Supplementary Online Appendix to "Scars of Recessions in a Rigid Labor Market."

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S.1 Variable Construction

This analysis exploits survey and administrative data from different sources.

- Individual control variables are taken from the Sonar surveys which was conducted on a representative sample of three birth cohorts, born in 1976, 1978, and 1980, and living in Flanders at age 23. The surveys (as well as follow-up surveys at ages 26 and 29) register the respondents' main activity, among which education, retrospectively and on a monthly basis since the beginning of secondary education. The original Sonar sample contains 9,858 individuals.[1]
- These observations are matched to the following administrative data from Belgian Social Insurance Institutions centralized at the Cross Roads Bank of Social Security (CBSS, hereafter, Data Warehouse).
  - Yearly data on the province of residence are provided by the Regional Register of Belgium. These data are available from the year in which individuals turn age 18 (1994, 1996 and 1998 for cohort born in 1976, 1978, and 1980, respectively) up to 2010.
  - Quarterly data on individual labor market performance are provided by the Regional Social Security office (RSZ), the Regional Social Security office of Provincial and Local Administration (RSZPPO), and the Regional Institute for the Social Security of the Self-employed (RSVZ) for the period 1998-2010.
- The unemployment rate series are provided by the Labor Force Surveys (LFS).

In what follows we describe these data and the construction of the variables used in the analysis.

S.1.1 Sonar Dataset: Educational Variables and Graduation Date

The Sonar dataset is exploited to construct the following variables: (a) the graduation date, (b) the years of successfully attained education at age 17 (hereafter, "completed education at age 17"), and (c) the total years of successfully attained education until graduation (hereafter, "completed education"). Based on the latter, we divide the sample into (d) low- and high-educated men. Finally, the survey gathers information about (e) parental education.

(a): *Graduation date* - The moment of graduation (month and year) is defined as the first exit from schooling after the completion of compulsory education (age 18 in Belgium). This variable is based on the individual status provided by the Sonar data, which reports on a monthly basis whether one is in full-time education, in part-time education while working, in employment, unemployment or non-employment, from December of the year in which he turns 17 until at least the year in which he turns age 26.[2] According to our definition, individuals are considered out of education whenever they are observed working, unemployed or not working. Those reporting to be in regular education and to work at the same time are still considered as in education. In December of the year in which

[1] For details, see SONAR (2004a, 2003, 2004b).

[2] For the 1978 wave, information is only collected until age 26. For the other waves, it is gathered until October or November of the year in which one turns 29, depending on the date of the survey.

they turn age 17 all individuals in the sample are observed in education.[3] Whenever we cannot observe directly the transition from education to employment or unemployment, the exit from education is defined as not being in education for more than 4 subsequent months, independently of the destination (employment, unemployment, non-employment, missing). This procedure allows us to define the age of first exit from education for 95.4% of the initial Sonar sample (i.e. of 9,858 individuals).[4] Among the remaining 4.6% for which the date of graduation is unknown, 3% are censored at age 23 or 26 while still in ongoing full-time education and 1.2% are censored at those age while in part-time education and working at the same time.[5]

Imputation procedure for censored observations in Sonar - Among the observations for which the age of first exit from schooling is unknown, some individuals are censored at age 23 or 26 while still in ongoing full-time education (3%): for these individuals - if possible - the age of first exit from schooling is inferred exploiting the socio-economic position reported by the Data Warehouse at the end of each quarter for the period 1998-2010. To do this, we assume that these observations remain in regular education from the moment of censoring in the Sonar dataset until when they are observed for the first time in the labor market according to the Data Warehouse, i.e. either employed or unemployed looking for a job.[6] If the first time one is observed in the labor market at the end of a quarter he is employed, he is assumed to have graduated at the end of the previous quarter. If instead the first time one is observed in the labor market he is an unemployed job-seeker, the imputation is different. The reason is that an unemployed appears in the database when he first receives the unemployment benefits (UB), but in Belgium the receipt of the UB implies a waiting period that varies between 9 and 12 months from the registration to the unemployment agency, depending on the age. This means that the actual entry in the labor market for the unemployed is the registration to the unemployment agency rather than the receipt of UB. Thus, the age of first exit from education for the unemployed takes into account this waiting period.

We cannot apply this procedure to individuals whose socio-economic position is never observed in the Data Warehouse: these individuals are dropped (0.1%). In some other cases, individuals are working according to the Data Warehouse even before censoring. Among these cases we retain only individuals who are employed in student jobs while still in full-time education according to the Sonar data (2.5%). In contrast, we drop those who result employed in regular jobs while still in full-time education according to the Sonar data (0.13%) due to inconsistency between the Sonar and the Data Warehouse. Student jobs are defined according to the following criteria: (1) we exploit a variable provided by the Data Warehouse that identifies jobs that are "typically" undertaken while studying. (2) If (1) is satisfied, we ensure that the time worked in this potential student job does not exceed the maximum time a child is allowed to work, for his parents not to lose the family allowance that they receive for their children: this threshold amounts to 240 hours (i.e. roughly 30 days) per quarter except in the summer quarter, during which a child is allowed to work more.

[3] We drop few observations who quit education before the end of compulsory education.

[4] Hereafter the percentages are computed relative to the size of the original Sonar sample (9,858 individuals).

[5] For 0.4% of the initial sample the graduation date cannot be computed according to the aforementioned criterion.

[6] We cannot apply this imputation method for those who are censored in part-time education and working as they appear in the labor market even before censoring and hence we cannot observe their labor market entry.

Hence, a potential student job is defined as such if one has worked at most 30 days for each quarter except the summer.

Check inconsistencies between the Sonar and the Data Warehouse - The graduation date is mostly defined based on information reported in the Sonar survey data. We verify the reliability of this information checking its consistency with the administrative data: i.e., we check whether individuals are observed in the labor market according to the Data Warehouse in the years when they report to be still in full-time education according to the Sonar data. Among the cases for which the graduation date is defined, 17.6% of the individuals are indeed observed in the labor market before their graduation. These cases are considered consistent if the individuals are employed in student jobs, based on the aforementioned "student job" criterion. Inconsistent observations are dropped from the sample (4%).

(b): Completed education at age 17 - The Sonar data contains detailed information about the educational path of the individuals since secondary education: in each year, one can observe the type of educational program in which one is enrolled (full-time general, vocational, or technical program, part-time vocational, and apprenticeship), the grade and whether it is successfully passed or not. This information is exploited to build completed education at age 17, which counts the number of grades repeated until the academic year in which one turns 17 (included). In the main analysis, it is expressed so to give information about the educational progression of the individual at age 17 with respect to the theoretical years of schooling: 0 means that the individual is on time, positive numbers indicate the number of repeated grades, and -1 indicates that the individual has skipped one academic year.

(c): Completed education - This is constructed similarly to completed education at age 17. It counts the years of schooling successfully attained since the beginning of secondary education until graduation. For individuals who are censored in the Sonar data at age 23 or 26 while still in ongoing education, completed education is imputed assuming that since the moment of censoring, all years in education were successfully passed until graduation. We ensure consistency between completed education and the graduation date dropping few individuals for which the imputed completed education is unrealistically too high with respect to the graduation date.

