i + \alpha_t + \beta' X_{it} + \sum_{\substack{j=-10 \\ j \neq -1}}^{j=10} \pi_j \mathbb{1}\{t - t_i^* = j\} + \varepsilon_{it} \tag{4}$$

Here, $Skill_{it}$ denotes a skills measure for worker i in year t. α_i and α_t are worker and year fixed effects and X_{it} contains age-specific fixed effects that vary for an individual respondent over time. The function $\mathbb{1}\{t - t_i^* = j\}$ represents event-study dummies that equal one if an observation is exactly j years from individual i's unemployment-onset date, and zero otherwise. The π_j coefficients capture the dynamics of the skills measure before and after the unemployment onset. To make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed, we exclude observations for a worker after he or she is employed. Identification comes from comparing workers that became unemployed in different years.

We measure $Skill_{it}$ by applying the same procedure as in Germany. First, we predict log earnings with elicited skills measures. Specifically, we regress contemporaneous log earnings on skill measures among workers with positive earnings before their first unemployment event. In the German data we used (daily) wages; in HRS, we use earnings because the coverage is much broader for earnings. The best predictor of log earnings is the cognitive score (t-statistic: 30.5) and the second one is fine motor skills (t-statistic: 13.5). We then predict log earnings using the model for each individual throughout the panel, generating a summary skill index, as we did for German workers. It bears mentioning that the skill index is scaled in log earnings which generates an easy interpretation: a coefficient captures the percent change in earnings predicted by changes in skills.

4.2 Results

Panel (a) of Figure 3 shows our main result. The skill index does not change around unemployment onset. With the additional pre-unemployment data, we see no pre-trends in skills leading up to the unemployment spell. This holds for the 10 years following the onset of the unemployment spell as well. The construction of the skill index does not drive this: individual event studies for memory, cognitive function, vocabulary, fine motor skills, and simple math show no systematic changes following the unemployment event (see Appendix Figure A.15).

To increase the power of detecting declines in skills, we pool all years in the event study together. Specifically, we adapt Equation 4 by replacing event-time dummies with a simple indicator for post-job-loss. The coefficient on this indicator reflects the average change in outcomes associated with unemployment, while accounting for differences in age, time, and persistent individual differences:

$$Skill_{it} = \alpha_i + \alpha_t + \beta' X_{it} + \pi \mathbb{1}\{t \geq t_i^*\} + \varepsilon_{it} \tag{5}$$

Like before, we account for differences across individuals (α_i), secular trends (α_t), and differences occurring systematically with aging (X_{it}). The coefficient on $\mathbb{1}\{t \geq t_i^*\}$ captures the change in $Skill_{it}$ a worker experiences when he or she becomes unemployed, holding year and age constant. In this pooled specification, the post-unemployment dummies corresponding to all cognitive measures are all statistically insignificant (see Table A.8). The confidence intervals rule out earnings declines greater than 2.2%, 3.2%, and 0.9%, respectively for TICS, COGTOT, and MSTOT. Similarly, the estimates for memory, numeracy, vocabulary, and fine motor skills rule out declines greater than 1.3%, 0.4%, 0.7%, and 1.8%, respectively.

Skill depreciation at retirement. Because the HRS is not only limited to the newly unemployed, we can validate the plasticity of skill measures by studying changes around other significant events. In particular, we study changes in skills around retirement by estimating equation 4 but defining $\mathbb{1}\{t - t_c^* = j\}$ based on the first year of retirement (and not unemployment onset). Panel (b) of Figure 3 plots estimates. The skill index is flat leading up to retirement but falls immediately after retirement. The post-unemployment point estimates correspond to a significant 10 log point decrease in skill-predicted earnings and are all statistically significant.

Alternative event-study specification. Recent literature highlights potential biases with the staggered event study implemented in equation 4 in the presence of treatment effect heterogeneity. We thus also implement an event-study estimator robust to these concerns (Borusyak, Jaravel and Spiess, 2021). Appendix Figure A.17 produces similar patterns and magnitudes. In the case of retirement, the alternative estimation method has slight positive pre-trends prior to unemployment, suggesting that the actual drop in skills could be even larger following retirement.

Change in life satisfaction at unemployment. Finally, we study the change in life satisfaction around unemployment events. Similar to our results from Germany, we find that life satisfaction significantly drops around unemployment. Appendix Figure A.16 shows that self-assessed measures of negative mood—depression, feeling alone, and feeling unmotivated—are flat leading up to unemployment but spike following unemployment. When pooling the post-unemployment periods, we find that unemployment coincides with a 0.21σ increase in depression, 0.16σ increase in loneliness, and a 0.16σ increase in feeling a lack of motivation. Each of these estimates is significant at the 0.001 level (see Table A.8, Panel B).

5 Conclusion

We provide direct evidence of a lack of skill depreciation among the unemployed in two different contexts: newly unemployed workers in Germany and the general population of older age workers in the United States. These skills are survey-based and include both objective cognitive performance and self-assessed noncognitive traits. In both contexts, panel data accounts for potentially time-invariant skill differences between workers with different lengths of unemployment.

Despite (i) substantial correlations between skills and earnings while employed and (ii) substantial earnings declines following unemployment, we find (iii) little evidence of skills declines during unemployment in our data. In the German data, we rule out changes in the general skills explaining a share larger than 28% after 6 months of unemployment and 6% after 12 months of unemployment. The lack of fall in skills during unemployment is not due to the immutability of the skills we observe: in the United States data, skills meaningfully decline following retirement.

While our measures of earnings-relevant skills do not decline during unemployment, both surveys reveal significant nonpecuniary costs of unemployment. In both contexts, various measures of life satisfaction decrease upon unemployment.

Taken together, while we confirm results from prior work showing persistently large pecuniary and nonpecuniary costs of unemployment, our evidence is inconsistent with a decline in general skills driving this. This does not necessarily mean general skills training is ineffective for the unemployed, but it casts doubt on the motivation that these people are likeliest to benefit due to recent skill declines.

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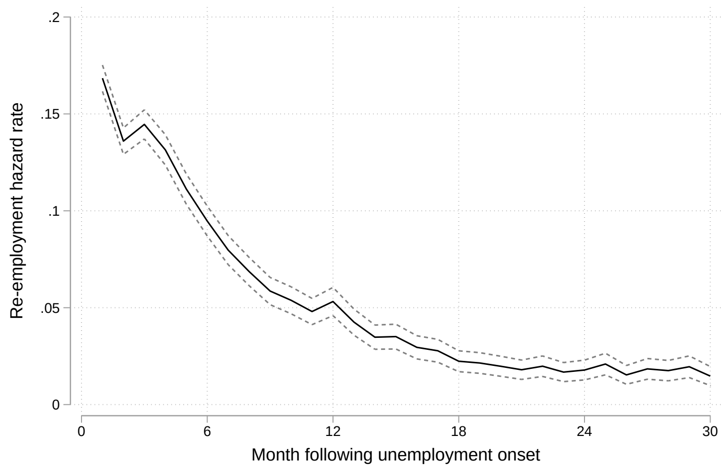
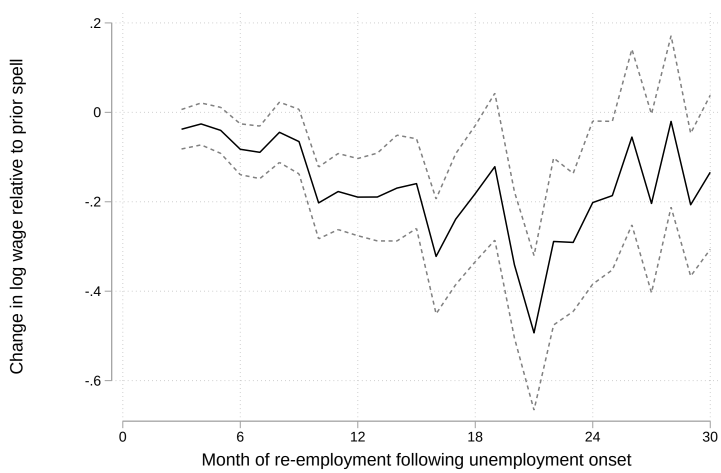
Figures and Tables

Figure 1: Reemployment Hazards and Reemployment Wages over the Unemployment Spell



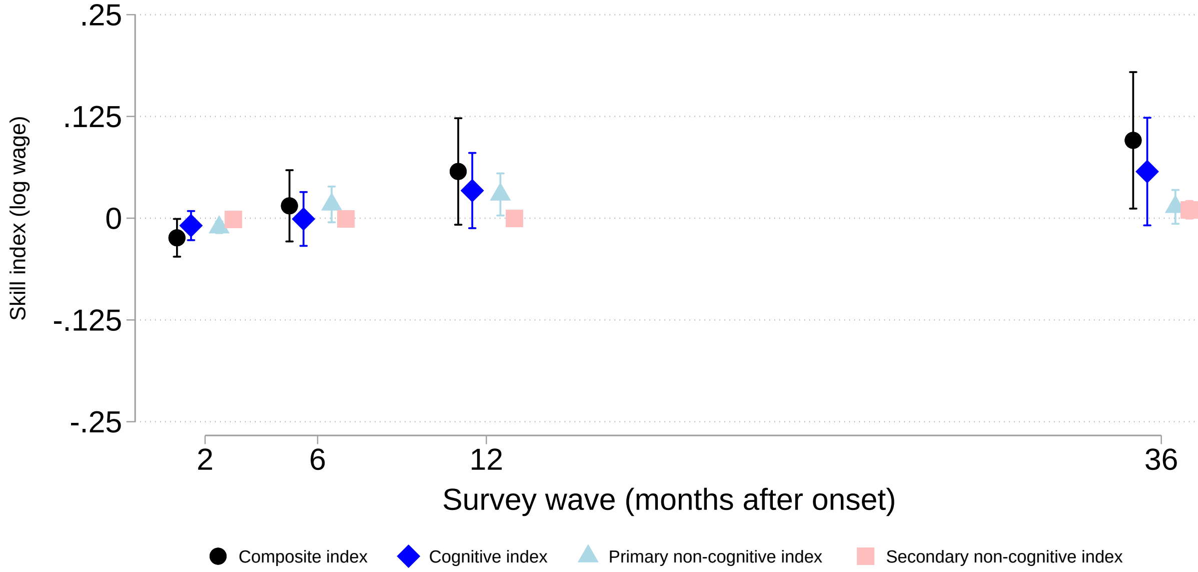
(a) Reemployment Hazard Rates



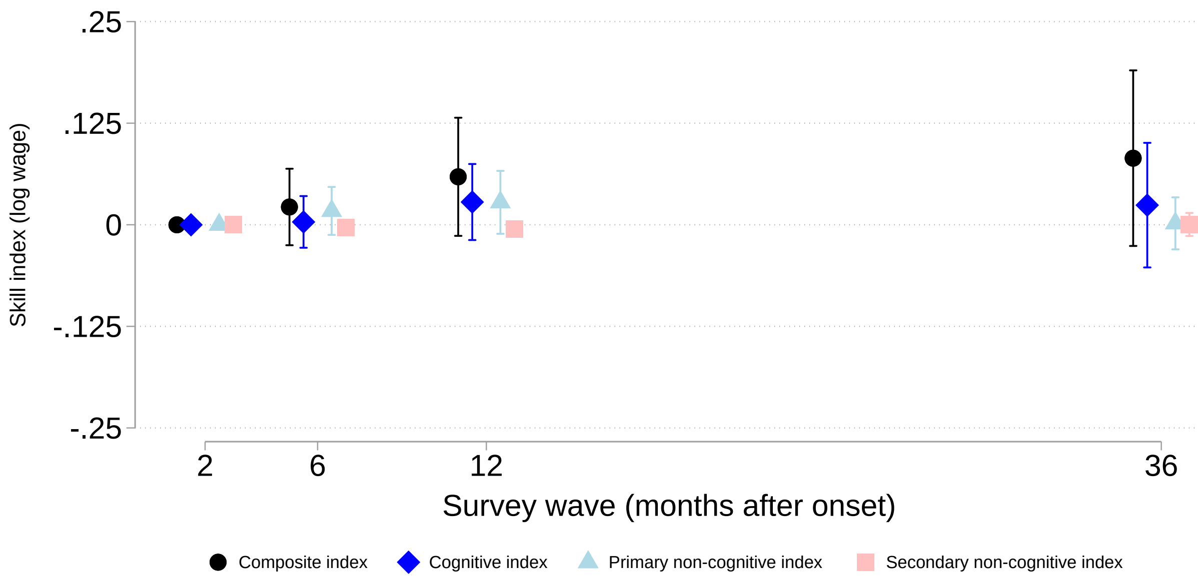
(b) Reemployment Wages

Notes: Panel (a) plots the reemployment hazard rates – the probability of finding a job conditional on being unemployed in the previous month. Panel (b) plots the reemployment wages – the difference between log wages upon reemployment (conditional on finding a job in that month) and log wages in the previous employment spell. To control for macroeconomic trends we adjust the series with the wage growth of workers always employed since the first survey. Unadjusted wage growth is shown in Panel (a) of Appendix Figure A.3. Wage is calculated as the employee's gross daily wage. In addition, panel (b) of Appendix Figure A.3 shows reemployment wages when employee's gross hourly wage is used. The dashed lines show the 95% confidence intervals around the estimates.

