Does Paternal Unemployment Affect Young Adult Offspring's Personality?

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Abstract

Using longitudinal data from the German Socio-Economic Panel (SOEP), we analyse the impact of paternal unemployment on the "Big 5" personality traits of young adult offspring aged 17 to 25. Results from longitudinal value-added models for personality show that paternal unemployment makes offspring significantly more conscientious and less neurotic. The uncovered effects are robust to the presence of selection on unobservables and of correlation between the error term and the lagged outcome. We also discuss the potential mechanisms behind our findings.

JEL classification: J24, J13, J64, C33.

Keywords: personality traits, unemployment, household behaviour, SOEP.

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1 Introduction

Recent empirical evidence both in economics and in psychology shows that personality traits have strong predictive power for a wide range of socio-economic outcomes (Almlund et al., 2011, Borghans et al., 2008, Brunello and Schlotter, 2011, Bucciol et al., 2015). Personality matters for job performances and wages (Barrick and Mount, 1991, Hogan and Holland, 2003, Nyhus and Pons, 2005, Salgado, 1997), educational attainment (Borghans et al., 2008, Duncan et al., 2007, Goldberg et al., 1998, Poropat, 2009), longevity (Friedman et al., 2010, Roberts et al., 2007, Savelyev, 2014), health-related behaviours (Hampson et al., 2007) and criminal behaviours (John et al., 1994, O'Gorman and Baxter, 2002). In their seminal work on the topic, Heckman et al. (2006) show that, by and large, the long-run effects of non-cognitive skills - among which personality is also included - on labour market outcomes and on social behaviour are comparable to the ones of cognitive skills.

In spite of this evidence, surprisingly little is known about the effects of economic variables on non-cognitive skills, and personality in particular. According to the psychological literature, individual personality is still malleable until the "impressionable years" of early adulthood, and then remains relatively stable throughout adulthood (Alwin, 1994, Costa and McCrae, 1994, Costa et al., 1980).[1]

Several papers have investigated how the economic external conditions experienced during the "impressionable years" shape young people's values, attitudes, beliefs, preferences and well-being (among others, see Cutler, 1974, Dennis, 1973, Easton and Dennis, 1969, Giuliano and Spilimbergo, 2014, Greenstein, 1965, Hess and Torney, 1967, Krosnick

[1]More specifically, psychologists (see Roberts and DelVecchio, 2000) broadly distinguish between intra-individual stability, i.e. stability of personality at the individual level over time in response to life events, mean-level stability, that is, population-level stability as time goes by, and rank-order stability, which refers to the relative placement of individuals within the population. The definition of stability that is relevant for our work is the "intra-individual" one.

and Alwin, 1989, Sears, 1975, 1981, 1983). As far as we know, however, there is limited empirical evidence on the contribution of both different socio-economic factors and positive and negative life events to shaping personality not only in adulthood, but also until the impressionable years.[2]

This paper contributes to the extant literature by estimating the effect of a relevant determinant of economic well-being of offspring,[3] paternal unemployment, on personality traits, focusing on the crucial years of their development. Indeed, several studies suggest that, by altering pre-existing socio-economic conditions of the family, paternal job loss has strong and persistent spillover effects on the life course of adolescents (Coelli, 2011, Kalil and Ziol-Guest, 2008, Kind and Haisken-DeNew, 2012, Pinger, 2015, Powdthavee and Vernoit, 2013, Rege et al., 2011, Stevens and Schaller, 2011).[4] However, evidence about its effects on personality is still lacking.[5] *A priori*, it is hard to sign such an effect, and empirical analysis is needed to settle the matter. On the one hand, offspring

[2]There is evidence suggesting that - at the individual level - personality traits are insensitive to changes in economic conditions (Cobb-Clark and Schurer, 2012) during the working age. However, the stability of personality traits in adulthood has been questioned by Roberts et al. (2006), Roberts and Mroczek (2008) and Lucas and Donnellan (2011). In a recent paper, Boyce et al. (2015) show that unemployment induces significant changes in personality, whereas re-employed individuals experience limited changes.

[3]We will use the terms "offspring" and "children" interchangeably.

[4]From a macroeconomic perspective, previous research showed that recession periods affect several aspects of health (among others, see Ruhm, 2015).

[5]An exception is Pinger (2015), who reports that paternal unemployment has negative effects on academic confidence and locus of control. However, she considers younger children and does not look at the "Big 5" personality traits. Additionally, her identification strategy instruments individual unemployment status with local labour market variables, raising several concerns about the validity of the implied exclusion restrictions. For instance, in our context it would be hard to exclude that local labour market variables may affect the unemployment probability of the fathers but not of the offspring.

may suffer from paternal job loss because of unemployment-induced parental depression, (Powdthavee and Vignoles, 2008) and deteriorated economic conditions of the family, which in turn are likely to generate a status of anxiety, frustration and disillusionment (Christoffersen, 1994, McLoyd, 1989). On the other hand, unemployment may allow fathers to have more time to spend with their offspring, which may have positive effects on their personality development (see Powdthavee and Vernoit, 2013, and the references therein). Finally, as adverse life events have the potential to foster future resilience (see Seery, 2011, Seery et al., 2010), fathers' negative experience may generate a coping mechanism on offspring, making them work hard and thoroughly to avoid to fall into unemployment themselves.

Our analysis is based on data from the German Socio Economic Panel (SOEP), a unique household survey about the German population collecting longitudinal information on respondents' demographics, socio-economic conditions, health, family composition, parental employment and, last but not least, personality traits. Since SOEP longitudinally tracks all original household members even in case they move out of the household, we can match offspring characteristics and the evolution of their personality traits over waves with the employment conditions of their parents. Hence, the comprehensiveness and the longitudinal nature of our data allow us to identify the link between the experience of paternal unemployment and offspring personality via a value-added model (see Guarino et al., 2014, Todd and Wolpin, 2003). More specifically, we consider all offspring aged 17-25[6] whose fathers worked as employees in private firms at a given personality assessment, and we compare post-treatment personality traits of offspring whose father did and did not experience unemployment between two consecutive personality assessments, conditional on offspring's baseline personality traits and on a rich set of observable characteristics of the offspring and their parents - including parental personality traits and labour market histories. We measure personality in terms of the "Big-5" model

[6]Although one could imagine that the effects of paternal unemployment shall be detected even at earlier ages, we can only start from age 17 because this is the earliest age at which individuals are interviewed in the SOEP.