(d): Low- and high-educated - The sample is divided in two educational groups based on completed education: the low-educated are individuals with a degree no higher than high school, i.e. who graduated at age 19 if enrolled in vocational program or at age 18 if enrolled in general, technical, part-time vocational or apprenticeship program. This is because the vocational track lasts 7 years while all other educational tracks last 6 years. The high-educated are those with a higher level of education. In the main analysis these two groups are studied separately.

(e): Mother's and father's education - These variables are defined as the number of years of completed education since the start of secondary education (age 12). Missing values are 10.69% and 8.86% for the father and the mother, respectively. To maximize the size of the sample used in the analysis, the missings are imputed according to a regression-based procedure which adds a randomized residual to the predicted variables.[7] The imputation exploits the individual controls

[7] This aims at improving the regression-based imputation, which alone shows the following drawbacks: (i) distortion

(number of brothers, number of sisters, educational track at age 17 and completed education at age 17) which have no missing,[8] and the mother's and the father's education with missings. Hence, for observations with missing values in one parent's education but not in the education of his/her partner, the linear predictions for the missings exploit the information of his/her partner's education in addition to the one provided by the controls with no missings. By contrast, for observations with missings in both the mother's and the father's education, the linear predictions for each parental education exploit only the information provided by the controls with no missings. In addition, an error term extracted from a logistic distribution is added to the linear predictions and the probability of an outcome is computed transforming the corresponding predictions by the inverse logit function. We assign to each missing the outcome for which the predicted probability is maximum.

S.1.2 Data Warehouse - Individual Labor Market Outcomes

Individual labor market outcomes are based on quarterly data from the RSZ and the RSZPPO and on yearly data from the RSVZ for the period 1998-2010. The RSZ and the RSZPPO data collect information on the salary, the earnings, and the time worked for salaried employment in the public and the private sector. The RSVZ data reports the registration in self-employment for the period 1998-2010 and the yearly earnings from self-employment for the period 1998-2007. Earnings from self-employment are not exploited since self-reported and thus likely to be under-reported.[9] For salaried workers we construct the following outcomes: (a) log of annual earnings, (b) log of annual hours worked and (c) log of average hourly wage. We complement this information with three annual indicators for employment: (d) self-employment (if registered as such part of the year, irrespectively of being a salaried worker in the same year); (e) salaried employment (strictly positive earnings and not being self-employed); (f) overall employment (either self- or salaried). Descriptive statistics of these outcomes are shown in Table S.1 of the Online Appendix of Cockx and Ghirelli (2015).

(a): Annual earnings - It is based on gross earnings from salaried employment, which in both the RSZ and the RSZPPO are defined as the sum of all remunerations that are subject to social contributions (including holiday allowances), excluding allowances from contract termination.

Earnings are provided in classes of 100 Euros, so that the earnings-class equal to 0 refers to earnings between 1 and 100 Euros. We transform earnings-classes in real earnings multiplying by 100 and adding 50 - the midpoint of the interval of each class - in order not to underestimate real earnings. In addition to the quarterly earnings by separated sources, the Warehouse Data provides us with the sum of all earnings in a year (adding up yearly earnings from the RSZ, the RSZPPO and the RSVZ). Thus, for the cases in which the individuals are not working as self-employed, we use this sum as a measure of the annual earnings from salaried employment, while for the years

of variance; (ii) normative decision of the covariates for the predictions (Kalwij and van Soest, 2005; Frick and Grabka, 2003; Särndal and Lundström, 2005).

[8] The procedure is implemented after having dropped individuals with missing in the aforementioned individual controls (2.19% of the initial Sonar sample).

[9] However, a worker is considered as self-employed if a given year he is registered as self-employed according to the RSVZ, or if he is not registered as such but reports positive earnings from self-employment to the RSVZ.

in which individuals are also self-employed, we compute by ourselves the sum of earnings from the RSZ and the RSZPPO. In this case, yearly earnings from the RSZPPO and the RSZ are first transformed from classes of 100 Euros in real earnings, and then summed up to obtain a yearly measure of earnings from salaried employment.

(b): Annual hours worked - The RSZ provides us with the number of working days in case of full-time salaried work and the number of working hours in case of part-time salaried work, while the RSZPPO gives us the number of working hours both for full-time and part-time salaried work. To clean the data, we compute the total number of working days in case of full-time work separately for the RSZ and the RSZPPO and drop the yearly observations whose values are above 312 working days per year, which corresponds to the maximum number of working days in case of full-time work in a 6 days per week regime. The equivalent number under a 5 days per week regime is 260. Then, for annual observations corresponding to full-time workers who work between 260 and 312 days per year, we assume a working regime of 6 days per week, while for the other cases we assume a working regime of 5 days per week. We decide to focus on hours worked in order to take into account also part-time work. Hence, for full-time work in the RSZ, we convert working days in working hours, assuming a working regime of 8 (7.6) hours per day for the period 1998-2002 (2003-2010). This is because the 7.6 hours per day regime was introduced by law in Belgium as from January 2003 to replace the 8 hours per day regime for full-time work. Then, we add up the yearly working hours in full-time and part-time work and across sources (the RSZ and the RSZPPO) to get a measure of the total number of hours worked in salaried employment in a year.

(c): Average hourly wage - The average hourly wage in salaried employment is obtained by dividing the annual earnings by the annual number of hours worked, i.e. $(a)/(b)$.

Cleaning procedure for (a),(b) and (c) - We check for the presence of outliers in (a), (b) and (c) as follows. Given the presence of minimum wages in Belgium, we detect the bottom outliers by comparing the average hourly wage (c) with the corresponding hourly minimum wage.[10] The official monthly minimum wages are provided by the Conseil Regional du Travail of Belgium each year. These numbers are adjusted by the Consumer Price Index (using the first quarter of 2011 as reference) and by age, as different percentages of the official minimum wage are applied for workers below age 21.[11] Then, for each minimum wage, year and age category, we construct the corresponding hourly minimum wages as follows. (i) Compute the total annual earnings of a full-time worker paid at the minimum wage multiplying the monthly minimum wage times 12. (ii) Compute the total number of working hours in full-time work under the 5 and 6 days per week regimes, assuming the 8 (7.6) hours per day regime for the period 1998-2002 (2003-2010). (iii) Divide the figures obtained in (i) by those obtained in (ii) to get the hourly minimum wages in full-time work under the 6 and 5 days per week regime for the period 1998-2002 and 2003-2010,

[10] To be conservative for this comparison we convert earnings-classes in real earnings assuming that the latter are at the top of each earnings-class instead of at the midpoint (i.e. multiply earnings-classes by 100 and add 100).

[11] Workers aged 17, 18, 19 and 20 receive 76%, 82%, 88% and 94% of the official minimum wage, respectively. Workers aged 21 or more receive the entire official minimum wage (Moulaert and Verly, 2006). To be conservative we take the minimum wage of the previous age (i.e. minimum wage of those aged 17 in the year one turns 18).

respectively. We detect as bottom outliers the annual observations in which the average hourly wage is below the corresponding hourly minimum wage: in this case, the annual hours worked, the annual earnings and the average hourly wage are all replaced to missing.