Figure 2: Evolution of Skills Over the Unemployment Spell



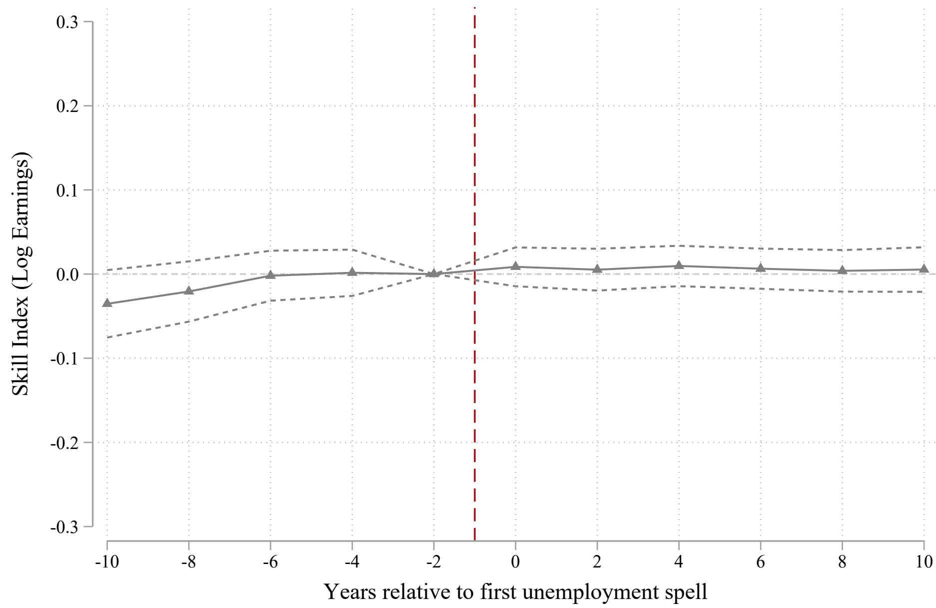
(a) Average Skill of the Unemployed over the Unemployment Spell



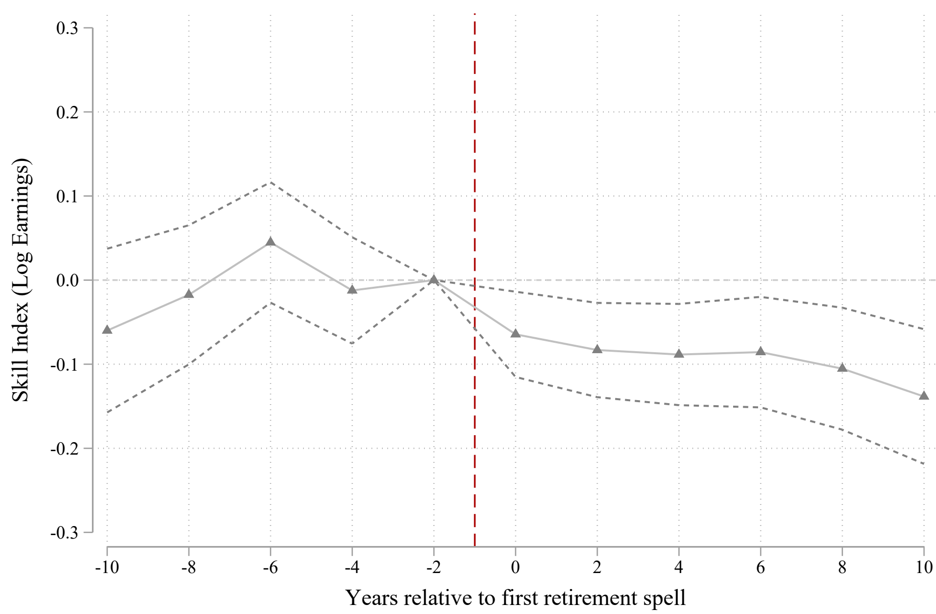
(b) Within-person Skill Changes over the Unemployment Spell

Notes: Both panels plot the change in skill indices of the unemployed relative to the reference group. Panel (a) reports the β_τ coefficients (along with the 95th percentile confidence intervals) from equation 1, where the skills of the unemployed at each wave are compared to those who found a job within 2 months. Panel (b) reports estimates with within-person fixed effects (see equation 2). The skill index is formed by predicting the prior employment spell's wages using OLS and treating survey responses as cardinal. The primary noncognitive index includes only the Big-5 and locus of control questions, the secondary noncognitive index includes the personality traits, and the composite index includes all cognitive and noncognitive questions. The y-axis scale represents approximately $\pm 1\sigma$ of the log predicted wages using the composite skills index as measured at baseline, which is 0.22.

Figure 3: Within-Person Skills Changes around Unemployment and Retirement Among Older American Workers



(a) Within-person Skill Changes around Unemployment



(b) Within-person Skill Changes around Retirement

Notes: This figure shows the within-person change in skills around unemployment (panel (a)) and retirement (panel (b)) events estimated using equation 4. Event time zero shows the first transition from employment to unemployment (retirement) for each worker in the survey (HRS). In panel (a), we exclude observations after unemployment in which the worker regains employment to make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed. In the regression, we control for worker age (fully saturated), person effects, and time effects. The skill index is formed by predicting the employed worker's earnings using OLS. The y-axis scale represents approximately $\pm 1\sigma$ of the skills index (log predicted earnings), which is 0.31.

Table 1: Demographic Characteristics and Skills by Eventual Unemployment Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sample	**By realized duration (months)**					**Correlation**
		0-2	2-6	6-12	12-30	30+	
Demographics							
Female	0.44	0.42	0.40	0.47	0.48	0.48	0.06
Age at UE	34.57	32.82	34.62	35.47	34.64	36.37	0.09
University degree	0.25	0.24	0.22	0.24	0.26	0.33	0.09
Immigrant	0.20	0.19	0.20	0.20	0.24	0.20	0.01
Previous Emp. Spell							
Prior wage (€)	57.57	56.39	57.38	56.69	54.97	61.45	0.05
Full-time	0.84	0.86	0.86	0.84	0.80	0.80	-0.07
Duration (years)	9.31	9.00	9.59	9.51	9.01	9.36	-0.00
Involuntary Unemp.	0.45	0.43	0.49	0.47	0.41	0.41	-0.04
Baseline Survey							
Life satisfaction	-0.01	0.16	-0.08	-0.18	-0.11	0.01	-0.02
Composite skill index (€)	60.49	60.87	59.73	60.11	58.74	62.11	0.03
Math	0.00	0.00	-0.03	0.01	0.02	0.03	0.01
Locus of control	-0.00	0.01	-0.05	-0.01	0.00	0.06	0.03
Extravert	-0.00	-0.02	-0.02	0.04	0.02	0.00	0.01
Stable	0.02	0.03	0.00	0.06	0.03	0.01	-0.00
Open	0.00	0.02	-0.05	0.00	0.02	0.07	0.03
Conscientious	0.02	-0.04	0.09	0.10	-0.04	-0.02	-0.02
Observations	11684	3264	3437	1568	1141	2274	11684

Notes: All columns except for the final one report the average value of the row variable within the column group. The final column reports the correlation coefficient between the variable and the realized months of unemployment. Wage is calculated as the employee's gross daily wage. The composite skill index predicts prior log wages using all cognitive and noncognitive items at baseline and so it is scaled in log wages. All baseline survey questions are expressed as z-scores.

Table 2: Contribution of Skill Changes to the Fall in Reemployment Wages

	(1)	(2)	(3)	(4)
	Change since baseline		**Contribution of skill (%)**	
	coeff	range	coeff	range
Panel A: Reemployed between 6–12 months				
Log wage	-.168	[-.26,-.08]		
N=252	(.045)			
Composite index (Wave 2)	.002	[-.05,.05]	-0.8	[-29,28]
N=210	(.025)		(14.6)	
Cognitive index (Wave 2)	-.004	[-.04,.03]	2.6	[-16,21]
N=217	(.016)		(9.6)	
Primary non-cognitive index (Wave 2)	.014	[-.01,.04]	-8.2	[-23,6]
N=242	(.012)		(7.3)	
Secondary non-cognitive index (Wave 2)	-.002	[-.01, .04]	1.2	[-2,5]
N=222	(.003)		(1.8)	
Panel B: Reemployed between 12–30 months				
Log wage	-.281	[-.34,-.22]		
N=635	(.03)			
Composite index (Wave 3)	.058	[-.01,.13]	-20.6	[-47,6]
N=57	(.036)		(13.0)	
Cognitive index (Wave 3)	.024	[-.02,.07]	-8.6	[-25,8]
N=100	(.024)		(8.6)	
Primary non-cognitive index (Wave 3)	.027	[-.002,.06]	-9.7	[-21,1]
N=179	(.015)		(5.5)	
Secondary non-cognitive index (Wave 3)	-.005	[-.01,.003]	1.7	[-1,5]
N=100	(.004)		(1.5)	

Notes: The table assesses the contribution of changing skills to the fall in reemployment wages. We report the change in wages and the within-person skill change for the unemployed finding a job between months 6 and 12 in Panel A, and between 12 and 30 months in Panel B. In both panels, we report changes in log wages in the top row of column (1). We report β coefficient estimated based on equation 3. The remaining rows in column (1) report the change in within-person skill estimated based on equation 2, but restricting the sample to those reemployed between 6 (12) and 12 (30) months in Panel A (B). Skill indices are formed by predicting the prior employment spell's daily wages using OLS and treating survey responses as cardinal. The primary noncognitive index includes only the Big-5 and locus of control questions asked to all respondents. The secondary noncognitive index includes only the personality traits asked to a subset of cohorts. The cognitive index measures math, memory and verbal fluency. The composite index includes all cognitive and noncognitive questions. All skill indices are scaled in log wages. We report point estimates and standard errors in parentheses below. In column (2) we report the corresponding confidence intervals at the 95th percentile. Column (3) calculates the ratio between the estimated change in skill index and the observed change in log wages (shown in row (1)) and converts it to percent by multiplying by 100. Standard errors are calculated using the delta method. Column (4) reports the corresponding confidence intervals at the 95th percentile. We report the number of observations (N) below each outcome variable.

Appendix A Additional Tables and Figures

Table A.1: Skill and Life Satisfaction Survey Content

Domain	**Detail**	**Question Type**
Cognitive Skills		
Math	3 free-response questions	easy, medium, hard
Short-term recall	Recall 10 words	Immediately after hearing + later during survey
Verbal fluency		List as many animals as possible in 1 minute
Primary non-cognitive		
Locus of Control	Agreement with statements about control over one's outcomes	Likert scale (1-7 agreement) with 10 questions
(4 of the) Big-5 Traits	Subjective evaluation of openness, conscientiousness, extraversion, and stability	Likert scale (1-7 agreement) with 3 questions for each trait
Secondary non-cognitive		
Other Personality Traits	Subjective evaluation of trust in others, patience, reciprocity, and risk tolerance	Likert scale (1-7 agreement) with 1 question each
Life Satisfaction		
Life Satisfaction	Subjective self-assessment	Cardinal assessment of life satisfaction on a 1-10 scale

Notes: This table shows the main contents of our survey on skills and life satisfaction. See Arni et al. (2014) for a detailed discussion of the survey content, questionnaire administration, and sample composition.

Table A.2: Out-of-Sample R^2 for Predicting Prior Wages with Baseline Skills

	OLS		LASSO	
	Linear in cardinal responses	Fully saturated CDFs	Linear in cardinal responses	**Fully saturated CDFs**
All skills	0.047	-0.032	0.082	0.010
Cognitive skills	0.051		0.067	
Primary noncognitive skills	0.031	0.032	0.033	0.049
Secondary noncognitive skills	-0.01	-0.02	-0.00	0.01

Notes: This table compares the out-of-sample performance of various prediction models. Each cell is the average out-of-sample R^2 with 10-fold cross-validation when predicting prior earnings with baseline surveyed skills. The prediction includes only previously full-time workers who were not yet re-employed by the initial survey. Each row represents the skills used in prediction: all, only cognitive, only primary noncognitive (the Big-5 and locus of control), and secondary noncognitive index (other personality traits). Each column represents the estimator used. The LASSO penalty is selected using a 3-step adaptive Lasso. Our main results use the OLS estimator linear in cardinal responses. Figure A.7 shows the estimates when a Lasso with fully saturated CDFs model is applied.

Table A.3: Summary Statistics of All Respondents vs. the Analysis Sample

	(1) **All**	(2) **Analysis Sample**
Demographics		
Female	0.47	0.44
	(0.50)	(0.50)
Age at Unemployment	33.76	34.57
	(10.78)	(10.67)
University Degree	0.26	0.25
	(0.44)	(0.43)
Immigrant	0.20	0.20
	(0.40)	(0.40)
Previous Emp. Spell		
Prior wage (€)	47.00	57.57
	(34.39)	(30.73)
Full-time	0.74	0.84
	(0.44)	(0.37)
Duration (years)	9.02	9.31
	(4.60)	(4.46)
Involuntary Unemp.	0.40	0.45
	(0.49)	(0.50)
Baseline Survey		
Life satisfaction (out of 7)	6.60	6.58
	(2.10)	(2.11)
Composite skill index (€)	57.53	57.68
	(10.57)	(10.56)
Correct math (out of 3)	1.77	1.77
	(0.75)	(0.75)
Listed words (1 minute)	23.56	23.33
	(7.02)	(7.00)
Immediate memory (out of 10)	6.59	6.58
	(1.67)	(1.66)
Recall memory (out of 10)	5.19	5.13
	(1.96)	(1.96)
Locus of control (out of 7)	4.77	4.77
	(0.82)	(0.82)
Extravert (out of 7)	5.17	5.16
	(1.13)	(1.12)
Stable (out of 7)	4.22	4.25
	(1.20)	(1.20)
Open (out of 7)	5.05	5.05
	(1.21)	(1.21)
Conscientious (out of 7)	6.20	6.22
	(0.89)	(0.88)
Observations	15173	11684

Notes: This table replicates the summary statistics shown in Table 1 separately for all respondents and the analysis sample. The analysis sample restricts to those with non-marginal employment immediately prior to the unemployment spell. Unlike Table 1, we report the raw values of survey responses rather than the z-scores.