(Barenbaum and Winter, 2008, Goldberg, 1993, Krueger and Johnson, 2008, Nyhus and Pons, 2005). According to this framework, personality can be summarised by 5 factors, namely Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

We find a positive effect of paternal unemployment on the "Big 5" personality traits of their offspring during the "impressionable years" of early adulthood: experiencing paternal unemployment makes them significantly more conscientious and less neurotic - although this latter result is less robust to specification changes - while no significant effect is detected on the remaining three personality traits.

Our results are robust to a large battery of sensitivity tests, including: *a*) different measurement methods for the "Big 5" personality traits; *b*) using robust regressions and simulations to verify that results from our relatively small sample are not driven by outliers; *c*) simulations to assess the bias of the effect of paternal unemployment caused by potential correlation between the error term and lagged personality - which would make OLS estimates of value-added models inconsistent; *d*) tests for selection on unobservables (Altonji et al., 2005, Oster, 2015); *e*) using semi-parametric estimators.

To assess the potential mechanisms behind our uncovered effects, we also show that the effects on conscientiousness are only positive and statistically significant for older and employed offspring, who are likely to be more time-constrained. This result implies that increased parent-child interactions are unlikely a mechanism behind our findings. Older and employed offspring are instead more exposed to the risk of unemployment, and scared by its consequences. Therefore, finding stronger effects for this group suggests that the experience of a negative change in paternal employment may lead them to improve their sense of responsibility, to avoid falling into unemployment themselves. As suggested by Heckman (2007) and Conti et al. (2010), this might in turn lead to a virtuous "self-productivity cycle", resulting in improved health and socio-economic conditions throughout the life-cycle.

2 Data and descriptive analysis

We use data from the German Socio Economic Panel (SOEP - v30). The SOEP is a representative annual panel survey of the German population, interviewing every year around 22,000 individuals living in 12,000 households across Germany (see Wagner et al., 2007, for details). It started in 1984 in West Germany and in 1990, after German reunification, in East Germany.

SOEP collects a wealth of information about respondents' demographics, health, family composition, economic conditions, labour market outcomes, subjective well-being, preferences and, last but not least, personality traits, making it a very attractive data source for our analysis. SOEP interviews all members of an eligible household aged 17+ at the moment of the first interview, and tracks all members even if they leave their original household. This feature allows us not only to match information on parental employment with information about offspring personality, but also to follow parents and children after they change household, for reasons that may include both nest-leaving of children and divorce of parents. Moreover, SOEP administered to respondents a comprehensive Big 5 personality questionnaire in three waves (2005, 2009 and 2013), allowing us to carry out a longitudinal analysis.

Our working sample is constructed as follows. We pool the 2005 and 2009 samples, which we consider as our baseline interviews, and respectively track individuals up to their 2009 or 2013 4-year follow-up interviews. We consider only respondents whose baseline interview takes place within the "impressionable years", i.e. those aged 17 to 25 at baseline, and whose fathers are aged below 63 - the early retirement age in Germany - at baseline. We restrict our sample to consider only fathers who are present in the survey throughout the 4 years between the baseline and follow-up interviews, and who work as employees in a private firm at baseline, since unemployment is more rare among public employees and among the self-employed.[7] Although these criteria for sample selection are quite restrictive, we believe that they help us narrowing down our sample to con-

[7]Needless to say, we only focus on fathers whose children are observed at both the baseline and the follow-up interviews. This is eased by the fact that SOEP longitudinally

sider only those truly at risk of experiencing unemployment, increasing internal validity. We also drop individuals whose mother is not in the survey, as our model makes use of information on mothers as well. After dropping observations with missing values in the children, mothers and fathers covariates included in the analysis - listed in Table 1[8] - our final sample consists of 893 respondents, 59.6 percent of which belongs to the 2005 baseline sample and 40.4 percent to the 2009 baseline sample.[9] Descriptive statistics for the variables used in the analysis - measured at baseline - are reported in Table 1.

Our outcome variables are individuals' Big 5 personality factors: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. These are measured in SOEP by a short but well-established personality questionnaire, unaltered across different waves of the survey and reported in Table A1 in the Appendix. Respondents were presented with a list of 15 statements (three for each trait), and were asked to rate how much they agreed with each of these statements on a 7-point Likert scale. As in Caliendo et al. (2014), we treat the response scales cardinally and compute respondents' score for each personality trait by simply averaging the scores from the three different statements referring to that factor, and standardizing the resulting measure to have 0 mean and unit variance in the final sample. Therefore, descriptive statistics for personality variables are not shown in Table 1, but we report the densities of baseline and follow-up personality of children in Figure 1.

As highlighted by Borghans et al. (2008) and Borghans et al. (2011), the simplicity

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tracks also individuals who leave the original household, with limited attrition. In total, only 70 offspring have missing data for the follow-up interview, and their characteristics are comparable to the full sample.

[8]Our models also control for the regional level of unemployment at the time of the baseline interview and for regional dummies. Because of small sample size by region, we have aggregated Hamburg, Mecklenburg-Vorpommern and Schleswig-Holstein, Niedersachsen and Bremen, and Saarland and Rheinland-Pfalz.

[9]We do not detect significant differential effects of unemployment by baseline survey year, therefore we pool the two samples throughout the analysis.

of this measurement approach is not exempt from critiques. In fact, while variables like height or weight can be measured directly, this is not true for personality, which must be inferred from responses to personality questionnaires like the one we use. This process is inevitably affected by measurement error. For instance, as suggested by Piatek and Pinger (2015), treating personality items cardinally can distort results if the Likert scale used has a limited support, or the distributions of the answers show high kurtosis. Furthermore, Almlund et al. (2011) highlight that cognitive skills and other non-cognitive traits and attitudes may also influence the answers to the personality questions, confounding the interpretation of the personality scores obtained in this simple way. On the one hand, there is not much we can do to address this latter problem, since contemporaneous or pre-determined measures of cognitive abilities and other non-cognitive traits are not available for the SOEP waves that we exploit. Hence, the interpretation of our results must take into consideration the fact that the personality scores we use also reflect the indirect influence that cognitive and other non-cognitive skills may have had on respondents' answers to the personality questions. On the other hand, to check the robustness of our results to problems related with the ordinal vs. cardinal treatment of the answers to personality items, we run a 5-factor Confirmatory Factor Analysis (CFA) on the personality items, and extract the latent scores for each factor. Differently from our simple methodology, which gives equal loadings to each item related to a given factor, CFA estimates the loading of each of the items from the data, allowing for more flexibility.[10] It turns out that the correlation between our simple average scores and the latent scores obtained via factor analysis is always around .9, and results of all the analyses are quantitatively and qualitatively similar when we use either of the two measures. Given the simpler nature of the measures obtained by averaging, we prefer to stick to these ones