Next, we check for the presence of outliers in the upper part of the distribution of annual earnings, average hourly wages and annual hours worked. We consider as top outliers the top percentile in the distribution of each of these variables. For the average hourly wage and the annual hours worked, we look at the distribution pooling all years together. For the annual earnings, we identify as outliers the last percentile of the distribution of annual earnings by age, assuming that earnings do not differ systematically across years but change over age. Similarly to the procedure used for the bottom outliers, we replace to missing each of the variables (a), (b) and (c) whenever a top outlier in any of these three variables is detected. In total, according to this procedure 3% of the annual observations are detected as outliers. Finally, the annual earnings, the annual hours worked and the average hourly wages are log-transformed.

(d): *Self-employment* - It is defined by a dummy equal to one if one is registered as self-employed in a given year - and zero otherwise. Workers who combine salaried and self-employment in the same year are considered self-employed and not salaried employed.

(e): *Salaried employment* - It is defined by a dummy equal to one if annual earnings from salaried employment are positive or missing since outliers - and zero otherwise. This is because outliers refer to employed individuals for whom one cannot calculate the earnings or the time worked. This dummy is replaced to zero if a worker is also self-employed during the year (as those combining self- and salaried employment are considered self-employed).

(f): *Overall employment* - It is defined by a dummy equal one if an individual is salaried or self-employed: it is the sum of (d) and (e).

S.1.3 Data Warehouse - Firm Characteristics and Firm Mobility

The Data Warehouse provides us with data on some characteristics of the firms in which individuals work in 1998-2010 and the firm identification number. We use the latter to come up with a measure of firm mobility. Among firm characteristics, quarterly data on the median daily wage paid out on June 30 in recruiting firms are exploited to build up an indicator of permanent firm quality. Descriptive statistics of these outcomes are shown in Table S.1 of the Online Appendix of Cockx and Ghirelli (2015).

Firm mobility - This variable exploits the changes in the quarterly firm identification number. Transitions between self-employment and salaried employment are included in the definition of firm mobility, as we assign to self-employment a specific firm identifier. An individual is defined as changing firms in year t if he is observed in a different firm in at least two quarters of year t, or if the first firm in which he was employed in t differs from the last firm in $t-1$.

Permanent firm quality - In order to obtain this indicator of permanent firm quality we apply the following procedure, which is very close to the one used by Oreopoulos et al. (2012). (i) Quarterly nominal values of median daily wages paid by the firm are deflated using two indexes of nominal wage trend from Belgostat (base year 1997) for white- and blue-collar workers, respectively; these are then converted in real terms using the CPI (base year 2011). (ii) The data are log-transformed. (iii) Seasonal effects are taken out by regressing the quarterly time-varying data on quarter dummies. (iv) The residuals from this regression are averaged by firm over the observed quarters, as many quarters as median daily wages are observed for each firm. These permanent characteristics are expressed in deviation from the average: i.e., a negative (positive) value of the median salary paid by the firm in a given quarter means that the firm paid less (more) compared to the average. (v) Since individuals may have changed firm within a calendar year, we average over the quarters of year t the permanent characteristics of the firms where one is observed working in t, so to get an annual indicator of the permanent characteristics of the average firm where one is employed.

S.1.4 Data Warehouse - Residence and Geographical Mobility

Province of residence - The province of residence is observed from the year in which one turns age 18 (i.e. 1994, 1996, and 1998 for cohort born in 1976, 1978, and 1980, respectively). This information is missing in 3.45% of the initial Sonar sample. To maximize the size of the sample used in the analysis, missings in residence are imputed if the following two conditions are met: (i) the socio-economic position of the individual is known (i.e. he still resides in Belgium) according to the Data Warehouse in the year in which residence is missing; (ii) the residence does not change in the year before and after missing(s). This imputation allows to retain 2.22% of the initial Sonar sample.

Geographical quality - Geographical mobility is based on the province of residence, which for year t is measured in December of year $t-1$. An individual is defined as moving in year t if he lives in another province at the end of year t than where he lived at the end of $t-1$. Differently from all other outcomes which are observed for the period 1998-2010, residence is observed since the year in which individuals turn age 18 (i.e. 1994, 1996 and 1998 for individuals born in 1976, 1978 and 1980, respectively) until 2010. Thus, we can define the province of residence from experience one onwards for all graduation cohorts - also for the low-educated who graduate in the period 1994-1996. Descriptive statistics of geographical mobility are shown in Table S.1 of the Online Appendix of Cockx and Ghirelli (2015).

S.1.5 Labor Force Surveys - Provincial Unemployment Rate

We use the 1994-2010 provincial unemployment rate series of the working population aged 15-64 (considering both men and women) based on the LFS, since these series use the internationally accepted definition of unemployment provided by the International Labour Organization. In order to check the reliability of the data we compared these series to the administrative ones provided by the National Employment Office of Belgium (RVA - Rijksdienst voor Arbeidsvoorziening) also available from 1994 onwards. In the latter series the unemployment rate is defined as the ratio of the number of unemployment benefit recipients searching for jobs to the number of individuals insured against unemployment. In general this results into higher unemployment rate figures than those of the LFS, but the evolution over time is overall very similar. Nevertheless, for the province Limburg, the two series displayed a very different pattern between 1994 and 1997. In those of the LFS the unemployment rates were increasing during these years while they were evolving downwards in the series of the RVA. Since the unemployment rates in the other provinces were moving down in this period according to both data sources, we believe that a serious measurement error biases severely the LFS unemployment rate of Limburg during these years. Based on the RVA data, we therefore adjusted the LFS series of the unemployment rate of Limburg for the period 1994-1997. The details of the adjustment procedure can be obtained from the authors upon request.

S.2 Sample Selection

The original Sonar sample contains 8,958 male and female individuals. From this sample we exclude the following individuals to enhance sample homogeneity: those who quit compulsory education by December 31 of the year one turns age 17 (0.17% of the original Sonar sample),[12] who attended special needs and arts education (0.92%), and who were not Flemish - i.e. either did not have Belgian nationality or did not speak Dutch at home (5.10%). Moreover, we focus on men (50.85%), since female labor supply is likely to differ from the male one due to fertility and caring responsabilities. We drop individuals with missing values in the following individual control variables, since this involves a small number of observations (2.19%): number of brothers, number of sisters, birth cohort, educational track at age 17 and completed education at age 17.[13] Finally, we drop 1.2% of the original Sonar sample for which we could not impute the residence for the entire time span.

We further restrict to individuals residing in Flanders in the graduation date (dropping 1.1%) and drop those graduating from age 25 onwards (2.15%). This leaves us with a sample of 3,624 men graduating between age 18 and 24. Last, to avoid complications in the two-step estimation approach (see Section S.4), we restrict the sample to graduation period 1994-2001 and 1997-2004 for the low- and the high-educated, respectively. The final sample consists of 3,514 men. Descriptive statistics of individual control variables are reported in Table A.1 of Appendix A of the main text.