Table A.4: Standard Deviation of Responses by Survey Waves

	(1) 2-month	(2) 6-month	(3) 12-month	(4) 36-month
Panel A: Skills indices				
Composite	13.34	14.13	14.36	14.88
Cognitive	10.16	10.85	11.40	11.53
Primary noncognitive	8.23	8.59	8.32	8.25
Secondary noncognitive	2.02	1.83	1.85	1.78
Panel B: Cognitive				
Math	0.99	1.01	1.01	1.03
Verbal fluency	1.00	1.05	1.15	1.01
Immediate memory	0.99	1.05	1.02	1.00
Recall memory	1.00	1.03	0.99	0.95
Panel C: Primary noncognitive				
Locus of control	1.00	1.00	0.97	0.95
Extravert	0.99	1.02	0.98	0.96
Open	1.00	0.97	0.98	0.96
Conscientious	0.99	0.91	0.95	0.95
Panel D: Secondary noncognitive				
Risk tolerance	1.01	0.90	1.04	1.00
Stable	1.00	0.99	0.97	0.98
Trust	1.01	0.90	0.90	0.88
Patience	1.00	0.94	0.89	0.91
Reciprocity	1.00	0.90	0.89	0.89

Notes: This table reports the standard deviation of given skills at each survey wave. Column (1) reports the standard deviation in wave 1 (month 2), column (2) in wave 2 (month 6), column 3 in wave 3 (month 12), column (4) in wave 4 (month 36). The rows in the table represent the relevant skills. Panel A reports skill indices, which are formed by predicting the prior employment spell's earnings using OLS and treating survey responses as cardinal. Panels B, C and D show the standard deviation of the individual cognitive, primary noncognitive, and secondary noncognitive skill items, respectively. In panels B through D, we report the standard deviation of the skill items standardized by the wave 1 (month 2) standard deviation.

Table A.5: Predictive Power of Skills Explaining Reemployment Wages

		(1) R^2	(2) N	(3) β	(4) SE(β)
Panel A: Reemployed at 6-12 months					
Composite	Baseline skills vs. prior wages	0.201	210	1.06	0.14
	6-month skills vs. reemployment wages	0.130	210	0.78	0.16
Cognitive	Baseline skills vs. prior wages	0.121	217	1.15	0.21
	6-month skills vs. reemployment wages	0.116	217	1.00	0.22
Primary noncognitive	Baseline skills vs. prior wages	0.075	242	1.22	0.27
	6-month skills vs. reemployment wages	0.080	242	1.02	0.26
Secondary noncognitive	Baseline skills vs. prior wages	0.004	222	1.08	1.17
	6-month skills vs. reemployment wages	0.021	222	2.46	1.06
Panel B: Reemployed at 12-30 months					
Composite	Baseline skills vs. prior wages	0.084	57	0.81	0.44
	12-month skills vs. reemployment wages	0.087	57	0.68	0.38
Cognitive	Baseline skills vs. prior wages	0.051	100	0.69	0.36
	12-month skills vs. reemployment wages	0.043	100	0.51	0.30
Primary noncognitive	Baseline skills vs. prior wages	0.053	179	0.90	0.29
	12-month skills vs. reemployment wages	0.012	179	0.36	0.25
Secondary noncognitive	Baseline skills vs. prior wages	0.019	100	2.36	1.73
	12-month skills vs. reemployment wages	0.014	100	1.75	1.65

Notes: This table studies the predictive power of skill indices explaining reemployment wages in different samples. Panel A focuses on those who become reemployed between the month 6 and 12, while panel B on those who reemployed between the month 12 and 30. Column (1) in panel A (B) reports the R-squared from a regression of 6 (12) month skills measured in wave 2 (3) and wages. In rows labeled "6-month (12-month) skills vs. prior wages" we use prior wages in the regression. Note that skill indices are trained to explain prior wages and so these rows serve as a benchmark. Rows labeled "6-month (12-month) skills vs. reemployment wages" use reemployment wages in the regression. Column (2) shows the sample size in the regression. Column (3) shows the regression coefficients of the regression, while column (4) reports the standard errors. For both panels we report results using composite skill index, cognitive skill index, primary non-cognitive (the Big-5 and locus of control), and secondary noncognitive index (other personality traits).

Table A.6: Change in Skills by Unemployment and Survey Attrition

	(1) Composite	(2) Cognitive	(3) Primary noncognitive	(4) Secondary noncogntive
Panel A: Change from 2-month survey to 6-month survey				
UE spell > 12 months	.027	.014	.017	.001
	(.027)	(.019)	(.015)	(.004)
Attrit at 12 months	-.038	-.003	-.022	.006
	(.036)	(.023)	(.018)	(.005)
Interaction term	.013	.000	.016	-.010
	(.043)	(.028)	(.022)	(.006)
Constant	.006	.000	.008	.002
	(.023)	(.016)	(.013)	(.003)
N	598	619	701	640
Panel B: Change from 2-month survey to 12-month survey				
UE spell > 30 months	.040	.027	.016	-.001
	(.051)	(.037)	(.020)	(.005)
Attrit at 30 months	-.025	-.005	.008	.005
	(.058)	(.044)	(.028)	(.006)
Interaction term	.029	.012	.024	-.001
	(.070)	(.050)	(.032)	(.008)
Constant	-.001	.006	-.006	-.000
	(.043)	(.034)	(.018)	(.004)
N	159	254	445	258

Notes: This table shows the within-person skill change since the 2-month baseline survey among those who are either continually re-employed or continually unemployed in the administrative data by the subsequent survey wave. Panel A is a regression of the skill change as of the 6-month survey on an indicator for being continually unemployed in the administrative data as of month 12, an indicator for not responding to the 12-month survey, and an interaction term. Panel B is a regression of the skill change as of month 12 on an indicator for being continually unemployed in the administrative data as of the 12-month survey, an indicator for not responding to the 30-month survey, and an interaction term. Each column within each panel represents a separate regression of a different skill index. Robust standard errors are shown in parentheses.

Table A.7: Survey Attrition by Employment Status

	Survey Wave		
	Month 6	**Month 12**	**Month 30**
Continually employed since 2-month survey	.018	0.039	0.028
	(.029)	(.018)	(.021)
Reemployed but not continually since 2-month survey	.056	0.032	0.028
	(.019)	(.010)	(.011)
Constant	.375	.427	.619
	(.013)	(.008)	(.010)

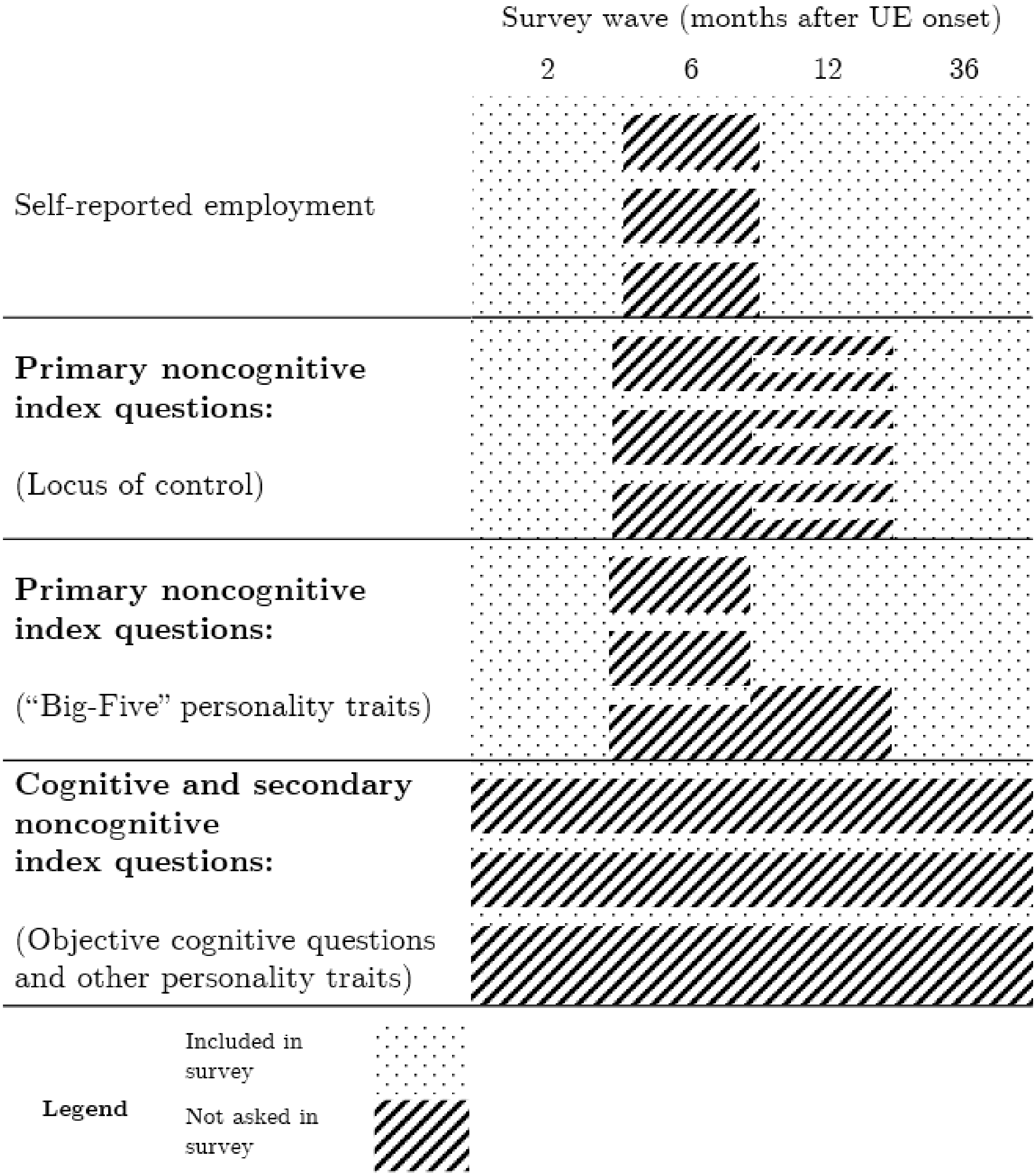
Notes: This table shows differences in attrition probability by employment status in the administrative data. Each column is a separate regression where the outcome is an indicator for attriting from the analysis sample by that survey wave. The independent variables are (1) an indicator for remaining continually employed since the baseline survey (the group we refer as the "reference group" in our main analysis) and (2) either becoming reemployed after the baseline survey but before the current survey or becoming unemployed after reemployment. The omitted category represented by the constant is remaining continually unemployed by that survey wave. Robust standard errors are shown in parentheses. Asterisks correspond to two-sided tests for differences relative to those who remain continually unemployed.

Table A.8: Change in Skills and Well-being Following Unemployment among Older American Workers

	(1) $\mathbb{1}\{t \geq t_i^*\}$ coeff	(2) 95% CI range	(3) Within R-squared	(4) N
Panel A: Skills (Scaled in log earnings)				
COGTOT (cognitive score 1)	-0.0087 (0.0118)	[-.032,.014]	0.0003	2,700
TICS (cognitive score 2)	-0.0047 (0.0087)	[-.022,.012]	0.0001	2,727
MSTOT (cognitive score 3)	0.011 (0.0102)	[-.009,.031]	0.0006	2,700
TR20 (simple math 1)	-0.0050 (0.0048)	[-.014,.004]	0.0002	8,395
SER7 (simple math 2)	0.006 (0.0053)	[-.004,.016]	0.0002	8,471
IMRC (immediate recall)	-0.0039 (0.0051)	[-.014,.006]	0.0001	8,395
DLRC (delay recall)	-0.0046 (0.0044)	[-.013,.004]	0.0002	8,395
VOCAB (vocabulary)	0.0222 (0.0148)	[-.007,.051]	0.0044	979
FINEA (fine motor skills)	-0.0091 (0.0044)	[-.018,.000]	0.0005	9,150
Composite Index	0.0102 (0.0094)	[-.008,.029]	0.0006	2,695
Panel B: Well-being (Z-Score)				
CESD (depression)	0.2121 (0.0309)	[-.151,.273]	0.0076	8,833
FLONE (loneliness)	0.1594 (0.0336)	[.094,.225]	0.0034	8,824
GOING (unmotivated)	0.1587 (0.0342)	[.092,.226]	0.0031	8,808
BMI (body-mass index)	0.0086 (0.0133)	[-.018,.035]	0.0001	9,265

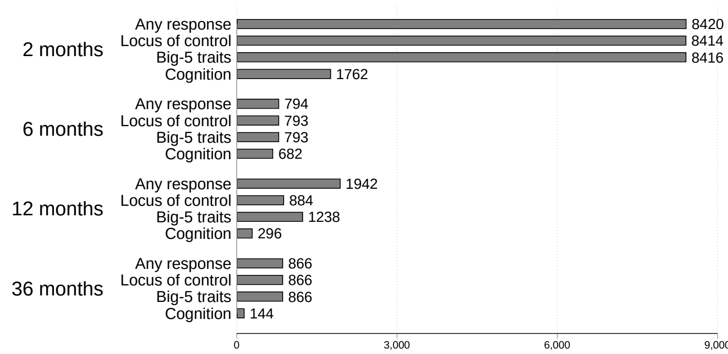
Notes: This table shows the within-person skill change following unemployment for older American workers. Column (1) reports the coefficients (with the corresponding standard errors) of $\mathbb{1}\{t \geq t_i^*\}$ estimated based on equation 5 for each skill and well-being measure separately. In the regression, we control for worker age (fully saturated), person effects, and time effects. We also exclude observations after unemployment in which the worker regains employment to make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed. In column (2) we report the corresponding 95% confidence intervals. Column (3) reports the within-person R-squared from the regression, while column (4) shows the number of observations in each regression. Panel A shows the skill measures, where the skills are scaled by their predicted pre-unemployment log earnings, and OLS is used as a prediction model. Panel B reports the change in well-being measured in z-scores. A positive increase in mood (loneliness, unmotivated, depression) is associated with a decline in well-being. In both panels, the acronyms come from the HRS survey.