[10]Other previous papers (see for instance Caliendo et al., 2014) carried out Exploratory Factor Analysis and have showed that the items of the personality questionnaire included in the SOEP load on different factors, which generally correspond very well to the personality traits identified ex-ante. Therefore, we do not repeat this exercise.

throughout the analysis.[11]

Following Boyce et al. (2015), we describe paternal unemployment - our treatment - with a dummy variable for whether the respondent's father reports to be unemployed in any SOEP interview between the baseline (2005 or 2009) and the follow-up (2009 or 2013, respectively). Looking at Table 1, we see that 8.9 percent of respondents' fathers (that is, 79 fathers) have experienced unemployed between the baseline and follow-up interviews. [12] Since both our sample and the number of treated fathers in it are small, we use robust regression and a simulation exercise to dispel the concern that our results may be only due to the presence of few outliers.

To gain a better understanding about the characteristics of fathers exposed or not exposed to unemployment, in Table 2 we report mean values of several paternal characteristics by treatment group. Results point to negative selection into unemployment, as fathers experiencing unemployment are on average 2.44 years older, have 1.1 less years of education, are 15.4 percentage points more likely to be in poor health, have lower life satisfaction and are 16.6 percentage points less likely to live with their child. Furthermore, their previous labour market career was also different, as they are 32.4 percent more likely to have ever experienced unemployment before the baseline interview (when they were employed), are more likely to work in smaller firms, have lower earnings and lower tenure, and are less likely to be homeowner (a proxy for wealth). We have also

[11]We present a replication of our main results using latent factors in the Appendix. Other results are available from the authors upon request.

[12]Unfortunately, we do not have precise information about the duration of unemployment, as the self-reported spell data available in SOEP are retrospective and may be severely affected by recall bias. We counted the number of interviews in which respondents report being unemployed, but there is very little variation in this variable. We also distinguished between different unemployment causes (see e.g. Kassenboehmer and Haisken-DeNew, 2009, Marcus, 2013), like lay-offs, quits, and plant closures, but our sample is too small to see enough of each of them (for instance, we only observe 12 instances of plant-closure induced unemployment).

tested for differences in fathers' personality at baseline (not reported to save space), and we find that those who will experience unemployment have a significant .39 standard deviations higher level of neuroticism with respect to the control group.

Table 3 reports instead the differences in children's personality by paternal unemployment. In spite of the negative selection of fathers into unemployment, we do not detect any statistically significant difference in baseline personality among the two groups of children. In fact, the two groups of children look well-balanced not only in terms of their own personality: we have tested for differences in other child-level baseline covariates, including age, gender, immigrant status, family composition, poor health, life satisfaction and employment status, and we only detect a statistically significant difference for age, which is marginally higher among treated kids, and life satisfaction, which is instead lower in the treated group.[13]

Results are different, however, when we repeat this exercise looking at differences in follow-up personality of children, as we see that treated children have a significant .29 standard deviations higher level of conscientiousness. This descriptive analysis suggests that paternal unemployment may have a beneficial effect on the personality of children, as it makes them more conscientious. The econometric analysis introduced in the next section aims at verifying the robustness of this univariate association.

3 Empirical Methodology

We frame the identification problem in terms of potential outcomes. Our setup is such that we observe individuals for two time periods, pre and post treatment, respectively defined as $t = 0$ and $t = 1$. Our treatment is defined by the dummy variable $DadU_i$, which indicates whether child i's father experiences unemployment between $t = 0$ and $t = 1$. We define the vectors of the five observed personality traits of child i at $t = 0$ and $t = 1$ as Y_i^0 and Y_i^1, respectively. On the other hand, we let Y_{1i}^1 and Y_{0i}^1 be the vectors of the five potential $t = 1$ personality traits of child i in the case in which the

[13]Results are not reported to save space, but are available upon request from the authors.

father does or does not experience unemployment between the baseline and follow-up interview, respectively. We are interested in the identification of the Average Treatment effect on the Treated (ATT), that is defined in terms of potential outcomes at $t = 1$ as $E[Y^1_{1i} - Y^1_{0i}|DadU_i = 1]$ and measures the average effect of paternal unemployment on children's personality for children whose fathers have experienced unemployment.

Of course, the unconditional comparison of $t = 1$ personality of treated and untreated children, which we have carried out in the previous section, is informative about the ATT only if $DadU_i$ can be considered to be as good as randomly assigned. Unfortunately, the evidence provided in Table 2 and Table 3 shows that - even if treated and control children are well-balanced in terms of their own baseline personality traits and of other observable characteristics - there are substantial differences in pre-determined observable characteristics between the fathers of the two groups of children. In particular, negative selection of fathers into unemployment implies that the unconditional comparison of children's personality is biased towards finding *negative* differences in personality between treated and control children if personality is positively associated with parental background (see Eisenberg et al., 2014). This would run *against* our descriptive finding of a positive effect of paternal unemployment on children's conscientiousness. We can instead rule out reverse causality issues, since the treatment pre-dates the follow-up personality assessment.

We take advantage of the longitudinal nature of our data to estimate value-added models of personality (see Guarino et al., 2014, Todd and Wolpin, 2003). These models exploit the information about Y^0_i, a vector of children's personality traits measured at $t = 0$, before the treatment took place, as a "sufficient statistic" for all pre-determined unobserved variables that may affect follow-up personality and are not included in the model. Formally, we estimate the following system of five linear equations, one for each follow-up personality trait, $Y^1_{ij}, j = 1, \ldots, 5$:

$$Y^1_{ij} = \alpha_j + \beta_j DadU_i + \delta'_j Y^0_i + \gamma'_j X^0_i + \varepsilon_{ij}, j = 1, \ldots, 5, \tag{1}$$

where X^0_i is the vector of baseline covariates listed in Table 1, a dummy for belonging to the 2009 baseline sample, the regional unemployment rate at baseline, regional dummies and a vector of maternal and paternal baseline personality traits. Finally, ε_{ij} is an error term, which we allow to be correlated across equations.