Note that we consider 12 years of experience for the low-educated and 10 years of experience for the high-educated: the former are followed longer since they graduate earlier. We make this selection based on the availability of the labor market outcomes, because we want to observe at least 4 graduation cohorts for a particular number of years of experience. The reason for that is that there needs to be some variation in the unemployment rate to identify the effect of the unemployment rate at graduation. For instance, since the labor market outcomes are observed until year 2010, experience 12 is observed for the low-educated graduating in 1994-1998, while experience 10 is observed for the high-educated graduating in 1997-2000.

S.2.1 Description of the Final Sample

This section provides additional descriptive statistics of the final sample.

[12] Recall that percentages are computed relative to the size of the original Sonar sample (8,958 individuals).

[13] For this retained sample, missing in mother and father education are imputed as explained in Section S.1.1.

Table S.1: Final entire sample by graduation year and birth cohort

Number of individuals					Fraction of sample				
grad_year	c76	c78	c80	Total	grad_year	c76	c78	c80	Total
1994	143	0	0	143	1994	0.04	0.00	0.00	0.04
1995	209	0	0	209	1995	0.06	0.00	0.00	0.06
1996	168	149	0	317	1996	0.05	0.04	0.00	0.09
1997	154	240	0	394	1997	0.04	0.07	0.00	0.11
1998	185	203	187	575	1998	0.05	0.06	0.05	0.16
1999	191	137	242	570	1999	0.05	0.04	0.07	0.16
2000	115	163	163	441	2000	0.03	0.05	0.05	0.13
2001	0	153	154	307	2001	0.00	0.04	0.04	0.09
2002	0	138	142	280	2002	0.00	0.04	0.04	0.08
2003	0	0	172	172	2003	0.00	0.00	0.05	0.05
2004	0	0	106	106	2004	0.00	0.00	0.03	0.03
Total	1,165	1,183	1,166	3,514	Total	0.33	0.34	0.33	1.00

Table S.2: Dividing the sample between low- and high-educated

completed education§	low-educated	high-educated	Total
2	39	0	39
3	89	0	89
4	113	0	113
5	185	0	185
6	1,096	0	1,096
7	363	224	587
8	0	53	53
9	0	710	710
10	0	371	371
11	0	236	236
12	0	34	34
13	0	1	1
Total	1,885	1,629	3,514

§Number of grades successfully attained since age 12. Low-educated have degree no higher than high school: 6 years if enrolled in general, technical, part-time vocational/apprenticeship program, 7 if in vocational program. High-educated have higher education.

Table S.3: Prevalent function§ undertaken in the observation period

	Low-educated			High-educated		
	Freq.	Percent	Cum.	Freq.	Percent	Cum.
blue-collar	1,297	68.81	68.81	177	10.87	10.87
white-collar	432	22.92	91.72	1,306	80.17	91.04
public servant	78	4.14	95.86	81	4.97	96.01
missing	78	4.14	100	65	3.99	100
Total	1,885	100		1,629	100	

§"Prevalent function" means the function that is undertaken more than 50% of the time in the observation period.

Table S.3 shows that the level of education gives a good approximation of the worker type: 69% of the low-educated are prevalently employed as blue-collar workers, while for the high-educated this figure is only 11%. This also shows up in the distribution across sectors of industry (see Table S.10 and the discussion in Section S.3 of the Online Appendix of Cockx and Ghirelli, 2015).

S.3 Testing for the Endogeneity of the Graduation Cohort

S.3.1 Is the Timing of Graduation Endogenous?

According to economic theory the effect of economic conditions on the timing of graduation is ambiguous. On the one hand, a recession decreases the expected labor market income and, hence, the opportunity cost of education. On the other hand, it also reduces the expected returns to education and liquidity of the parents to finance education, so that early school leaving is enhanced. Existing empirical evidence is also mixed, but usually finds that unemployment raises the enrollment rate (see e.g. Card and Lemieux, 2001 and Clark, 2011). Micklewright et al. (1990) by contrast find that the regional unemployment rate tends to reduce the demand for schooling. Petrongolo and San Segundo (2002) and more recently Tumino and Taylor (2013) report that the youth unemployment rate, as proxy for the opportunity cost, raises the probability of remaining in education, while the adult unemployment rate, as proxy for the returns, reduces this probability.

For our purpose it is important to rule out that the adult unemployment rate affects the timing of graduation. If this were the case, then it would affect the composition of the graduation cohort over the business cycle and any association between the unemployment rate and some labor market outcome could just reflect this variable composition rather than a causal effect. To test this we check whether the age of graduation is related to the provincial unemployment rate in that year. Since in Belgium education is compulsory until age 18, we can implement this test by estimating a discrete duration model in which we regress an indicator of graduating since age 17 on birth cohort dummies, individual characteristics x_i and the province of residence measured at age 17, the elapsed duration in education since age 17, and the unemployment rate in each potential year of graduation (interacted with the elapsed duration), and by subsequently testing whether the coefficients of latter interactions are jointly significantly different from zero. We deal with selectivity induced by unobserved heterogeneity. The data are clustered in 15 clusters according to the birth year b (1976, 1978 or 1980) and the five provinces p of residence at age 17. Problems of inference induced by the small number of clusters are solved in a similar two step approach as in the main analysis.[14]

We follow Kiefer (1988) and Jenkins (1995) to estimate the discrete duration model as a sequence of (yearly) binary choices from age 17 until age 24 ($a \in \{17, 18, ..., 24\}$).[15] In order to obtain correctly sized standard errors, we first regress the discrete-time hazard rate of graduating at a particular age on x_i and the group-age fixed effects $\mu^h_{bpa^*}$, where superscript h allows distinguishing these effects

[14] Notice that the size of all groups always satisfy the aforementioned rule of Cochran (1954), so that the asymptotic inference should work in this case.

[15] To maintain the same data as those that are used in the main analysis as well as to avoid problems of inference induced by too small cell sizes, we right censor duration at the end of the year in which individuals become 24.

from the μ_{gpt} in the main analysis and $a^* \equiv a - 17$. In a second step the estimated $\hat{\mu}^h_{bpa^*}$ are then linearly regressed on the covariates that vary at the group-age level, one of which is the provincial unemployment rate.

In the first step, the conditional discrete-time hazard $h_{ibpa^*}(x_i, \epsilon^h)$ is assumed to take on the complementary log-log specification:

$$h_{ibpa^*}(x_i, \epsilon^h) \equiv P(A^*_{ibp} = a^* | A^*_{ibp} \geq a^*; x_i, \epsilon^h) = 1 - \exp\left[-\exp\left(\mu^h_{bpa^*} + x_i'\delta^h + \epsilon^h\right)\right] \tag{S.1}$$

where A^*_{ibp} is the random age (minus 17) at which individual i of birth cohort b and living at age 17 in province p graduates and ϵ^h is realization of a random individual unobserved heterogeneity term $\mathcal{E}^h$ that is independently distributed from x_i, b and p.