Figure A.1: Included Questions by Survey Wave and Cohort

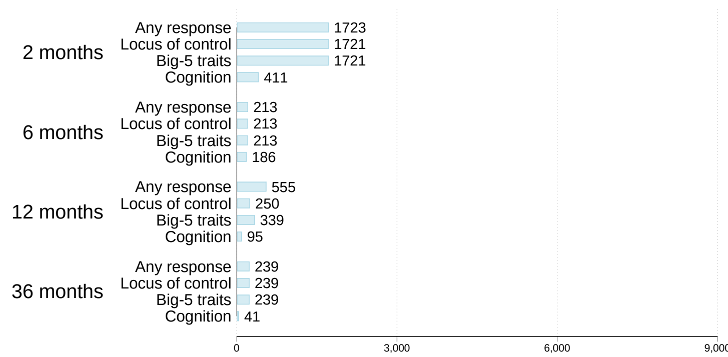


Notes: This figure indicates available data for the twelve cohorts over time for different question topic groups. Within each question topic group, the first row corresponds to the June 2007 cohort and the last row corresponds to the May 2008 cohort. Dots indicate that relevant questions in the topic group were solicited from that cohort at the given point in time, while diagonal lines indicate that they were not. For example, the June 2007, October 2007, and February 2008 cohorts were always asked cognitive and secondary noncognitive questions; no other cohorts were ever asked these questions.

Figure A.2: Sample Sizes by Survey Wave and Included Questions



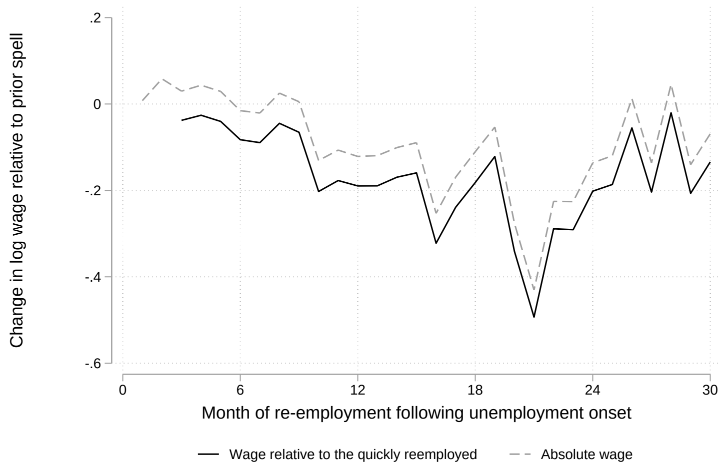
(a) Continually Unemployed Since Unemployment Entry



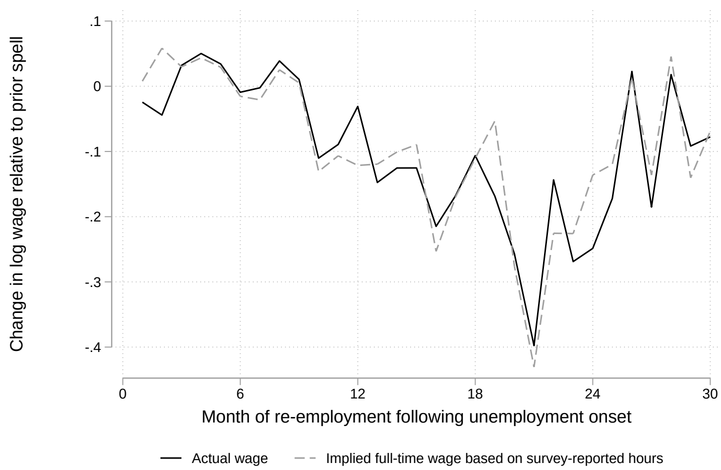
(b) Continually Employed Since Survey Two Months After Entry

Notes: This figure shows the number of observations for each question type for wave 1 (2 months), wave 2 (6 months), wave 3 (12 months) and wave 4 (36 months). Bars represent survey respondents in the analysis sample for each wave. Panel (a) restricts to respondents without any form of employment since unemployment entry, and Panel (b) restricts to respondents who were reemployed by the wave 1 survey and continually employed since then. Employment is defined as non-marginal employment in the administrative data.

Figure A.3: Evolution of Reemployment Wages over the Unemployment Spell: Robustness



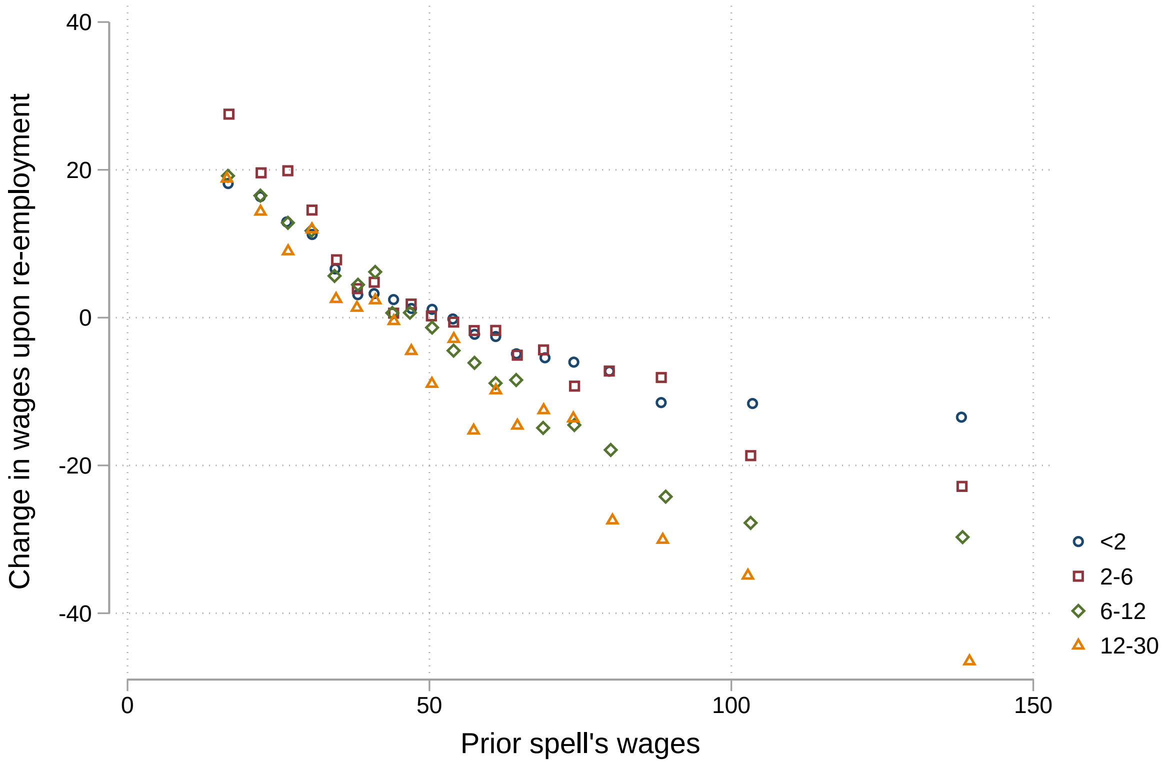
(a) Raw vs. Adjusted for Macroeconomic Trends



(b) Daily vs. Hourly Wages

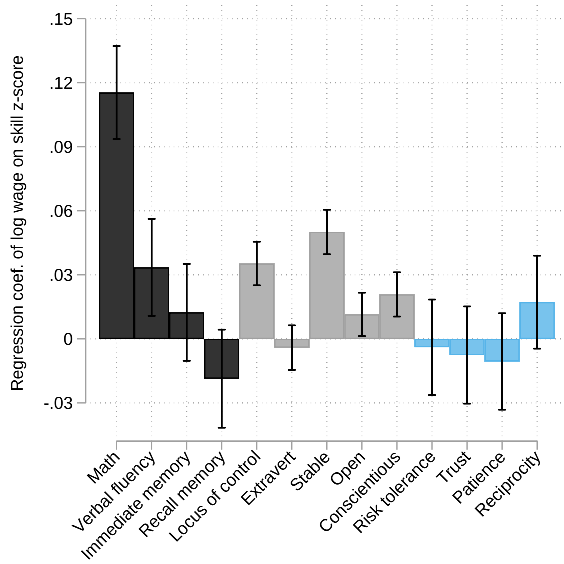
Notes: Both panels plot administrative wages upon reemployment by the month of reemployment as in panel (b) of Figure 1. Reemployment wages are calculated as the within-worker difference between the wages upon reemployment relative to wages prior to unemployment. In panel (a), the gray line shows this "raw" reemployment wages. The solid black line reproduces our main specification where we control for macroeconomic trends as well by comparing the wage changes relative to the wages of those who were reemployed quickly (within 2 months) and stayed employed after that. In panel (b) reemployment wages are calculated as the employee's gross *daily* wage (our benchmark definition, solid line) or as the employee's gross *hourly* wage (dashed line). The latter is calculated using the self-reported weekly hours measured in our survey.

Figure A.4: Relationship between Reemployment Wage Change and Prior Wages by Unemployment Duration

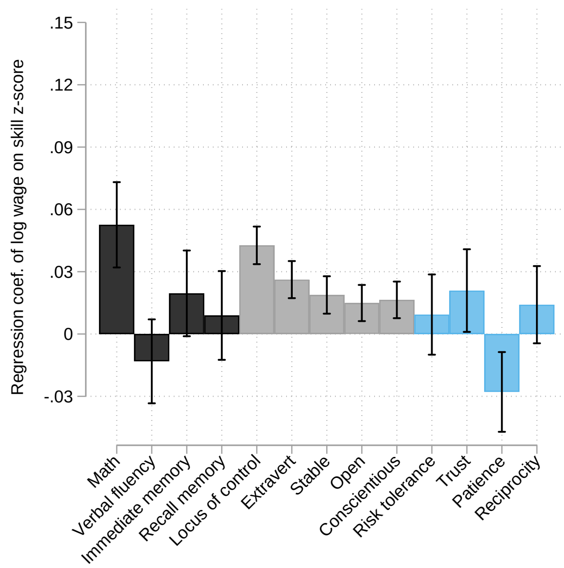


Notes: We report the non-parametric binscattered relationship between reemployment wages and prior wages by unemployment duration. Reemployment wages are calculated as the within-worker difference between the wages upon reemployment and the wages prior to unemployment. Wages are calculated as the employee's gross *daily* wage measured in €.