By allowing the coefficient for the lagged outcome to be different from 1, value-added specifications leave more flexibility than first-differences (or "diff-in-diffs") models. In addition, the absence of statistically significant differences in baseline personality between treated and untreated offspring also points against using first-differences models.

Todd and Wolpin (2003) derive the (undoubtedly stringent) assumptions that relate reduced-form value-added specifications like the one described in equation (1) to a linear structural model of cognitive skills formation. Their work has been extended by Cunha and Heckman (2008) and Cunha et al. (2010) to consider also the production of non-cognitive skills and non-linear models with endogenous inputs. In their set-up, OLS estimation of the reduced-form model in equation (1) is inconsistent, because of correlation between the lagged outcome and the error term of the structural model. However, according to the simulation study carried out by Guarino et al. (2014) this is not a first-order problem for the identification of the ATT of paternal unemployment. In fact, Guarino et al. (2014) show that, by including the baseline level of the outcome, the dynamic OLS specification of value-added models is very effective at controlling for several sources of unobserved heterogeneity, and it performs better than other estimators derived on the basis of structural modelling considerations, that draw attention to second-order identification concerns (e.g. endogenous lags).

On the basis of these considerations, we estimate the 5-equation system described in (1) via OLS,[14] and we further dispel concerns related with the endogeneity of the lagged outcome by carrying out a simulation exercise, where we show that our estimated effect of *DadU* is robust even when we introduce different degrees of positive or negative cor-

[14]We always use heteroskedasticity-robust standard errors. Since the error terms associated to the different traits can be correlated, we also jointly estimate the system using seemingly unrelated regressions. However, we find no significant change in the standard errors with respect to estimation equation-by-equation. This is not surprising, as all models include the same explanatory variables.

relation between the lagged outcome and the error term of the model.

Consequently, as stated in Angrist and Pischke (2008, chapter 5), identification of the ATT from model (1) relies on the following assumption:

$$E[Y_{0i}^1|DadU_i = 1, Y_i^0, X_i^0] = E[Y_{0i}^1|DadU_i = 0, Y_i^0, X_i^0] \quad (2)$$

which implies that, conditional on the baseline covariates and on the baseline personality traits of the children, we can take the (observed) average follow-up personality scores for the control group as a plausible average counterfactual outcome for the treatment group, had it not experienced the treatment. Under assumption (2), in each equation of model (1) the coefficient β_j identifies the ATT of paternal unemployment on the j-th personality trait.

It is worth remarking that the set of baseline covariates included in X_i^0 is unusually rich, as it includes a comprehensive set of paternal characteristics, and in particular a thorough description of paternal labour market history (earnings, tenure, firm size, occupation, previous experience of unemployment), characteristics of the mother, of the family of origin, and of the child. Together with indicators of baseline personality of both the parents and the child, we do believe that these are sufficient to grant conditional independence of the treatment and potential outcomes.

In the light of the wide evidence about the stability (i.e. intra-individual changes in personality traits in response to life events) of personality traits (see Cobb-Clark and Schurer, 2012, for recent evidence), we consider specification (1) to be demanding enough so that any effect that should survive could be interpreted as causal. Nevertheless, we also carry out a set of tests aimed at gauging the robustness of our results to selection on unobservables, based on the estimators proposed by Altonji et al. (2005) and by Oster (2015), described below. Finally, we also show that our estimates are qualitatively similar when we use semi-parametric estimators based on propensity score weighting (see Hirano et al., 2003) and on entropy balance weighting (see Hainmueller, 2012).

4 Results

4.1 Main results

Table 4 reports our main results. In each column we report the ATT of paternal unemployment on each of the Big 5 personality traits, estimated as described in the previous section. The four columns report results when we progressively add a richer set of controls to the model. In particular, Column (1) includes only the baseline personality traits of the child, Column (2) adds wave dummies, regional dummies, and child and parents' baseline covariates (listed in Table 1), Column (3) adds parental baseline personality traits, and Column (4) adds the baseline employment status of the child.

Our main result is that paternal unemployment increases children's level of conscientiousness by .203 to .228 standard deviations, depending on the specification adopted. This difference is not only statistically significant but also relevant in magnitude. For instance, looking at the fathers' sample, we observe a raw difference in conscientiousness of similar magnitude between fathers with secondary education or more than secondary education. The result confirms the descriptive evidence presented in the previous section, and is qualitatively and quantitatively robust to the inclusion of a progressively more demanding set of controls. We also find that paternal unemployment reduces children's neuroticism by -.132 to -.187 standard deviations, but this effect is only marginally significant, and its magnitude is more dependent on the set of controls included in the model. The other personality traits are instead not affected by the experience of paternal unemployment.

All in all, our main results suggest that paternal unemployment improves children's personality. This evidence is consistent with the psychological literature on the effects of negative events on personality (see Seery, 2011, for a review), which has shown that, while experiencing no or high level of adversity has negative consequences on the development of the individual, moderate levels of adversity, such as paternal job loss, can actually be beneficial by building resilience. It is also worth noticing that, as we only observe two measures of personality traits with a 4-year gap between them, we can only estimate a short-term effect of unemployment experienced between the two waves, and cannot assess whether these effects would persist in the long run.

4.2 Robustness tests

Before presenting results from sub-group analysis, we describe a large battery of tests that we have carried out to verify the robustness of our main results.

As a first robustness check, we replicate our main analysis using personality scores obtained by extracting latent factors via a confirmatory factor analysis instead of using the raw means, as described in Section 2. Results - presented in Table A.2 in the Appendix - are qualitatively and quantitatively similar to those presented in Table 4, although in this case the negative effect on neuroticism is larger in magnitude and more strongly significant when we add the full set of controls.