This model is estimated by maximum likelihood. To form the likelihood, note that the discrete survival rate at age a^* is simply $\prod_{s=1}^{a^*} \left(1 - h_{ibps}(x_i, \epsilon^h)\right)$. Consequently, if c_i denotes an indicator that is equal to zero in case of right censoring, i.e. in case that individual i is still in education at the start of the calendar year in which he becomes 25 ($a^* = 25 - 17 = 8$), and one otherwise. Then the log-likelihood function (from which the unobserved heterogeneity is integrated out) can be expressed as follows:

$$\log \mathcal{L} = \sum_{i=1}^{N} \log \int_{-\infty}^{\infty} \left[h_{ibpa^*}(x_i, \epsilon^h)\right]^{c_i} \prod_{s=1}^{a^*-1} \left(1 - h_{ibps}(x_i, \epsilon^h)\right) dG(\epsilon^h) \tag{S.2}$$

where N denotes the total number of observations and $G(\epsilon^h)$ is the distribution of unobserved heterogeneity. We perform a sensitivity analysis in which (i) $\epsilon^h = 0$, (ii) ϵ^h is Normally distributed with mean zero, or (iii) $\exp(\epsilon^h)$ is Gamma distributed with mean one.

In the second step, the following linear regression is estimated by FGLS according to the methods described in Section S.4:

$$\hat{\mu}^h_{bpa^*} = \gamma^h_{a^*} + \beta^h_{a^*} u_{pt} + \eta^h_p + \lambda^h_b + v^h_{bpa^*} \tag{S.3}$$

where $t \equiv b + a$ is the year of potential graduation, $\gamma^h_{a^*}$ is an age specific fixed effect describing the evolution of the baseline hazard, η^h_p a provincial specific effect, λ^h_b a birth cohort fixed effect, and $v^h_{bpa^*} = e^h_{pba^*} + (\hat{\mu}^h_{bpa^*} - \mu^h_{bpa^*})$ is completely analogously defined as in Section S.4. The parameters of interest are $\beta^h_{a^*}$. They measure the effect of the provincial unemployment rate u_{pt} on the hazard rate of graduating in that year. We test their joint significance.

Table S.4: Test for exogenenous timing of graduation: second step FGLS

	(1)	(2)	(3)
Unobserved heterogeneity (UH)	without UH	Gamma distributed	Normally distributed
Top panel: β^h_{a*} restricted to be equal for all ages			
β^h_{a*}	0.0239	0.0497	0.0438
	(0.0299)	(0.0347)	(0.0369)
Parameters in second step	14	14	14
Obs in second step	105	105	105
P-value of chi2 test	0.2983	0.7168	0.9251
Bottom panel: β^h_{a*} allowed to vary over ages			
β^h_{a*} at a*=1	-0.0039	-0.0021	0.0033
	(0.0488)	(0.0547)	(0.0640)
β^h_{a*} at a*=2	0.1172**	0.1401**	0.1513**
	(0.0504)	(0.0575)	(0.0642)
β^h_{a*} at a*=3	0.0319	0.0705	0.0683
	(0.0524)	(0.0559)	(0.0581)
β^h_{a*} at a*=4	0.0486	0.0647	0.0540
	(0.0613)	(0.0653)	(0.0671)
β^h_{a*} at a*=5	-0.0646	-0.0498	-0.0545
	(0.0619)	(0.0656)	(0.0675)
β^h_{a*} at a*=6	0.0452	0.0878	0.0794
	(0.0529)	(0.0592)	(0.0617)
β^h_{a*} at a*=7	-0.0908	-0.0377	-0.0514
	(0.0807)	(0.1048)	(0.1019)
Parameters in second step	20	20	20
Obs in second step	105	105	105
P-value of chi2 test	0.423	0.800	0.948
Test of joint significance of β^h_{a*} (p-val)†:	0.334	0.075	0.118
log variance of UH (first step)§	-	-0.0041	1.3160***
	-	(0.0827)	(0.2398)

Significance level: *** p<0.01, ** p<0.05, * p<0.1. Standard errors between parentheses. The table shows the effect of increasing the provincial unemployment by one *pp* on the hazard rate of graduating in that year. Since the event starts from age 18 and is right-censored after age 24, the baseline hazard $a^* = age - 17$ ranges from 1 to 7. The top panel reports the estimate of β^h_{a*} in Eq. (S.3); the bottom panel reports the estimates of β^h_{a*} obtained from estimating Eq. (S.3) in which the provincial unemployment rate is interacted with age specific fixed effects of the baseline hazard. The estimates are obtained from a two-step FGLS, as described in Section S.4 below. If the χ^2 goodness-of-fit statistic rejects the model (p-value>0.05), standard errors clustered at the *bp* level are reported; otherwise conventional ones. The estimations are computed on the pooled sample, i.e. without distinguishing between the low- and the high-educated.

†For the bottom panel it tests the null hypothesis that all β^h_{a*} are equal to zero.

§The estimated log of the variance of the unobserved heterogeneity is obtained from the first step.

Table S.4 presents the outcome of the test regarding the exogeneity of the timing of graduation. We report for all three duration models (without, Gamma and Normally distributed unobserved heterogeneity) the parameters of interest in the second step FGLS regression of Eq. (S.3), i.e. the coefficients β^h_{a*} of the provincial unemployment rate u_{pt}, and the log of the variance of the distribution of unobserved heterogeneity (if applicable). In the top panel we report the results of the models in which we restrict all β^h_{a*} to be equal over age, while the bottom panel the results of the unrestricted models are displayed.

According to the χ^2 goodness-of-fit statistics none of the six specifications can be rejected against the saturated model, so that the conventional standard errors are reported. The unrestricted model assuming Normally distributed unobserved heterogeneity provides the best fit to the data. In line with theory, the estimated coefficients in the models accounting for heterogeneity are in most cases larger in absolute value than in the models neglecting it. In the restricted models none of the parameters of interest are significantly different from zero. In the unrestricted models, a higher unemployment rate highly significantly accelerates school leaving at age 19 ($a^* = 2$). However, the coefficients at other ages are never significant, do not display any systematic pattern and can even have the opposite sign. Moreover, we do not have any clear explanation for this finding. We therefore argue that the significant result is obtained by chance. The fact that we cannot reject the hypothesis that all $\beta^h_{a^*}$ are equal to zero (see the bottom line of bottom panel in Table S.4), is in line with this interpretation. We therefore conclude that the timing of graduation is exogenous to the business cycle. Further evidence for this conclusion is reported in Section S.7, where we show that our main findings are not sensitive to the inclusion of the completed number of years of education as a control variable.

S.3.2 Is the Province of Residence at Graduation Influenced by Local Labor Market Conditions?

Our identification strategy requires that youths (or their parents, if youth still live at their parents' house) do not move prior to graduation to provinces where the unemployment rate falls relatively to other provinces. For then the composition of recent graduates in provinces would be correlated with local labor market conditions, and it would no longer be possible to disentangle the effects of the latter from the former. To check whether this is a threat to the identification, we measured the fraction of youth in our sample that has changed residence between the first year that our data inform about the place of residence, i.e. on December 31 of the year in which the individual turns 17, and the moment at which the unemployment rate at graduation u_{gp}, our main regressor of interest, is measured, i.e. at the start of the year of graduation. Since only 0.44% of the individuals in the sample changed residence in that period, the issue can be safely ignored.