Figure A.5: Relationship Between Previous Wages and Baseline Skills



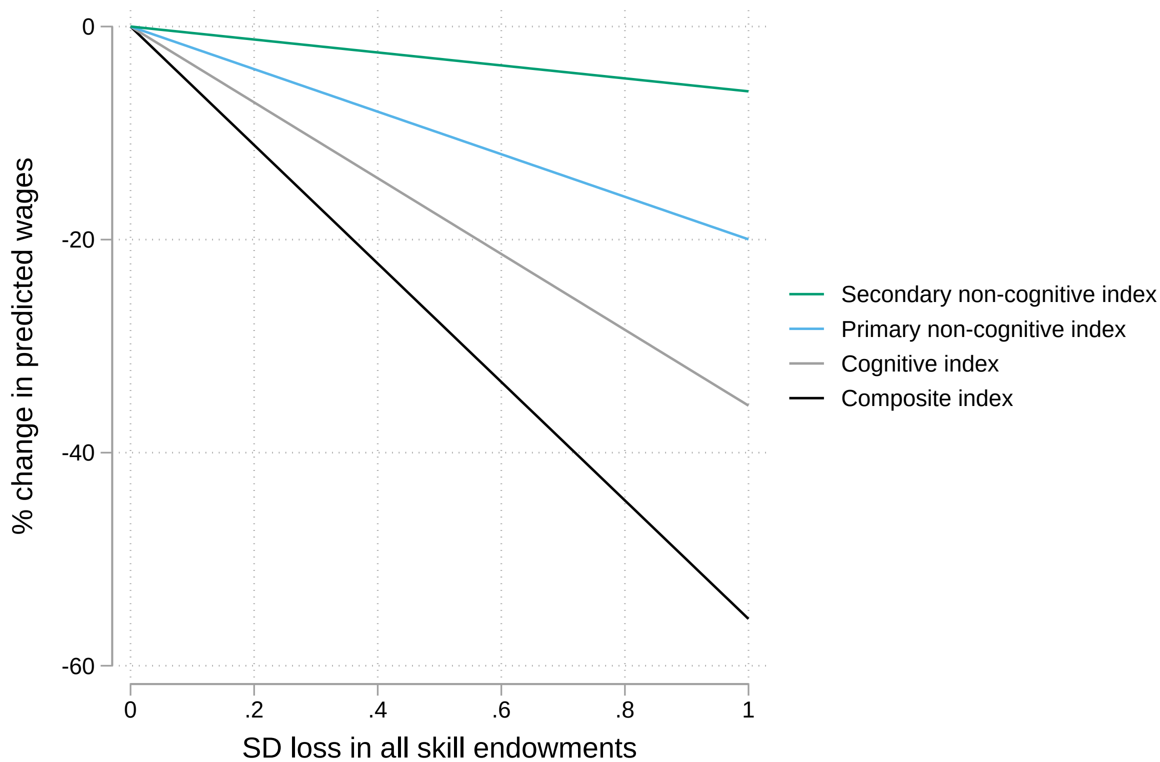
(a) Raw Relationship



(b) Relationship Conditional on Demographics

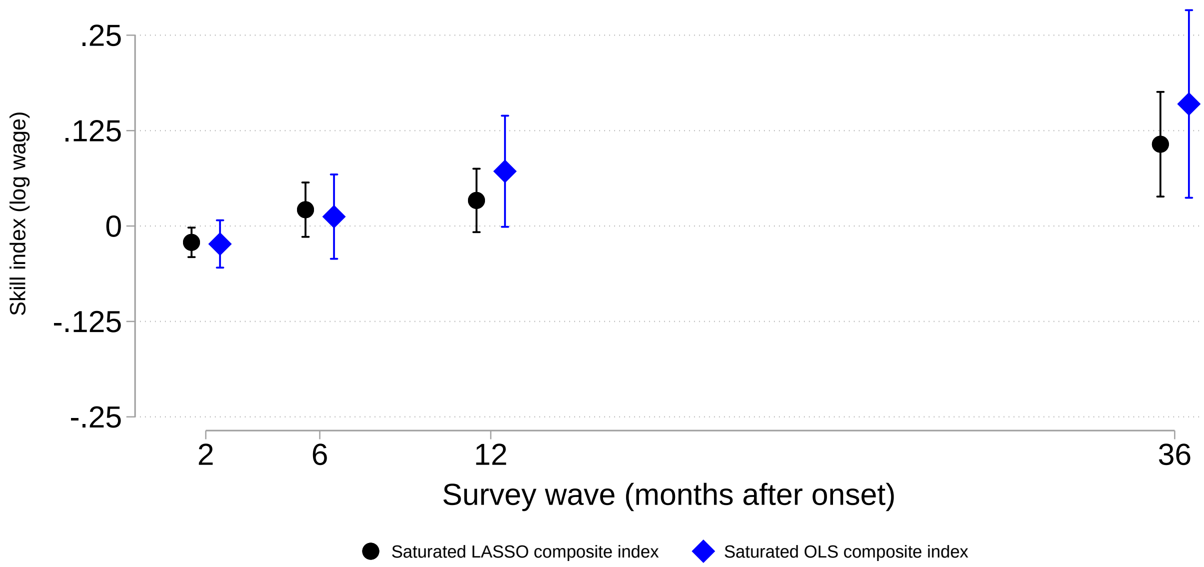
Notes: The figures show the relationship between wages in prior jobs and skills measured at the baseline wave (month 2). We report the coefficients and 95% confidence intervals from separate regressions of the previous employment spell's wages on each baseline survey measurement. Surveyed skills are measured as z-scores, so each coefficient can be interpreted as the predicted change in log wages for a one standard deviation change in the surveyed skill. Panel (a) shows the raw relationship, while panel (b) shows the relationship conditional on worker demographics. Demographic controls include an age quadratic term, gender, migrant status, and categories for education and professional certifications. The bar colors correspond to different skill groups: cognitive (black), primary noncognitive (gray), and secondary noncognitive (blue).

Figure A.6: Relationship Between Baseline Skills and Prior Wages

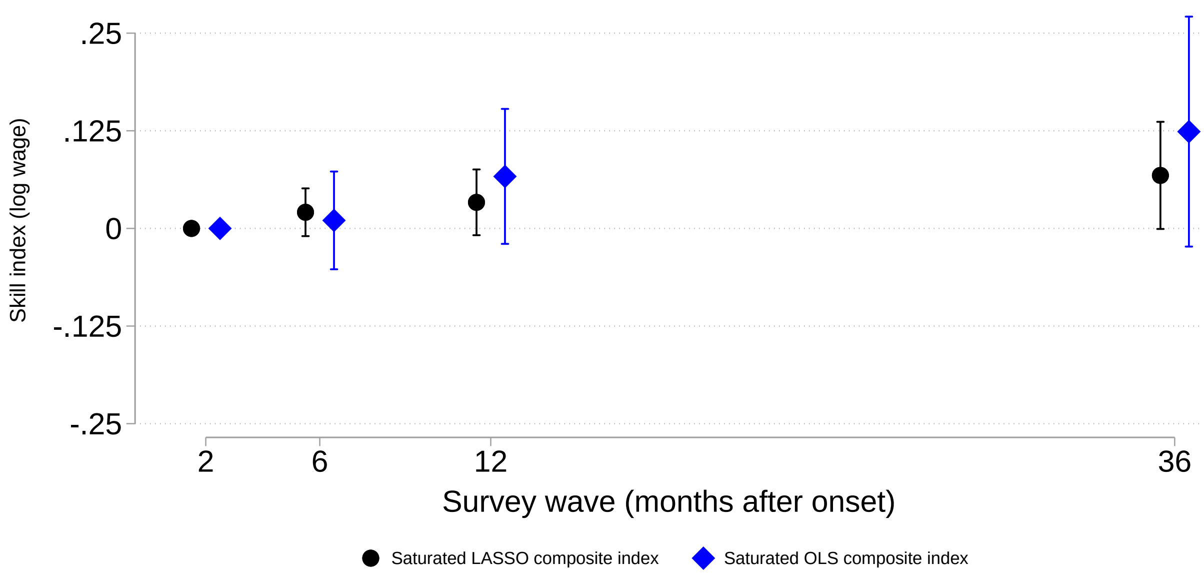


Notes: This figure plots the implied decrease in wages in response to the depreciation of the underlying skills. We apply our preferred prediction model to create skill indices. We apply OLS regression of prior wages on each individual baseline skill question, where Likert scale questions are treated as cardinal. Moving along the x-axis from 0 to 1 corresponds to a 1 standard deviation depreciation of skills in every underlying question in that skill category. Depreciation is defined as a change that is associated with lower prior wages in the prediction model. In particular, we assume that items with positive (negative) coefficients in the prediction model are decreased (increased) by one standard deviation.

Figure A.7: Evolution of Skills Over the Unemployment Spell: Fully Saturated Indices



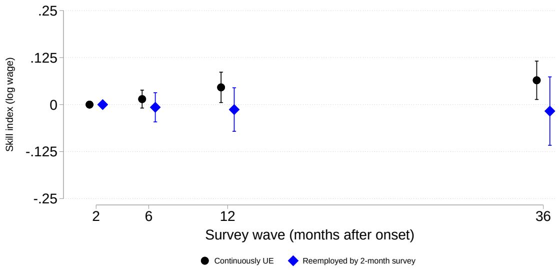
(a) Average Skill of the Unemployed over the Unemployment Spell: Fully Saturated Indices



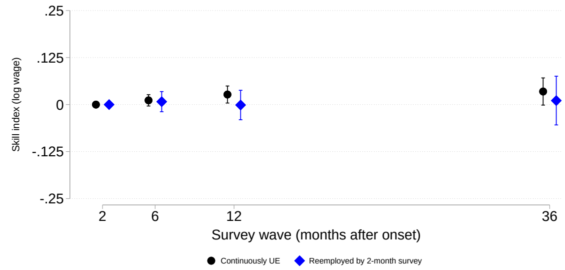
(b) Within-person Skill Changes over the Unemployment Spell

Notes: This figure explores whether the pattern shown in Figure 2 is robust to applying alternative methods for constructing the composite skill index. Both panels plot the change in skill indices of the unemployed relative to the reference group. Panel (a) reports the β_τ coefficients (along with the 95th percentile confidence intervals) from equation 1, where the skills of the unemployed at each wave are compared to those who found a job within 2 months. Panel (b) reports estimates including within-person fixed effects (see equation 2). The skill index is formed by predicting the prior employment spell's wages using either OLS (blue diamond) or adaptive LASSO (black dots). Both skill indices use all available skill items. The predictors are all binary. We convert any ordinal skill item, such as a Likert scale response, into a fully saturated set of indicators. The y-axis scale represents approximately $\pm 1\sigma$ of the log predicted earnings using the composite skills index as measured at baseline, which is 0.22.

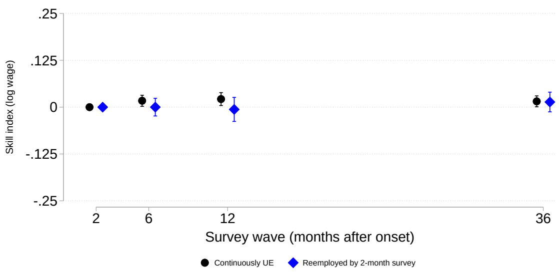
Figure A.8: Evolution of Skill Index Over Time for the Reference Group and for the Unemployed



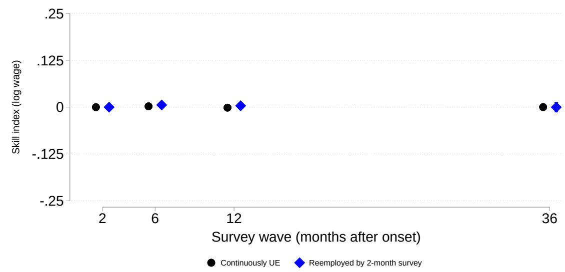
(a) Composite Skill Index



(b) Cognitive Skill Index



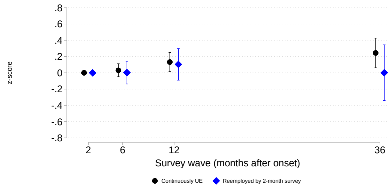
(c) 1$^{\text{st}}$ Noncognitive Skill Index



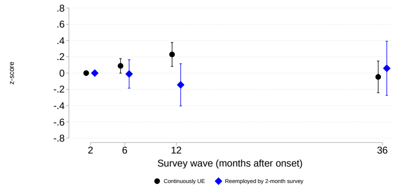
(d) 2$^{\text{nd}}$ Noncognitive Skill Index

Notes: This figure shows the within-person skill index change separately for the reference group (reemployed within two months and continuously employed afterward) and for the unemployed (we report the result for each individual skill items separately in Figure A.9). In all panels, we report estimates based on equation 2. The blue diamonds represent changes since the baseline for the reference group (α_τ in equation 2), while the black dots represent changes for the continuously unemployed ($\alpha_\tau + \beta_\tau$ in equation 2). The skill index is formed by predicting the prior employment spell's wages using OLS and treating survey responses as cardinal. The primary noncognitive (panel (c)) index includes only the Big-5 and locus of control questions, the secondary noncognitive index includes the personality traits (panel (d)), the cognitive skill index (panel (b)) includes fluency, maths, and short-term recall, and the composite skill index (panel (a)) includes all cognitive and non-cognitive questions.

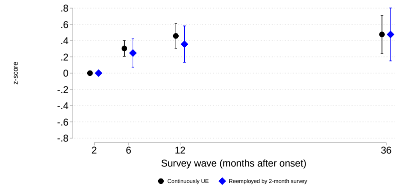
Figure A.9: Evolution of Individual Skill Items Over Time for the Reference Group and for the Unemployed



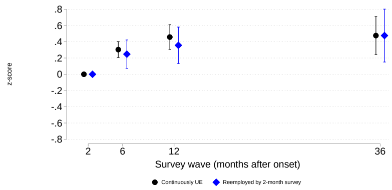
(a) Math



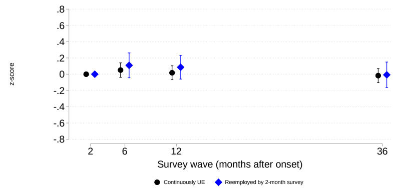
(b) Verbal fluency



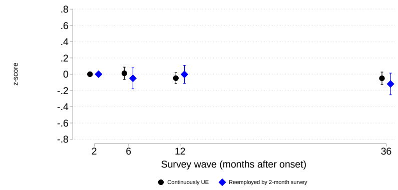
(c) Immediate memory



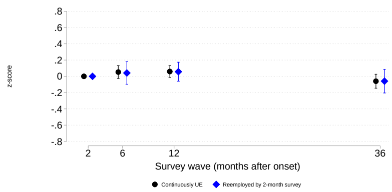
(d) Recall memory



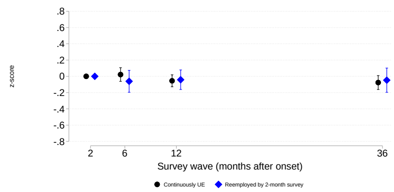
(e) Locus of control



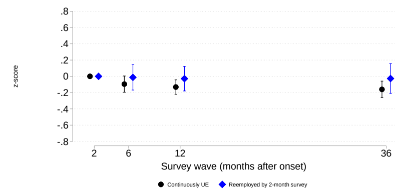
(f) Extravert



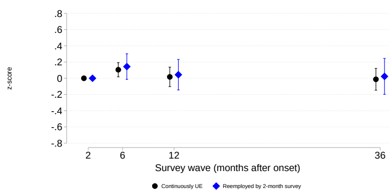
(g) Stable



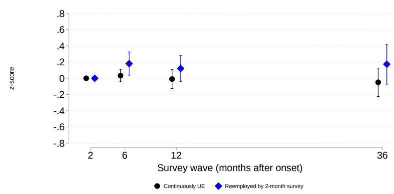
(h) Open



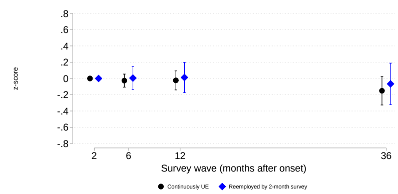
(i) Conscientious



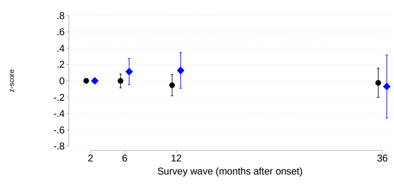
(j) Risk tolerance



(k) Trust



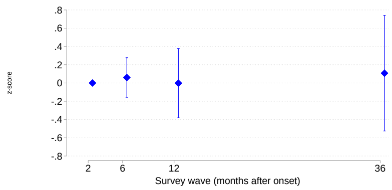
(l) Patience



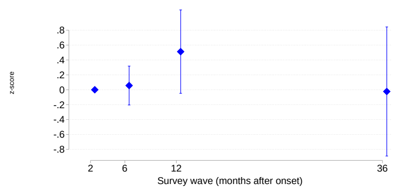
(m) Reciprocity

Notes: This figure shows the within person-change for the reference group (reemployed within two months and continuously employed afterward) and for the unemployed for each individual skill items separately (we report the result for skill indices in Figure A.8). Responses are treated as cardinal and signed appropriately. When a category has multiple underlying questions, each question is first converted to a z-score and then those z-scores are averaged together. The z-score standardized is based only on the initial survey and then applied to all surveys.