Second, we use robust regressions and run a simulation exercise to verify that our estimated effects are not due to outliers - a relevant concern given that our sample is relatively small. On the one hand, robust regression is an alternative to least squares that allows to detect and to give low weight to outliers in the estimation of a regression model. On the other hand, to assess that no small group of observations are the main driver of our results, we also randomly drop 1% of the sample and re-estimate the model 1,000 times. We only drop 1% of the sample in each iteration to avoid losing precision. For conscientiousness - the only trait for which we estimate a consistently significant ATT - and considering the model with all covariates, our robust regression coefficient is equal to 0.22 (p-value = 0.048) - indistinguishable from our baseline estimate. Using our simulation strategy, the coefficient on *DadU* ranges between a minimum of 0.18 and a maximum of 0.25, and is not statistically significant in less than 1 percent of the repetitions. Therefore, both tests lead us to reject the possibility that our main effect is driven by outliers.[15]

Third, we also use simulations to dispel concerns related with correlation between

[15]Results for other outcomes and specifications are also robust - and are available from the authors.

the lagged outcome and the error term, which could make OLS estimates of the effect of paternal unemployment in our value-added model inconsistent. Again, we focus on conscientiousness and on the model for all covariates, but results for other outcomes and specifications are also robust and available from the authors. We proceed as follows: first, we simulate a random normal error term e_i that has the same mean and standard deviation as the estimated residual from model (1). Second, we introduce correlation between the error term e_i and the baseline value of the outcome by computing a fictitious baseline outcome $\widetilde{Y_i^0} = Y_i^0 + \omega \times e_i$. We allow ω to vary between -1 and +1 in steps of 0.2, therefore allowing for different degrees of correlation between $\widetilde{Y_i^0}$ and e_i. Third, for each value of ω, we generate the simulated outcome $\widetilde{Y_i^1}$ using $\widetilde{Y_i^0}$, our observed data for the other covariates, the estimated coefficients from the observed data in model (1) and the simulated error term e_i. We repeat this procedure 1,000 times for each value of ω, and re-estimate model (1) each time. For each value of ω, the 2.5th, 50th and 97.5th percentiles of the empirical distribution of the coefficient of *DadU* are reported in Table A.3 in the Appendix. For all values of ω, the median is close to the value of the coefficient in the original data, and the empirical confidence interval at the 5 percent level of confidence does not include zero, leading us to conclude that our estimated effect is robust to the presence of an arbitrary degree of correlation between the baseline outcome and the error term.

Next, although our estimates control for a very rich set of observables, it could still be the case that other unobserved characteristics of the child, the mother or the father that are correlated with selection into unemployment could be driving our results. Hence, following Altonji et al. (2005) and Nunn and Wantchekon (2011), we use selection on observables to assess the potential bias of our estimates presented in Table 4 from unobservable omitted variables. To do so, we compare the effects estimated in Column (1), $\hat{\beta}^R$, that only controls for a restricted set of covariates (children's baseline personality), and Column (4), $\hat{\beta}^F$, that includes the full set of controls, by computing the following ratio: $\hat{\beta}^F/(\hat{\beta}^R - \hat{\beta}^F)$. This ratio is informative about how strong should selection on unobservables be, with respect to selection on observables, to entirely account for the estimated effects. On the one hand, the larger is $\hat{\beta}^F$, the larger the effect that needs to be explained by selection on unobservables. On the other hand, the smaller the denominator, the less our estimate is affected by selection on observables, and the stronger selection on unobservables needs to be to explain away the entire effect. For conscientiousness, we compute a ratio equal to 12.76. Hence, selection on unobservables should be at least 12 times stronger than selection on observables to explain away the *entire* effect of paternal unemployment on conscientiousness, putting us in a safe position.[16]

In a recent study, Oster (2015) extends the arguments of Altonji et al. (2005) about estimating the degree of selection on unobservables that would be required to drive the ATT to zero (called δ) to consider both coefficient movements *and* movements in R-squared values after the inclusion of controls. In fact, coefficient changes are informative about omitted variables bias only if these are *rescaled* by the movement in R-squared, i.e., by the additional fraction of variance of the outcome that is explained by the included controls. If this fraction is large, then the remaining variance of the outcome that can be explained by selection on unobservables, and thus bias coefficients, is negligible. Contrarily, changes in coefficients are less informative about the effects of unobservables' selection if this fraction is small. To apply this method, we need to set a maximum *attainable* value of the R-squared, $Rmax$, that indicates the maximum share of variance of the outcome that could be explained by *any* set of observable and unobservable covariates. Assuming that there is at least some random noise in empirical data, a value of $Rmax = 1$ is viewed by Oster as too conservative. We follow the rule proposed by Oster of setting $Rmax$ equal to 1.3 times the R-squared of the model that includes all covariates.[17] In

[16]The ratio is equal to -3.475 for neuroticism. A negative ratio means that, if anything, the estimated effect is biased downwards by selection on unobservables, so long as selection on observables and selection on unobservables are positively correlated - a tenable assumption.

[17]This is computed by Oster as the value that would allow 90 percent of *randomised control-trial* studies published in the Top 5 economics journals between 2008 and 2013 to survive in rejection-of-zero tests like the one we are using.

our case, this implies to set $Rmax = 0.42$ for conscientiousness and $Rmax = 0.38$ for neuroticism. For conscientiousness, we compute that $\delta_{0.42} = 4.66$, that is way above the suggested threshold of 1. Indeed, our results would be robust even with higher values of $Rmax$. For instance, setting $Rmax = 0.9$ would still leave us with $\delta_{0.9} = 1.06$.[18]

Additionally, to verify the robustness of our main results to the linear parametric specification of our model, we also exploit semi-parametric estimation methods based on propensity score weighting (see Hirano et al., 2003), and entropy balance weighting (see Hainmueller, 2012). The former method uses Horowitz-Thompson weights estimated on the basis of a propensity score to re-weight the data and achieve balancing on the observables. Since this method relies on an *estimated* propensity score, it may fail to improve balancing in finite samples. The latter method, instead, overcomes this drawback by using a maximum entropy reweighting scheme, that weighs each unit in the control group in such a way that the covariates distributions in the reweighted data have the same means as in the treatment group, thereby obtaining a reweighted sample that is *perfectly* balanced on the means of the included observable covariates, even in small samples. Obtaining similar results with OLS, propensity score weighting and entropy balance weighting should be reassuring about the robustness of our results to different parametric specifications of the model. Results that use the same controls included in Column (4) of Table (4) - our most comprehensive specification - are reported in Table A.4 in the Appendix, and portray a very similar picture to the one reported in Table 4. We still find a statistically significant positive effect of paternal unemployment on children's follow-up level of conscientiousness, and we also still find a negative effect of paternal unemployment on neuroticism, but this effect is not significant when we use Entropy Balancing. Also in this case, the ATT on other personality traits is close to zero in magnitude and not statistically significant.