S.4 Inference with a Small Number of Clusters

If there are a small number of clusters, Cameron et al. (2008) and Cameron and Miller (2015) propose using the wild bootstrap to obtain correctly sized tests and confidence intervals. The method is, however, complex to implement in this framework and, as acknowledged by the authors, computationally intensive for forming confidence intervals.[16] Moreover, the method does not exploit the possibility of enhancing the power of the statistical tests. Brewer et al. (2013) recently proposed a

[16] We aim to identify the effect of increasing the unemployment rate at graduation by one percentage point for each year up to 12 years after graduation. This requires forming confidence intervals of the values of the linear spline defined in Eq. (2) of main text for each year after graduation. These values involve linear combinations of the parameter estimates. Apart from further intensifying the computational burden, it is not obvious how to proceed in this case.

straightforward method for inference that addresses these limitations in a difference-in-differences (DiD) design. They demonstrate in Monte Carlo analysis that correctly sized tests can be obtained by using bias corrected clustered standard errors in an ordinary least squares (OLS) regression of the covariate-adjusted group-time means of the dependent variable on the covariates varying at the group-time level. The bias correction is simple to implement, because STATA correctly scales the standard errors by default. To enhance the power of this approach, the authors exploit the serial correlation in the grouped errors using the feasible generalized least squares (FGLS) estimator proposed by Hansen (2007)[17] that explicitly allows for a common autocorrelation pattern (e.g. AR(2)) across groups. To allow for misspecification of this autocorrelation process the aforementioned cluster robust inference is applied to this FGLS estimator. This delivers, as the wild bootstrap, correctly sized tests and, if the number of time periods is sufficiently large (from about 10 time periods), yields substantial power gains.

Since our model can be seen as a generalized DiD setting, in which we have variables that vary at the group level (gp), i.e. each combination of graduation year (g) and province (p) is a cluster, at the time level ($t = g+e$), and at the group-time level (gpt), this approach can be applied to our analysis. However, in contrast to Brewer et al. (2013), group-time cells in our sample contain a relatively small number of observations, so that we cannot ignore measurement error in the covariate-adjusted group-time means of the dependent variables. To generalize their approach, we build on the work of Wooldridge (2006, 2010). Wooldridge proposes a FGLS estimator in case of cross-sectional data with only measurement error and no unobserved group effects. We adjust this method for panel data and show how, as in Brewer et al. (2013), autocorrelated unobserved group effects can be integrated in this approach.

In a first step, run a regression of y_{igpt} on x_i and group-time dummies using the micro-data on the individual level:

$$y_{igpt} = \mu_{gpt} + x_i'\delta + \epsilon_{igpt} \tag{S.4}$$

where μ_{gpt} are the group-time fixed effects, i.e. the covariate-adjusted group-time means, and ϵ_{igpt} is the error term of this micro regression. In a second step, the estimated group-time fixed effects $\hat{\mu}_{gpt}$ are regressed on the group-time level covariates:

$$\hat{\mu}_{gpt} = f_g(e)u_{gp} + f_{gu}(e)u_{gp}\mathbf{1}[u_{gp} < u_{(g-1)p}] + \theta_e + \phi_t + f_t(e)u_{pt} + \eta_p + \omega_p t + f_0(g) + v_{gpt} \tag{S.5}$$

where $v_{gpt} = e_{gpt} + (\hat{\mu}_{gpt} - \mu_{gpt})$, e_{gpt} is the unobserved group-time shock measured at calendar time t and $(\hat{\mu}_{gpt} - \mu_{gpt})$ is the measurement error in the covariate-adjusted group-time means. Brewer et al. (2013) assume the latter to be zero. Consequently, even if cluster robust standard errors still result in correct inference, taking the (co-)variances of the measurement errors into account could enhance efficiency.

In the case of cross-sectional data, Wooldridge (2006, 2010) proposes implementing the *efficient* Minimum Distance (MD) estimator, also called the "Minimum Chi-Square" estimator, of the covariate-adjusted group means on the group level explanatory variables. This consists in estimating (a cross-sectional) version of (S.5) by FGLS. If $e_{gpt} = 0$, the optimal weight in the FGLS is the

[17] Brewer et al. (2013) show that Hansen's *bias-corrected* FGLS delivers only little more power than *ordinary* FGLS.

inverse of the variance matrix of $(\hat{\mu}_{gpt} - \mu_{gpt})$ estimated in the first step. Since the efficiency of this procedure depends on whether unobserved group-time shocks e_{gpt} are indeed zero, it is useful to notice that this can be tested for. If the observed group level explanatory variables cannot fully explain the variation in $\hat{\mu}_{gpt}$, the regression model (S.5) is likely to be rejected against the saturated model, i.e. the weighted sum of squared residuals (WSSR), distributed χ^2 with degrees of freedom equal to the number of groups minus the number of estimated parameters, is larger than the conventional rejection level.

Generalizing Wooldridge (2006, 2010)'s approach to panel data requires accounting for the serial correlation in the error term ϵ_{igpt} of the first step regression. We do this by taking the individual i as clustering unit in the first step and use the conventional cluster-robust variance matrix of the $\hat{\mu}_{gpt}$ estimated in the first step as weighting matrix in the second step.[18] The χ^2 goodness-of-fit statistic allows testing for the presence of unobserved group-time shocks, i.e. $e_{gpt} \neq 0$. In case of no rejection, the conventional standard errors can be used for inference. In case of rejection,[19] we could attempt to increase the power by explicitly allowing for the variance in e_{gpt} in addition to that of the measurement error, and for a particular serial correlation pattern in e_{gpt}, as in Brewer et al. (2013). However, because in this application we find for most outcomes that $\hat{\sigma}_e^2 < 0$, we refer the reader to Cockx and Ghirelli (2015, p. 17-18) for a discussion how to proceed in this case.[20] Since the cluster robust standard errors calculated after the FGLS that just takes measurement error into account still result in correct inference we therefore report these ones in our estimations when the goodness-of-fit statistic rejects the model.

Finally, we explain how we deal with a number of practical issues encountered with the proposed inference methods. First, the benchmark outcomes must satisfy adding-up constraints: (i) the indicator of salaried employment and the one of self-employment sum to the indicator of overall employment; (ii) log hourly wages and log annual hours worked sum to log annual earnings; (iii) the sum of the annual number of hours worked full-time and part-time is equal to the total annual hours worked. These adding-up constraints are automatically satisfied if the first and second step regression models, (S.4) and (S.5), are estimated by OLS. However, this is no longer true if FGLS is applied in the second step on each outcome separately, since then the weighting matrices ignore the correlation that these constraints impose on these outcomes. To overcome this problem, we jointly estimate both the first and the second step in a *seemingly unrelated regression* (SUR), as proposed by Zellner (1962). Since the adding-up constraint makes the variance matrix of the three outcomes singular and hence non-invertible, we leave out one of the three outcomes and calculate the parameters and standard errors of the third model from the constraint.[21] An estimate of the

[18]Since the individual is taken as clustering unit, the number of clusters is sufficiently large to implement conventional inference procedures.