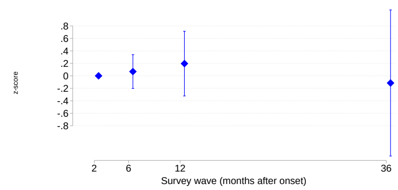
Figure A.10: Evolution of Individual Skill Items Over the Unemployment Spell



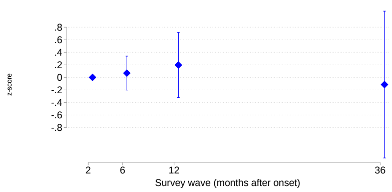
(a) Math



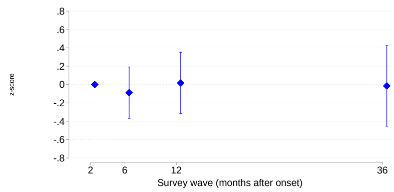
(b) Verbal fluency



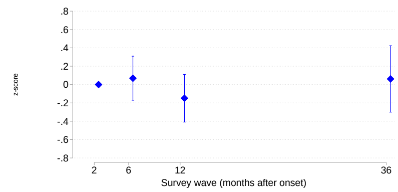
(c) Immediate memory



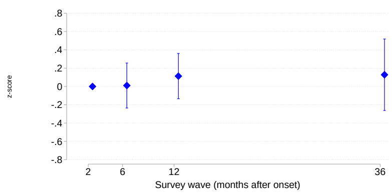
(d) Recall memory



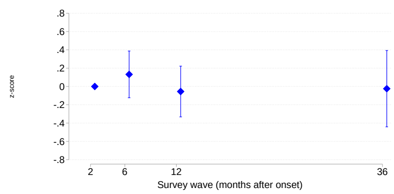
(e) Locus of control



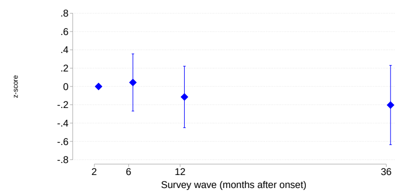
(f) Extravert



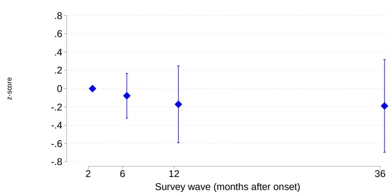
(g) Stable



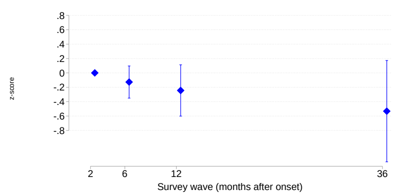
(h) Open



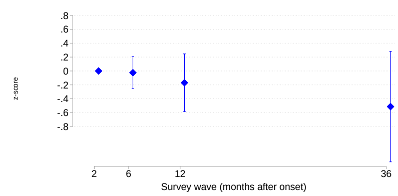
(i) Conscientious



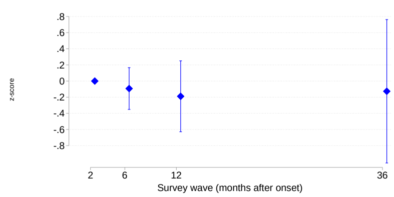
(j) Risk tolerance



(k) Trust



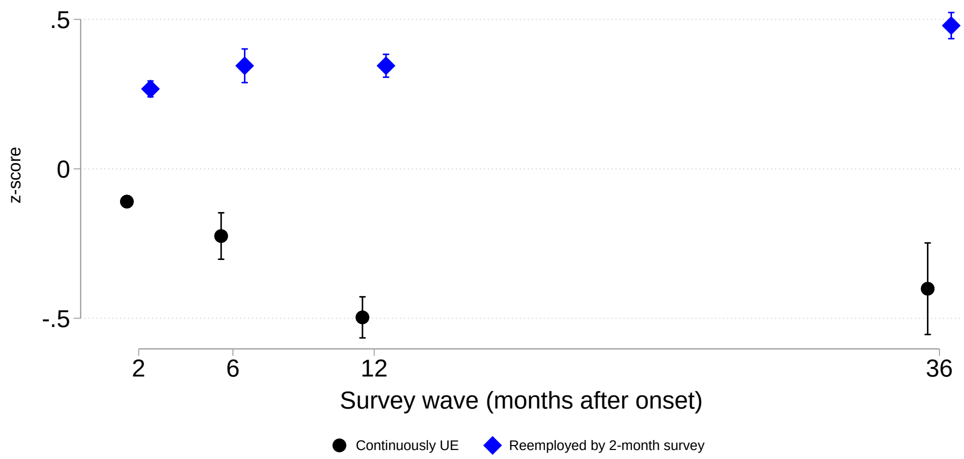
(l) Patience



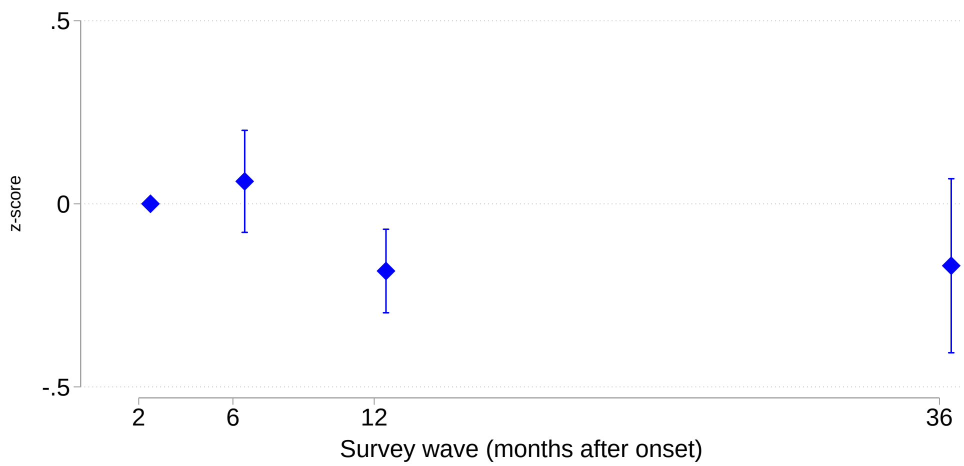
(m) Reciprocity

Notes: This figure recreates panel (b) of Figure 2 for each individual skill items separately. We report the β_τ coefficients (along with the 95th percentile confidence intervals) from equation 2. Responses are treated as cardinal and signed appropriately. When a category has multiple underlying questions, each question is first converted to a z-score and then those z-scores are averaged together. The z-score standardized is based only on the initial survey and then applied to all surveys.

Figure A.11: Evolution of Life Satisfaction over Time



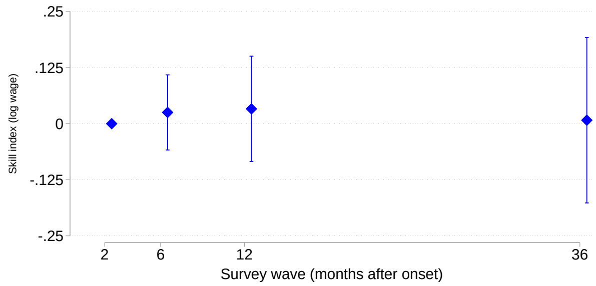
(a) Life Satisfaction over Time for the Unemployed and for the Reference Group



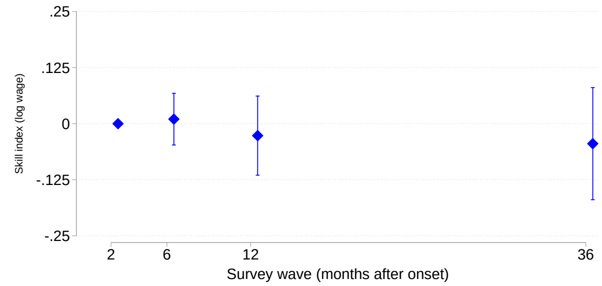
(b) Within-person Change in Life Satisfaction for the Unemployed (relative to the Reference Group)

Notes: This figure shows the evolution of self-reported life satisfaction over time. Panel (a) shows life satisfaction separately for the reference group (reemployed within two months and continuously employed afterward) and for the unemployed. We report the average level of life satisfaction at each survey wave by estimating equation 1. The blue diamonds represent changes since the baseline for the reference group (α_τ in equation 1), while the black dots represent changes for the continuously unemployed ($\alpha_\tau + \beta_\tau$ in equation 1). In panel (b) we show the within-person change in life satisfaction of the unemployed relative to the employed by estimating equation 2. The blue diamonds show the estimated β_τ in equation 2. We standardize the self-reported life satisfaction based on responses to the initial survey. Due to panel response availability, unemployment duration is defined using survey responses for life satisfaction.

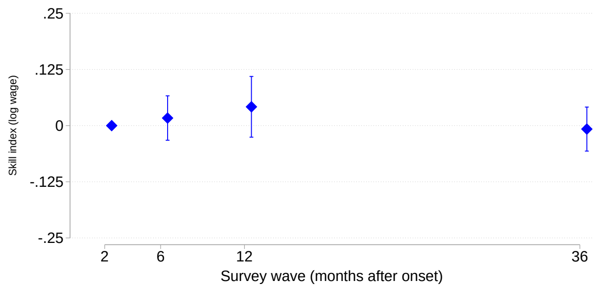
Figure A.12: Evolution of Individual Skill Items Over the Unemployment Spell: Restricting to Involuntary Losers of Full-time Employment



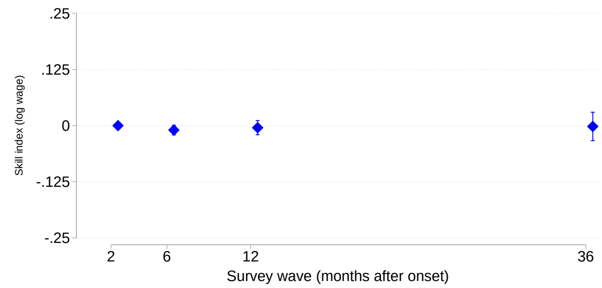
(a) Composite Skill Index



(b) Cognitive Skill Index



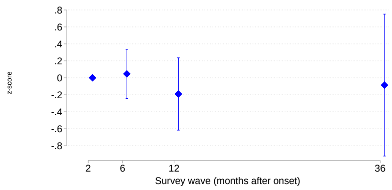
(c) 1st Noncognitive Skill Index



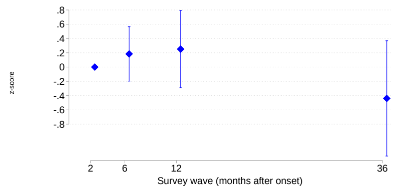
(d) 2nd Noncognitive Skill Index

Notes: This figure recreates panel (b) of Figure 2 but restricts respondents who involuntarily lost a full-time job. In all panels, we report estimates with within-person fixed effects (the β_τ coefficient from equation 2). The skill index is formed by predicting the prior employment spell's wages using OLS and treating survey responses as cardinal. The primary noncognitive (panel (c)) index includes only the Big-5 and locus of control questions, the secondary noncognitive index includes the personality traits (panel (d)), the cognitive skill index (panel (b)) includes fluency, maths, and short-term recall, and the composite skill index (panel (a)) includes all cognitive and non-cognitive questions. The y-axis scale represents approximately $\pm 1\sigma$ of the log predicted wages using the composite skills index as measured at baseline, which is 0.22.

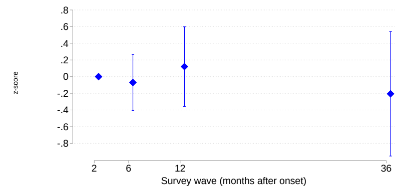
Figure A.13: Evolution of Individual Skill Items Over the Unemployment Spell: Restricting to Involuntary Losers of Full-time Employment