In a final robustness test, we also verify that our results are not driven by the presence in our control group of both fathers that have been working throughout the period

[18]Even in this case, we compute a negative value of δ for neuroticism, since $\delta_{0.38} = -1.99$ and - in the extreme case where $Rmax = 0.9$ - $\delta_{0.9} = -.37$.

between the baseline and follow-up interview and fathers who have left the labour force by the follow-up interview - most likely because of retirement. To this end, we introduce in our regression a dummy variable that is equal to one for the latter group of fathers and to zero for the former one. Even in this case, results are qualitatively and quantitatively equal to our baseline, and are therefore omitted.[19]

4.3 Discussion: Investigating Potential Mechanisms

To understand the potential mechanisms behind our estimated effects, our final analysis investigates heterogeneous effects by subgroups of the population. We estimate heterogeneous effects with linear models akin to (1), by interacting the treatment dummy with two dummies, one for each of the groups that we are interested in, and by excluding the constant from the model. Since this analysis only aims at explaining the mechanisms behind our main findings, we only consider conscientiousness and neuroticism. Unfortunately, we do not have enough power to test whether the effects are statistically different between groups. Therefore, results in this sub-section should be taken as suggestive at best.

Since we find positive causal effects, we confidently rule out that these are a direct consequence of the economic and mental distress of unemployed fathers. Our most-plausible remaining explanations are improved father-children interactions and psychological resilience to avoid falling into unemployed later on.

To distinguish among these competing stories, we first consider heterogeneous effects between offspring that are younger and older than 20 at baseline, the median age in the sample. On the one hand, younger offspring are the ones with whom fathers may interact more if unemployed, as they are less likely to be time-constrained by work. Younger offspring are also more likely to co-habit with fathers, but since only 17.8 percent of offspring do not cohabit with fathers at baseline we consider this as a second-order chan-

[19] Results are also robust when we instead drop fathers who leave the labour force from our sample (a total of 34 fathers).

nel.[20] On the other hand, older offspring are more likely to be employed, and therefore more exposed to a direct threat of unemployment - and scared by its consequences.

Panel A of Table 5 shows that - for conscientiousness - older offspring are indeed the sole group affected by paternal unemployment, suggesting that improved parent-child interactions are unlikely to be a plausible explanation behind our estimated positive effects. This hypothesis is further confirmed by results reported in Panel B of Table 5, where we estimate heterogeneous effects for employed and not employed offspring at baseline, and find that - for conscientiousness - the first group is the only one for whom the effect is statistically significant. For neuroticism, we do not find evidence of heterogeneous effects.

Taken together, these pieces of evidence suggest that the effect we have detected on conscientiousness can be interpreted as a psychological coping device that mostly affects employed offspring, who face a direct risk of unemployment and may be more prone to improve their work attitude in order not to experience the negative consequences of unemployment experimented by their fathers.

5 Conclusions

Using longitudinal data about the German population, we are the first to identify the effects of paternal unemployment on the Big 5 personality traits during adolescence and early adulthood. Our estimates from value-added models suggest that paternal unemployment has a surprisingly positive effect on children's personality, as it improves their conscientiousness and decreases their levels of neuroticism. Our results are robust to a large set of specification checks, including simulations for correlation between the baseline outcome and the error term and tests for selection on unobservables - which could make OLS estimation of the effect of paternal unemployment inconsistent in our value-added models. Since in the models of Heckman (2007) and Conti et al. (2010) conscientiousness affects the educational, labour market and health behaviour choices made by individuals, an increased level of conscientiousness in young age might lead to a virtu-

[20] We have also tried to estimate heterogeneous effects by co-residence status at baseline, but effects are similar and not statistically different between the two subsamples.

ous "self-productivity cycle", resulting in improved health and socio-economic conditions throughout the life-cycle. However, we would need data that cover a longer time period to understand whether the estimated effects are persistent or transitory.

Two aspects of our results are worth of further discussion. First, it is not difficult to explain why we detect an effect of paternal job loss on conscientiousness and neuroticism of children, exclusively. Indeed, among the Big 5 dimensions, these two traits are the most related to children's work vision and the ability to deal with their uncertain future. Second, our findings are in line with several psychological studies (see Seery, 2011, for a review) that show how experiencing moderate levels of adversity, such as paternal job loss, can be beneficial to the individual development by building resilience.

To understand the mechanisms that can explain our effects, we have shown that - for conscientiousness - older and employed offspring are the ones for whom we detect positive and statistically significant effects of paternal unemployment. This result suggests that increased time spent by unemployed parents with their offspring is unlikely a mechanism at play. We are instead more prone to suggest that the negative scars that unemployment left on their fathers may have improved the work attitude of employed offspring, who want to avoid falling into unemployment themselves. Needless to say, further research that uses more extensive data should investigate this important aspect more in depth.