[19]We use the conventional 5% as threshold for the size of the test.

[20]We only find $\hat{\sigma}_e^2 > 0$ for salaried employment rate in the aggregate model, both the low- and high-educated group (see Section S.9 of the Online Appendix of Cockx and Ghirelli, 2015).

[21]Barten (1969) has shown that the parameter estimates are invariant to the equation deleted. However, Berndt and Savin (1975) have demonstrated that in case a model with autoregressive disturbances is modeled invariance requires restrictions on the parameters of the autoregressive process.

variance matrix, the inverse of which is used as weight in the second step FGLS SUR, is obtained from the conventional cluster robust estimate of the variance matrix of the covariate adjusted means $\hat{\mu}_{gpt}$ calculated after a pooled OLS on the first step SUR. By clustering at the individual level in the first step, the variance matrix accounts not only for unrestricted serial correlation in the outcomes, but also for unrestricted correlation across outcomes.

Second, in our data we find cases in which the employment status of all individuals belonging to a cluster gp does not vary over some calendar years t. This induces perfect serial correlation in the covariate-adjusted group-time means μ_{gpt} and, hence, the cluster robust variance matrix of these $\hat{\mu}_{gpt}$ is singular. Thus, we use in these cases the Moore-Penrose generalized inverse of the variance matrix as weight in the second step FGLS. To avoid numerical imprecision, we manually set as many eigenvalues to zero as the number of times that the employment rate for particular groups is repeated over time. This accordingly reduces the number of degrees of freedom in the second step.

Finally, asymptotic inference for the Minimum Chi-Square estimator is only valid if groups are sufficiently large. In the statistical literature some rules of thumb are suggested for what is large enough for the Central Limit Theorem to apply. For continuous outcome variables (such as log hours, log wages or log earnings) a group size (N_{gpt}) of 30 observations is typically considered sufficient, while for dichotomous outcomes (such as the employment rate) the minimum of the expected number of *successes* and *failures* should be sufficiently large. A commonly accepted rule for the latter is that $\min\{N_{gpt}P_{gpt}, N_{gpt}(1 - P_{gpt})\} \geq 5$, where P_{gpt} denotes the probability of success and which can be estimated by aggregating the individual predictions of this probability in the first step OLS regression of (S.4) to the cluster-time level gpt. According to Cochran (1954) the approximation is, however, still acceptable if for less than 20% of the groups this expectation is smaller than 5 while remaining larger than 1.

For the national model these rules are satisfied if we restrict the analysis to graduation years 1994-2001 for the low-educated and to 1997-2004 for the high-educated. For the provincial model we must drop additional groups. For the continuous outcomes, applying the aforementioned rule reduces the sample size too much, so that we retain groups-time cells containing between 16 and 30 observations, which still delivers a reasonable approximation if the distribution of the underlying random variable does not differ too much from the Normal. For the dichotomous outcomes, we calculate for each group-time cell and outcome the aforementioned expectations, take the minimum of these expectations over the outcomes retained in the same SUR, and drop group-time cells with the smallest minimum until the aforementioned Cochran's rule is satisfied.

Dropping these cells introduces, however, a concern of selectivity. We therefore test for this. We construct for each outcome an indicator that is equal to one if the individual belongs to a group-time cell that is dropped according to the aforementioned rules and zero otherwise. Subsequently, we use these indicators as dependent variable in a one-step regression on model (1) of the main text in which we impose the same restrictions as the ones used for the corresponding outcome, and in which we cluster the standard errors by group gp. Finally, we test the null hypothesis that all the coefficients of the linear spline ($f_g(e)$) that interacts the unemployment at graduation (u_{gp}) are jointly significantly different from zero. Since the number of clusters is small, we tend to over-reject the null-hypothesis. But the null hypothesis is never rejected in any of the considered outcomes, so that we can therefore be confident that selectivity is not an issue.

In Table S.5 we report for the benchmark continuous and dichotomous outcomes the number of cells that are dropped and retained, as well as the mean and maximum size of these cells. We also provide the aforementioned statistics for cells that are retained, but that do not satisfy the aforementioned stricter rules, i.e. for cell sizes between 16 and 30 if the outcome is continuous, and for cells for which the minimum of the aforementioned expectation is smaller than 5 in case of a dichotomous outcome. Finally, we also include the P-value of the joint test of selectivity mentioned in the previous paragraph.

Table S.5: Descriptive Statistics on Selection Rules for Benchmark Outcomes in Provincial Models*

	Low-educated		High-educated	
Graduation period:	1994-2001		1997-2004	
Outcomes§	Continuous	Discrete	Continuous	Discrete
Number of cells (total)	420	420	350	350
Number of dropped cells	42	138	27	109
Number of retained cells	378	282	323	241
Statistics on dropped cells				
Mean size dropped cells	10.29	30.97	13.11	27.95
Max size dropped cells	15	111	15	66
Statistics on retained cells				
Mean size retained cells	45.19	57.56	37.64	47.48
Max size retained cells	104	111	79	89
Statistics on retained cells for which $16 \leq N_{gpt} < 30$ *(continuous) or* $EXP^{\dagger}_{gpt} < 5$ *(discrete)*‡				
Number of retained cells	94	38	123	46
Avg size retained cells	23.06	45.08	23.08	34.07
Max size retained cells	29	111	29	66
P-value joint test for selectivity§§				
Specification used for log hourly wage	0.322		0.637	
Specification used for log hours worked	0.091		0.105	
Specification used for all discrete outcomes		0.379		0.207

$*$ The following selection rules are imposed to avoid too small cell sizes. For continuous variables, drop cells gpt with size $N_{gpt} < 16$. For discrete variables, drop cells gpt with the smallest $EXP^{\dagger}_{gpt}$ until at most 20% of retained cells are such that $EXP_{gpt} < 5$ (Cochran, 1954).

†$EXP_{gpt} = \min\{N_{gpt}P_{gpt}, N_{gpt}(1 - P_{gpt})\}$, where P_{gpt} denotes the probability of success which is estimated according to Eq. (S.4) in Section S.4 aggregating the individual predictions of this probability to the cell level gpt. The aforementioned minimum is computed for each outcome in SUR and the selection rule is applied based on the smallest minimum across these outcomes.

§Benchmark continuous outcomes in SUR are log wage and log hours; benchmark discrete variables in SUR are salaried and self-employment. The statistics in the table refer to one outcome, as they are identical for each outcome retained in a SUR.

‡These groups would have been dropped according to more stringent selection rules, i.e. $N_{gpt} < 30$ for continuous outcomes and $EXP_{gpt} < 5$ for discrete ones.