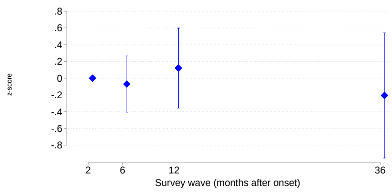
(a) Math



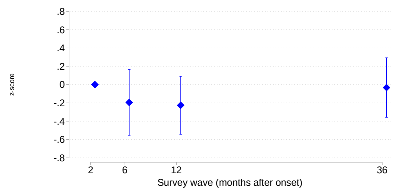
(b) Verbal fluency



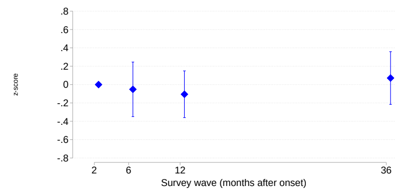
(c) Immediate memory



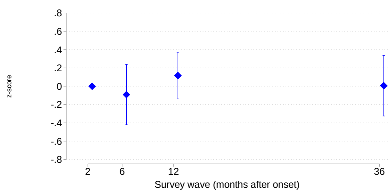
(d) Recall memory



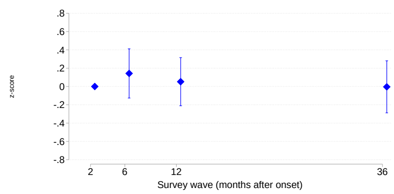
(e) Locus of control



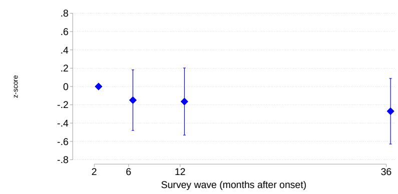
(f) Extravert



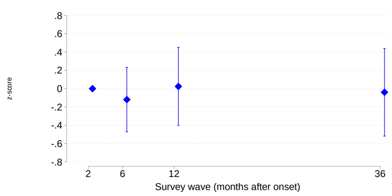
(g) Stable



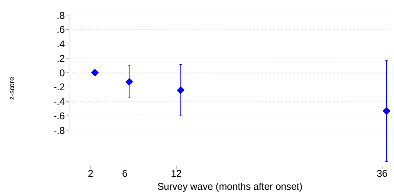
(h) Open



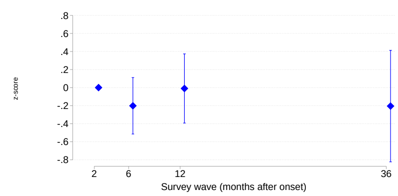
(i) Conscientious



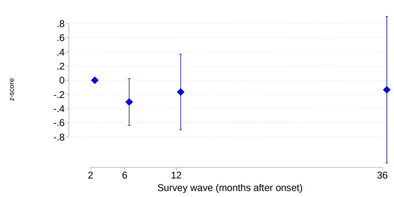
(j) Risk tolerance



(k) Trust



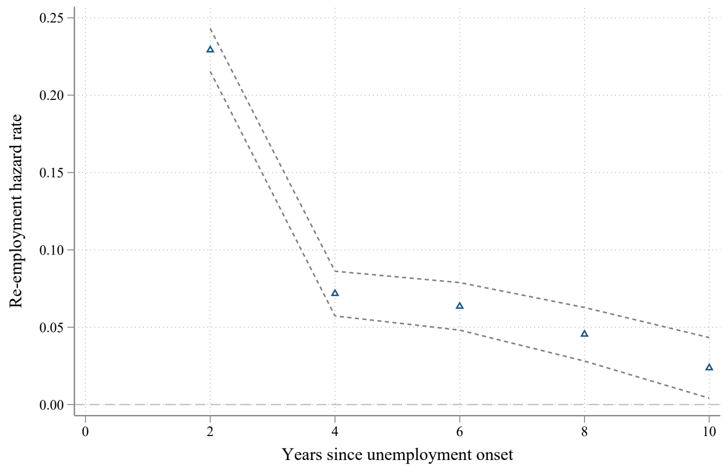
(l) Patience



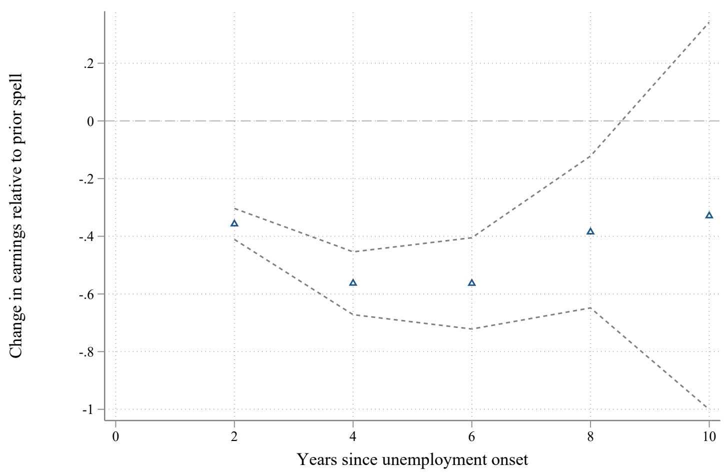
(m) Reciprocity

Notes: This figure recreates panel (b) of Figure 2, restricting to respondents who involuntarily lost a full-time job. We report the result for each individual skill item separately (for skill indices see Figure A.13). In all panels, we report estimates with within-person fixed effects (the β_τ coefficient from equation 2). Responses are treated as cardinal and signed appropriately. When a category has multiple underlying questions, each question is first converted to a z-score and then those z-scores are averaged together. The z-score standardized is based only on the initial survey and then applied to all surveys.

Figure A.14: Reemployment Hazards and Reemployment Wages over the Unemployment Spell Among Older American Unemployed



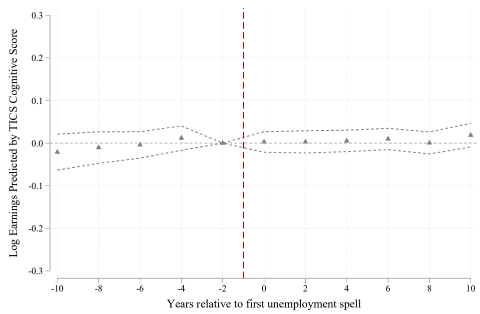
(a) Reemployment Hazard Rates



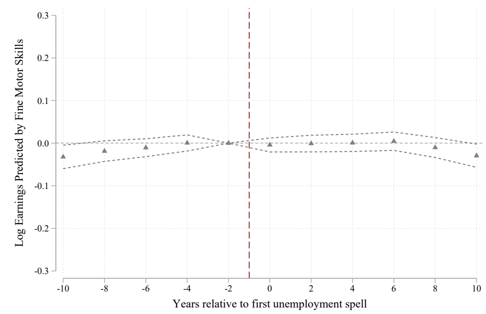
(b) Reemployment Earnings

Notes: Panel (a) plots the reemployment hazard rates – the probability of finding a job conditional on being unemployed two years before. Panel (b) plots the reemployment earnings – the share difference between earnings upon reemployment (conditional on finding a job) and earnings in the previous employment spell. In both panels, we use the HRS. The dashed lines shows the 95% confidence intervals around the estimates.

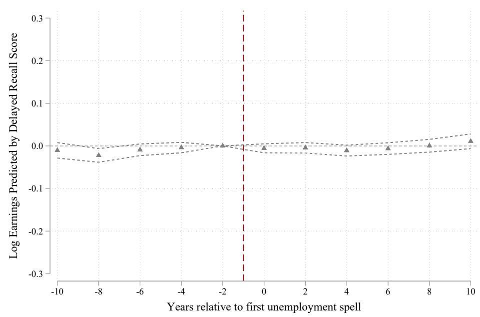
Figure A.15: Within-Person Skill Changes around Unemployment Among Older American Workers: Individual Skill Items Measured as Predicted Log Earnings



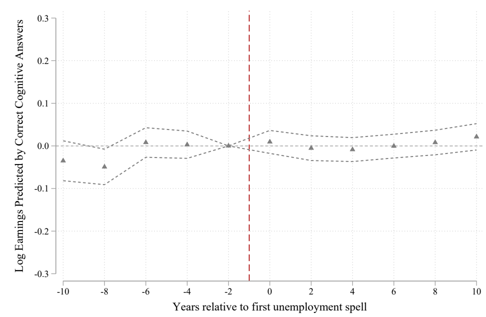
(a) Interview for Cognitive Status



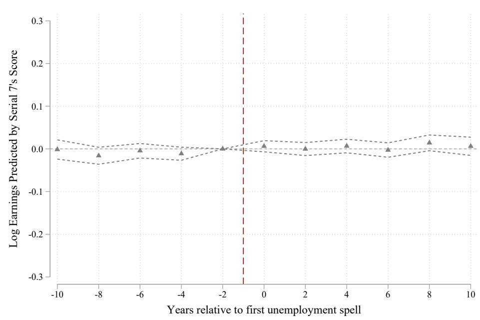
(b) Fine Motor Skills



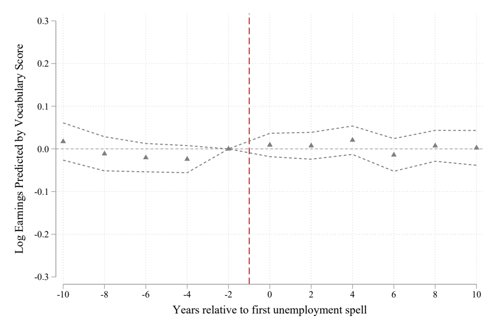
(c) Memory Recall



(d) Cognitive Total



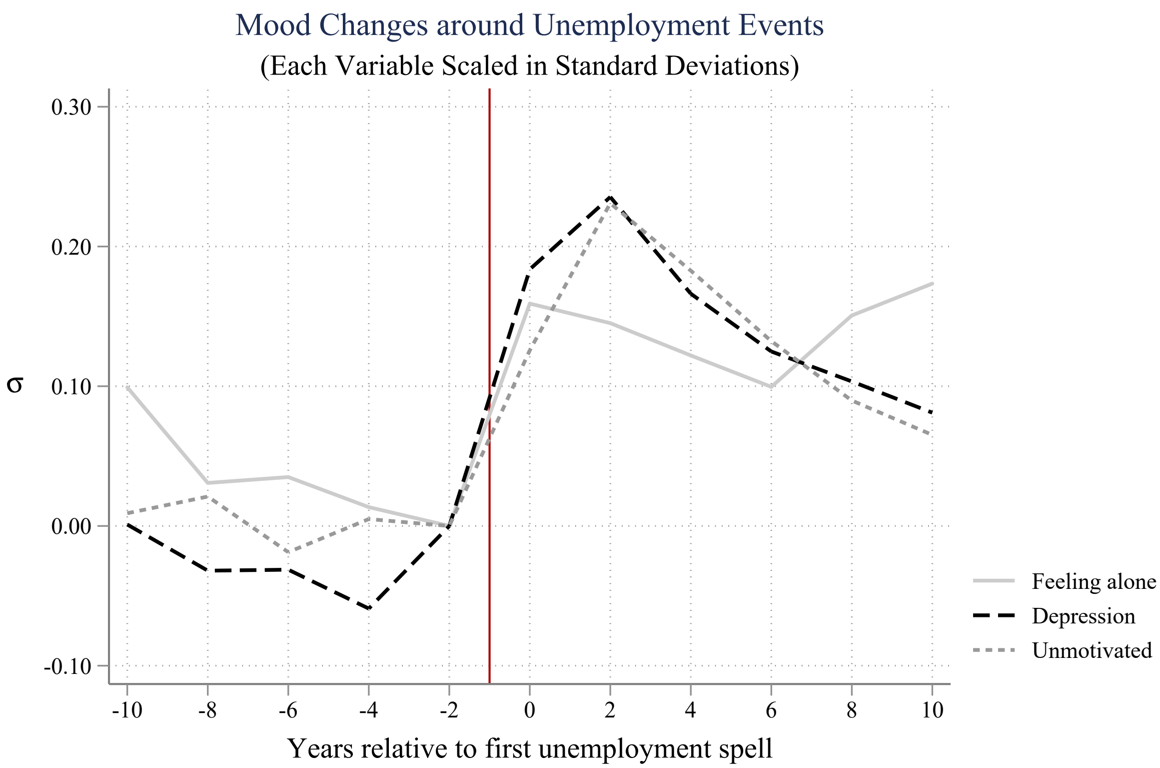
(e) Simple Math



(f) Vocabulary

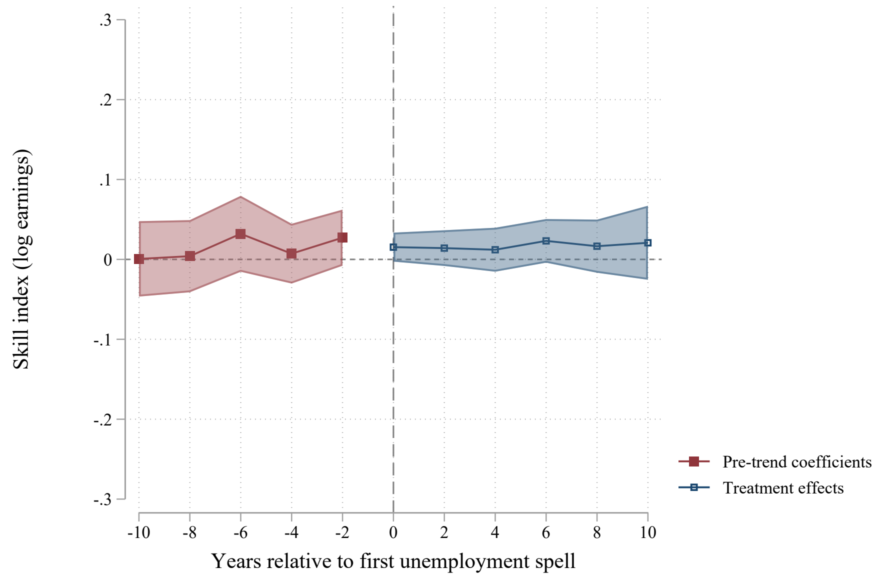
Notes: This figure shows the within-person change in skills around unemployment separately for individual skill items (see Figure 3 for the composite skill index). Event time zero shows the first transition from employment to unemployment for each worker in the survey (HRS). We exclude observations after unemployment in which the worker regains employment to make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed. In the regression, we control for worker age (fully saturated) and person effects. Skills are scaled by their predictive power of pre-unemployment log earnings, where is OLS used as a prediction model.

Figure A.16: Within-Person Mood Changes around Unemployment Among Older American Workers

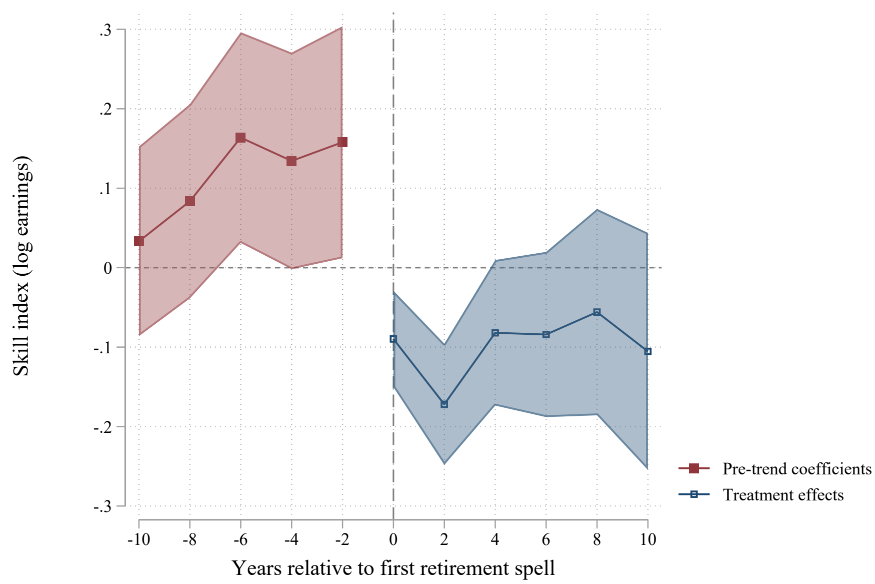


Notes: This figure shows the within-person change in mood among older American workers. Event time zero shows the first transition from employment to unemployment for each worker in the survey (HRS). We exclude observations after unemployment in which the worker regains employment to make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed. In the regression, we control for worker age (fully saturated), person effects, and time effects. Each well-being variable measured in z-scores. A positive increase in mood (feeling alone, unmotivated, depression) is associated with a decline in well-being.