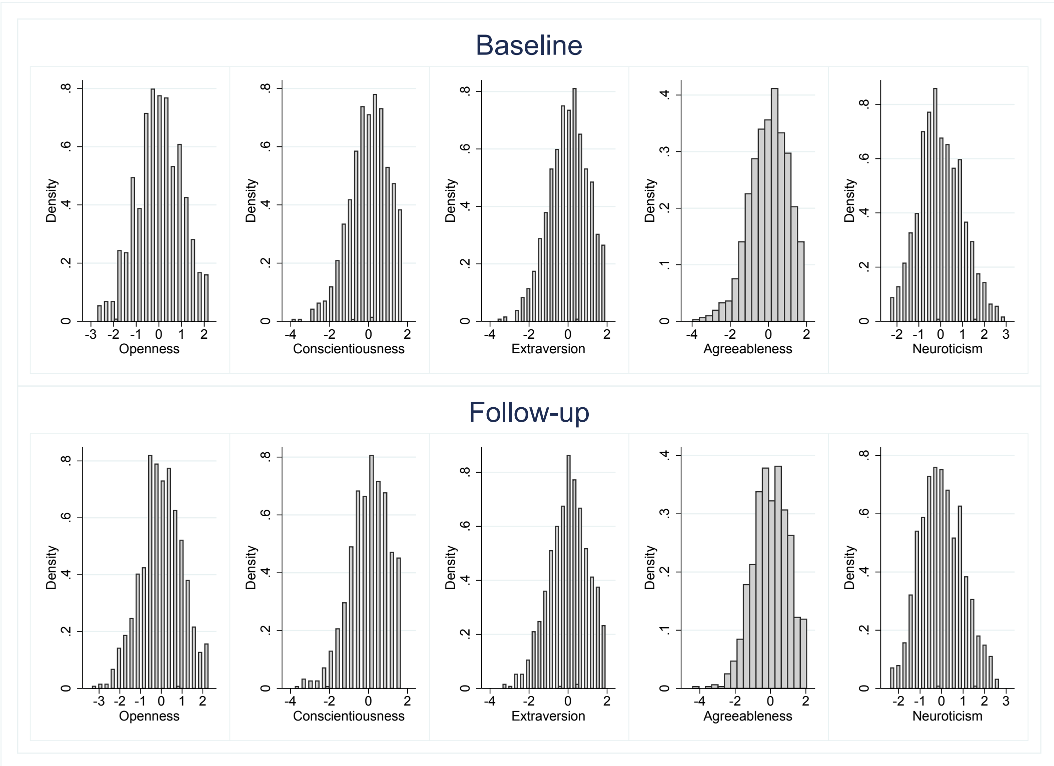
Acknowledgements

We especially thank James MacKinnon, who provided invaluable suggestions for the design of our simulation exercises. We are also grateful to Giorgio Brunello, Alessandro Bucciol, Deborah Cobb-Clark, Christopher Cotton, Arnaud Dellis, Monica Langella, Riccardo "Jack" Lucchetti, Jochen Mierau, Nattavudh Powdthavee, Paolo Roberti, Lorenzo Rocco, Nicolas Salamanca and Davide Ticchi for comments on earlier versions of this work, and to the audiences at the 2015 Brucchi Luchino Workshop, the 2016 ESPE Conference and at seminars at the University of Ancona, the Univerisity of Quebec at Montreal, Queen's University and the University of Padova for useful discussions. We

also thank Michaela Engelmann at DIW for providing us access to the data. The usual disclaimer applies.

Figures

Figure 1: Distribution of personality traits at baseline and follow-up



Tables

Table 1: Descriptive Statistics - Number of Observations: 893

	Mean	SD	Min	Max
DadU	0.088	0.284	0	1
Offspring baseline controls				
Female	0.462	0.499	0	1
Age	20.646	2.453	17	25
Immigrant	0.054	0.226	0	1
Firstborn child	0.064	0.245	0	1
Has siblings	0.887	0.317	0	1
Poor health	0.037	0.189	0	1
Life satisfaction	7.439	1.560	1	10
Offspring baseline employment status				
Employed	0.604	0.489	0	1
Unemployed	0.039	0.194	0	1
In education	0.330	0.471	0	1
Mother baseline controls				
Age	47.287	4.809	35	68
Employed	0.793	0.406	0	1
Years of education	12.232	2.458	7	18
Immigrant	0.078	0.269	0	1
Poor health	0.114	0.318	0	1
Life satisfaction	7.058	1.681	0	10
Does not live with the offspring	0.160	0.367	0	1
Father baseline controls				
Age	49.685	5.015	34	62
Years of education	12.450	2.618	7	18
Immigrant	0.078	0.269	0	1
Poor health	0.125	0.331	0	1
Life satisfaction	6.946	1.746	0	10
Does not live with the offspring	0.178	0.383	0	1
Never unemployed before baseline	0.637	0.481	0	1
Employed in firm $\leq$ 200 employees	0.508	0.500	0	1
ln(labour earnings)	10.573	0.665	6.802	13.039
Tenure in the firm	15.513	10.737	0	45
Homeowner	0.742	0.438	0	1
Living in urban area	0.625	0.484	0	1

Table 2: Mean of selected father controls at baseline - by paternal unemployment

	Mean Employed Father	Unemployed - Employed Father
Age	49.469	2.442***
		(0.622)
Years of education	12.547	-1.098***
		(0.225)
Immigrant	0.075	0.039
		(0.037)
Poor health	0.112	0.154***
		(0.051)
Life satisfaction	7.053	-1.205***
		(0.259)
Never unemployed before baseline	0.666	-0.324***
		(0.056)
Does not live with the offspring	0.163	0.166***
		(0.055)
Employed in firm $\leq$200 employees	0.484	0.276***
		(0.051)
ln(labour earnings)	10.621	-0.562***
		(0.090)
Tenure in the firm	16.107	-6.716***
		(1.179)
Homeowner	0.759	-0.190***
		(0.058)
Lives in urban area	0.633	-0.088
		(0.059)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Mean offspring personality traits at baseline and follow-up, by paternal unemployment

	Mean Employed Father	Unemployed - Employed Father
Baseline		
Openness	0.002	-0.017
		(0.121)
Conscientiousness	-0.011	0.125
		(0.112)
Extraversion	0.010	-0.116
		(0.105)
Agreebleness	0.011	-0.121
		(0.110)
Neuroticism	-0.007	0.079
		(0.133)
Follow-up		
Openness	-0.005	0.057
		(0.124)
Conscientiousness	-0.026	0.291***
		(0.097)
Extraversion	0.000	-0.003
		(0.114)
Agreebleness	-0.007	0.085
		(0.129)
Neuroticism	0.008	-0.096
		(0.117)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Main results

	(1)	(2)	(3)	(4)
Openness	0.057	0.058	0.061	0.054
	(0.102)	(0.114)	(0.114)	(0.113)
Conscientiousness	0.228***	0.203**	0.211**	0.211**
	(0.081)	(0.088)	(0.090)	(0.090)
Extraversion	0.044	0.055	0.050	0.052
	(0.107)	(0.119)	(0.118)	(0.117)
Agreebleness	0.132	0.116	0.113	0.106
	(0.109)	(0.111)	(0.110)	(0.108)
Neuroticism	-0.132	-0.187*	-0.181*	-0.185*
	(0.099)	(0.108)	(0.107)	(0.106)
Offspring's baseline personality	Yes	Yes	Yes	Yes
Offspring and parents' baseline controls	No	Yes	Yes	Yes
Parents' baseline personality	No	No	Yes	Yes
Offspring's baseline employment status	No	No	No	Yes
Observations	893	893	893	893

Notes: The table reports the effect of *DadU* on each personality trait. Controls included in each model are listed at the bottom of the table (see also Table 1). The equations for the different personality traits in each model are estimated jointly, using seemingly unrelated estimation. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Heterogeneous effects

	(1) Cons	(2) Neur
Panel A. Heterogeneous effects by offspring‘s age		
DadU - Younger offspring	0.132	-0.276
	(0.144)	(0.172)
DadU - Older offspring	0.272***	-0.096
	(0.103)	(0.123)
Difference (P-value)	0.411	0.376
Panel B. Heterogeneous effects by offspring‘s employment status		
DadU - Employed offspring	0.259**	-0.130
	(0.104)	(0.121)
DadU - Not employed offspring	0.129	-0.278
	(0.152)	(0.187)
Difference (P-value)	0.468	0.491
Offspring’s baseline personality	Yes	Yes
Offspring and parents’ baseline covariates	Yes	Yes
Parents’ baseline personality	Yes	Yes
Offspring’s baseline employment status	Yes	Yes
Observations	893	893

Notes: The table reports the heterogeneous effects of *DadU* on conscientiousness and neuroticism. Panel A reports heterogenous effects for offspring younger and older than 20 years of age. Panel B reports heterogeneous effects for employed and not employed offspring. The effects are estimated by running a model interacting *DadU* with dummies for each group, and omitting the constant. The p-value for the significance of the difference in the effects across genders is also reported. The specification adopted is equal to the one shown in Column 4 of Table 4. The equations for the different personality traits are estimated jointly, using seemingly unrelated estimation. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A.1: SOEP personality questionnaire

Big 5 personality factor	Statement
	I see myself as someone who...
Openness	...is original, comes up with new ideas
Openness	...values artistic experiences
Openness	...has an active imagination
Conscientiousness	...does a thorough job
Conscientiousness	...does things effectively and efficiently
Conscientiousness (reversed)	...tends to be lazy
Extraversion	...is communicative, talkative
Extraversion	...is outgoing, sociable
Extraversion (reversed)	...is reserved
Agreeableness	...has a forgiving nature
Agreeableness	...is considerate and kind to others
Agreeableness (reversed)	...is sometimes somewhat rude to others
Neuroticism	...worries a lot
Neuroticism	...gets nervous easily
Neuroticism (reversed)	...is relaxed, handles stress well

Notes: respondents were asked to state how much they agreed with each statement on a 7-point Likert scale. Some items' scales are reversed when computing the personality scores.

Table A.2: Robustness test - personality traits obtained via confirmatory factor analysis

	(1)	(2)	(3)	(4)
Openness	0.094	0.082	0.085	0.081
	(0.100)	(0.111)	(0.111)	(0.110)
Conscientiousness	0.224***	0.234***	0.249***	0.251***
	(0.080)	(0.089)	(0.091)	(0.090)
Extraversion	0.054	0.066	0.060	0.063
	(0.102)	(0.112)	(0.112)	(0.111)
Agreebleness	0.124	0.106	0.115	0.105
	(0.103)	(0.104)	(0.102)	(0.101)
Neuroticism	-0.146	-0.207*	-0.207*	-0.214**
	(0.100)	(0.109)	(0.109)	(0.108)
Offspring's baseline personality	Yes	Yes	Yes	Yes
Offspring and parents' baseline covariates	No	Yes	Yes	Yes
Parents' baseline personality	No	No	Yes	Yes
Offspring's baseline employment status	No	No	No	Yes
Observations	893	893	893	893

Notes: The table reports the effect of *DadU* on each personality trait. Controls included in each model are listed at the bottom of the table. The equations for the different personality traits in each model are estimated jointly, using seemingly unrelated estimation. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Simulation exercise - 2.5th, 50th and 97.5th percentiles of the empirical distribution of β_{cons} for various degrees of correlation between the baseline outcome and the error term

	(1)	(2)	(3)
Percentile:	2.5	50	97.5
$\omega = -1$	0.14	0.25	0.34
$\omega = -0.8$	0.12	0.25	0.34
$\omega = -0.6$	0.09	0.25	0.38
$\omega = -0.4$	0.07	0.24	0.40
$\omega = -0.2$	0.04	0.23	0.41
$\omega = 0$	0.02	0.22	0.41
$\omega = 0.2$	0.01	0.21	0.39
$\omega = 0.4$	0.02	0.19	0.36
$\omega = 0.6$	0.04	0.19	0.32
$\omega = 0.8$	0.06	0.19	0.30
$\omega = 1$	0.08	0.18	0.27

Notes: The simulation methodology is described in the text. The model is the one in Table 4, column 4. For each value of ω we have used 1,000 replications.

Table A.4: Robustness test - Inverse Probability Weighting and Entropy Balancing

	(1) IPW	(2) EBAL
Openness	-0.029	0.047
	(0.148)	(0.154)
Conscientiousness	0.368***	0.293**
	(0.139)	(0.149)
Extraversion	-0.110	0.001
	(0.129)	(0.140)
Agreebleness	0.132	0.071
	(0.152)	(0.159)
Neuroticism	-0.272**	-0.225
	(0.122)	(0.139)
Offspring's baseline personality	Yes	Yes
Offspring and parents' baseline covariates	Yes	Yes
Parents' baseline personality	Yes	Yes
Offspring's baseline employment status	Yes	Yes
Observations	893	893

Notes: The table reports the effects of *DadU* on each personality trait using different semiparametric estimators. Column 1 balances treated and control units using Inverse Probability Weights obtained via propensity score estimation. The covariates included in the model for the propensity score are listed at the bottom of the table. Inference is carried out as in Cattaneo, 2010. Column 2 presents results obtained via entropy balancing (see Hainmueller, 2012) to balance the means of the same covariates included in the estimation of the propensity score in Column 1. *** p<0.01, ** p<0.05, * p<0.1.

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