Figure A.17: Within-Person Skills Changes around Unemployment and Retirement Among Older American Workers: Applying Borusyak, Jaravel and Spiess (2021)



(a) Unemployment Events



(b) Retirement Events

Notes: This figure reproduces Figure 3 using the event study specification from Borusyak, Jaravel and Spiess (2021). Event time zero shows the first transition from employment to unemployment (retirement) for each worker in the survey (HRS). In panel (a), we exclude observations after unemployment in which the worker regains employment to make sure that the post-unemployment effects reflect the skills of those who are continuously unemployed. In the regression, we control for worker age (fully saturated), person effects, and time effects. The skill index is formed by predicting the employed worker's earnings using OLS.

Appendix B Validating Administrative Unemployment Duration with Survey-Reported Employment

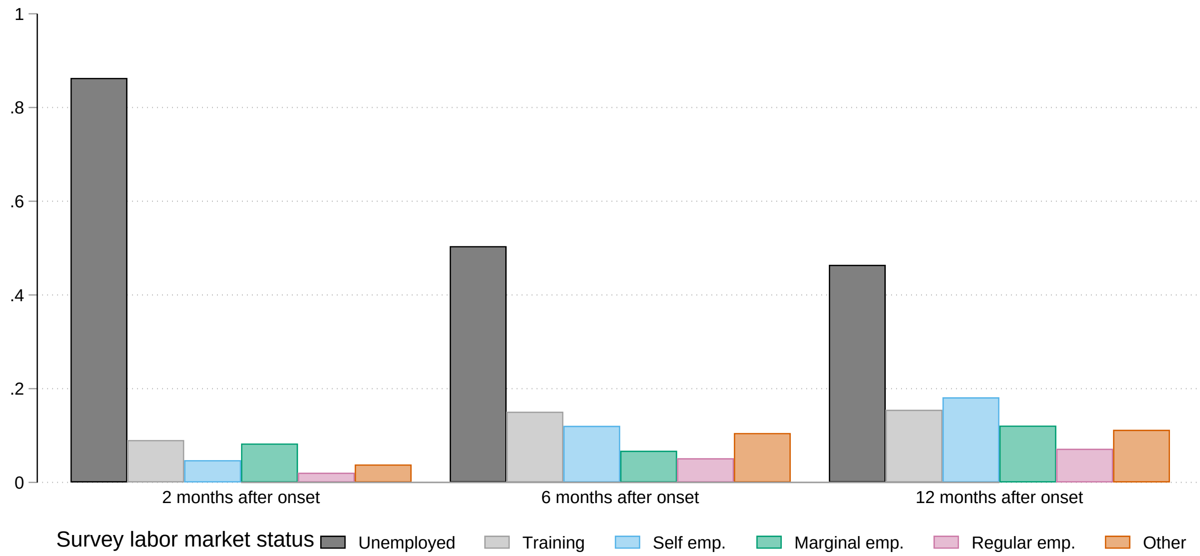
A novel feature of our data is that we observe both self-reported employment status and employment status in the social security records. In some cases, there is a discrepancy between the two measures. We demonstrate this in Figure B.1, which shows the self-reported employment status of individuals who are unemployed (or not marginally employed) according to the administrative data in the month 2, 6 and 12 survey waves.[21]. A majority—but not all—of these individuals identify as unemployed or marginally employed. This is more relevant later on in the unemployment spell. By month 12, 55% of unemployed or marginally employed individuals in the administrative data self-report the same status. The rest are a mix of activities: almost 20% are self-employed, 10% are in training, 5% are in regular activities and 10% are in other-category (family care, homemaking, illness/handicap, extended holiday).

We confirm the robustness of our main results using a narrower definition of unemployment based on the combination of survey and administrative data. Rather than viewing unemployment as the absence of non-marginal employment, we define it as the absence of all forms of employment and training in the survey or administrative data. This conservatively zooms in on those who are plausibly at the highest risk of skill depreciation while unemployed. When controlling for survey wave effects, however, we maintain the reference group of the quickly reemployed based on non-marginal employment in the survey data. This conservatively compares the unemployed to those who are most likely to be building skills during employment.

In Figure B.2 and in Figure B.3 we replicate our main findings in this more restricted sample. The estimated changes in skill throughout the unemployment spell are almost identical though the estimates are somewhat noisier. These findings highlight that our main conclusions about the lack of skill depreciation over the unemployment fact are not driven by measurement errors in reemployment status.

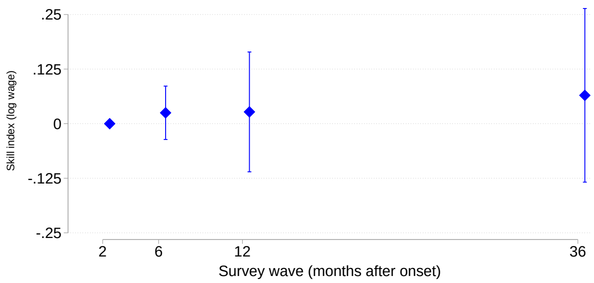
[21] We observe administrative records for only 30 months after unemployment onset, so we are not able to complete this exercise for the survey 36 months after unemployment onset. In the main analysis, as we explained in Section 2.2, we define labor market status at thirty-six months using the observed labor market status at thirty months.

Figure B.1: Distribution of Self-Reported Status Among Unemployed in the Administrative Data

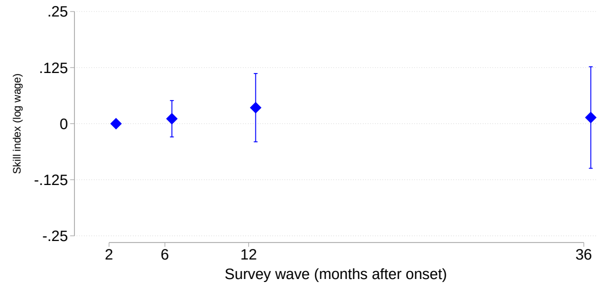


Notes: The sample at each survey wave corresponds to those in the administrative data without contemporaneous non-marginal employment, which is our benchmark definition of unemployment. Each stacked bar is the share of respondents reporting being engaged in the labeled labor force activity. The "other" category aggregates family care, homemaking, illness/handicap, extended holiday, and other reasons. Respondents could report multiple activities in 2-month (wave 1) and 12-month (wave 3) surveys.

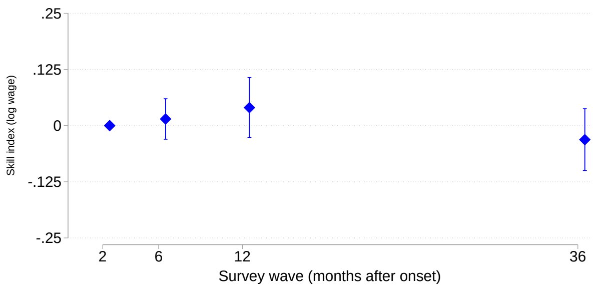
Figure B.2: Relative Changes in Skill Indices Over the Unemployment Spell: Combined Survey and Administrative Definition of Unemployment



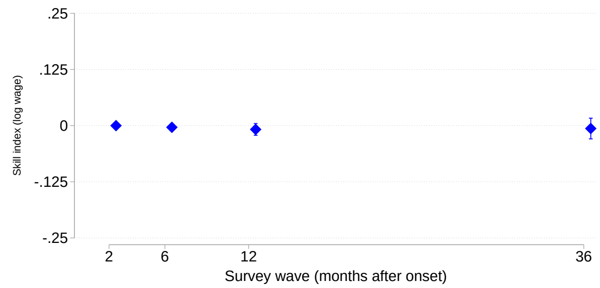
(a) Composite Skill Index



(b) Cognitive Skill Index



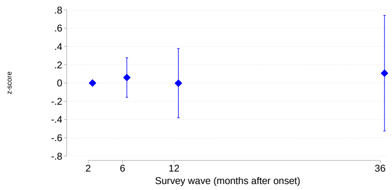
(c) 1$^{\text{st}}$ Noncognitive Skill Index



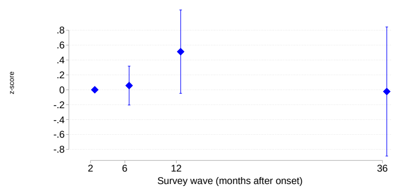
(d) 2$^{\text{nd}}$ Noncognitive Skill Index

Notes: This figure recreates panel (b) of Figure 2 but restricts to the definition of unemployment as the absence of all types of employment and training in both survey and administrative data. In all panels, we report estimates with within-person fixed effects (the β_τ coefficient from equation 2). The skill index is formed by predicting the prior employment spell's wages using OLS and treating survey responses as cardinal. The primary noncognitive (panel (c)) index includes only the Big-5 and locus of control questions, the secondary noncognitive index includes the personality traits (panel (d)), the cognitive skill index (panel (b)) includes fluency, maths, and short-term recall, and the composite skill index (panel (a)) includes all cognitive and non-cognitive questions. The y-axis scale represents approximately $\pm 1\sigma$ of the log predicted wages using the composite skills index as measured at baseline, which is 0.22.

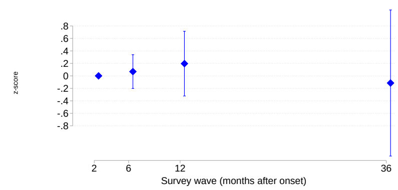
Figure B.3: Evolution of Individual Skill Items Over the Unemployment Spell: Combined Survey and Administrative Definition of Unemployment



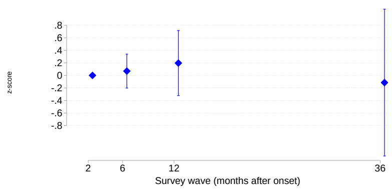
(a) Math



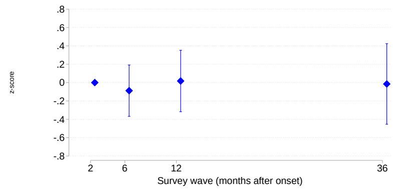
(b) Verbal fluency



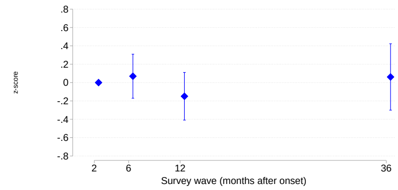
(c) Immediate memory



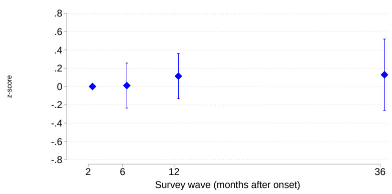
(d) Recall memory



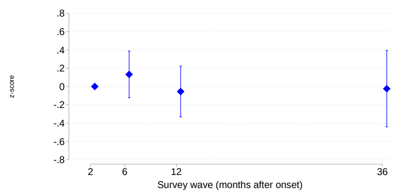
(e) Locus of control



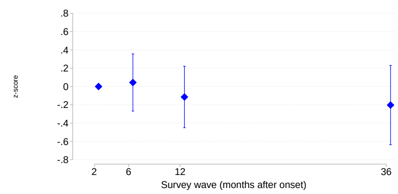
(f) Extravert



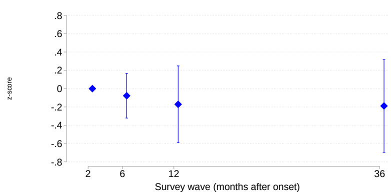
(g) Stable



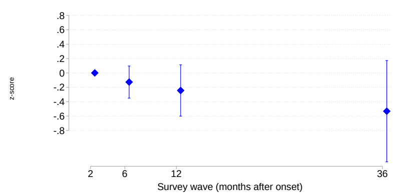
(h) Open



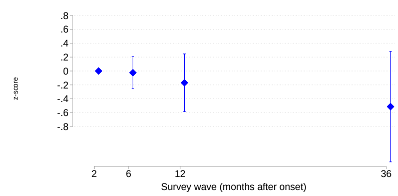
(i) Conscientious



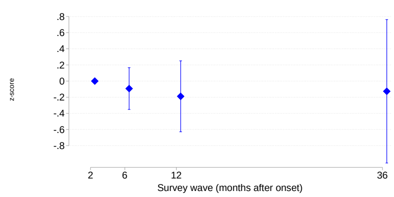
(j) Risk tolerance



(k) Trust



(l) Patience



(m) Reciprocity

Notes: This figure recreates panel (b) of Figure 2 and Figure A.10 for each individual skill items separately, restricting to the definition of unemployment as the absence of all types of employment and training in both survey and administrative data. We report the β_τ coefficients (along with the 95th percentile confidence intervals) from equation 2. Responses are treated as cardinal and signed appropriately. When a category has multiple underlying questions, each question is first converted to a z-score and then those z-scores are averaged together. The standardized z-score is based only on the initial survey and then applied to all surveys.