§§Selectivity test is based on one-step estimation of Eq. (1) in main text where the dependent is an indicator equal to one if one belongs to a cell that is dropped according to selection rules mentioned in ($*$). Standard errors are clustered by gp. For each outcome retained in SUR we impose the same restrictions as we do in the benchmark (see Table B.1 (C.1) of main text for low- (high-) educated). Since different restrictions are imposed on the regression of log wage than on that of log hours, we report two P-values for these outcomes. Same restrictions are imposed on discrete outcomes and thus only one P-value is reported.

The two-step FGLS approach should generally deliver more precise estimates than those obtained by two-step OLS approach with cluster robust standard errors or those obtained by one-step OLS approach with clustered robust standard errors. We relegated a discussion on the comparison of standard errors across these methods in Section 6.3 of Cockx and Ghirelli (2015) and in Section S.9 of the corresponding Online Appendix.

S.5 Complete Estimation Results of the Second Step FGLS of the Two-step Approach

The complete estimation results of the first step and of the second step OLS of the two-step approach can be obtained from the authors upon request. Here we provide the second step FGLS estimates.

Table S.6: Second step FGLS regression for the low-educated

Outcomes:	discrete		continuous			
	salaried	self-empl.	log wage	log hours§	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
URate_grad	-0.0238	0.0501**	0.0100	-0.0525*	-164.8746***	56.8591***
	(0.0220)	(0.0236)	(0.0154)	(0.0275)	(39.6889)	(16.4111)
URate_grad*lin_exp	0.0063	-0.0144*	-0.0055	0.0087	41.1335***	-20.5795***
	(0.0063)	(0.0075)	(0.0037)	(0.0092)	(8.4565)	(5.3600)
URate_grad*lin_exp|exp>3	-0.0040	0.0087	0.0040	-0.0085	-30.4640***	18.6047***
	(0.0079)	(0.0089)	(0.0037)	(0.0118)	(8.9870)	(6.7193)
URate_grad*lin_exp|exp>6	-0.0026	0.0074*	0.0042**		-24.5012***	10.5285**
	(0.0047)	(0.0042)	(0.0018)		(6.8968)	(3.9159)
URate_grad*lin_exp|exp>9	0.0017	-0.0057*	-0.0058**	-0.0030	19.8884***	-8.1435*
	(0.0034)	(0.0033)	(0.0022)	(0.0079)	(6.9654)	(4.0476)
URate_grad*lin_exp*upturn				-0.0108		
				(0.0075)		
URate_grad*lin_exp|exp>3*upturn				0.0183		
				(0.0117)		
URate_grad*lin_exp|exp>6*upturn						
URate_grad*lin_exp|exp>9*upturn				0.0013		
				(0.0115)		
d_exp1	0.8569***	0.0796	2.2692***	7.1194***	1,225.9931***	182.0557***
	(0.0646)	(0.0637)	(0.0378)	(0.1094)	(126.8483)	(58.2625)
d_exp2	0.8516***	0.0793	2.3175***	7.2186***	1,415.8790***	91.2670
	(0.0639)	(0.0617)	(0.0359)	(0.0974)	(114.1311)	(54.6505)
d_exp3	0.8457***	0.0847	2.3647***	7.2388***	1,465.8398***	73.3560
	(0.0623)	(0.0600)	(0.0350)	(0.0838)	(105.5893)	(50.3020)
d_exp4	0.8543***	0.0972	2.4002***	7.2710***	1,500.8617***	66.5529
	(0.0613)	(0.0599)	(0.0347)	(0.0741)	(99.0005)	(47.0799)
d_exp5	0.8612***	0.1073*	2.4316***	7.2705***	1,525.3920***	81.6274*
	(0.0609)	(0.0595)	(0.0343)	(0.0647)	(91.6504)	(44.6073)
d_exp6	0.8524***	0.1058*	2.4691***	7.3052***	1,532.2297***	94.6461**
	(0.0602)	(0.0594)	(0.0348)	(0.0572)	(86.7440)	(40.3467)
d_exp7	0.8530***	0.1226**	2.5001***	7.3216***	1,543.8087***	95.9874**
	(0.0601)	(0.0594)	(0.0346)	(0.0525)	(84.4805)	(38.9072)
d_exp8	0.8633***	0.1165*	2.5330***	7.3568***	1,520.6944***	109.3179***
	(0.0605)	(0.0602)	(0.0354)	(0.0570)	(87.0377)	(36.0375)
d_exp9	0.8576***	0.1263**	2.5667***	7.3706***	1,528.2080***	141.4640***
	(0.0614)	(0.0612)	(0.0369)	(0.0624)	(89.3094)	(34.8296)
d_exp10	0.8578***	0.1340**	2.5935***	7.3918***	1,530.9900***	152.9140***

Continued on next page

Table S.6 – continued from previous page

	salaried	self-empl.	log wage	log hours§	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0632)	(0.0628)	(0.0394)	(0.0699)	(100.0108)	(37.5158)
d_exp11	0.8569***	0.1404**	2.6227***	7.4047***	1,534.6193***	148.0725***
	(0.0652)	(0.0652)	(0.0425)	(0.0844)	(112.5650)	(39.2476)
d_exp12	0.8533***	0.1350**	2.6424***	7.4290***	1,524.9435***	148.2635***
	(0.0683)	(0.0677)	(0.0461)	(0.0995)	(128.1002)	(43.1278)
current_URate*lin_exp			-0.0008	-0.0073**	-2.7920	4.4547*
			(0.0011)	(0.0035)	(3.9967)	(2.5871)
current_URate*lin_exp|exp>3			-0.0011	0.0070	4.0244	-7.0951
			(0.0021)	(0.0065)	(8.6607)	(5.0969)
current_URate*lin_exp|exp>6			0.0025	-0.0032	8.6961	3.2832
			(0.0024)	(0.0058)	(9.5344)	(3.8670)
current_URate*lin_exp|exp>9			0.0020	0.0117*	-9.0042	-5.1401
			(0.0029)	(0.0067)	(7.4738)	(3.7716)
lin_grad_year	0.0173	-0.0100	0.0396***	0.0264	19.0216	16.0035
	(0.0201)	(0.0197)	(0.0102)	(0.0258)	(35.5687)	(15.2251)
lin_grad_year|trend>3	-0.0012	0.0030	-0.0235*	0.0277*	21.4500	-10.2731
	(0.0221)	(0.0218)	(0.0124)	(0.0164)	(37.5160)	(14.2848)
lin_grad_year|trend>6	-0.0152	0.0060	0.0087	-0.0004	44.8529	-23.3993**
	(0.0283)	(0.0270)	(0.0157)	(0.0200)	(37.5199)	(11.1892)
d_y2000			-0.0089	-0.0207	-21.8402	0.0906
			(0.0066)	(0.0233)	(23.2243)	(10.8590)
d_y2001			-0.0108	-0.0419	-5.2062	-20.1063
			(0.0116)	(0.0399)	(38.5634)	(17.5764)
d_y2002			-0.0049	-0.0355	10.6677	-53.7633***
			(0.0151)	(0.0489)	(54.0165)	(19.3777)
d_y2003			0.0292	-0.0821	-69.3960	-74.0548***
			(0.0199)	(0.0697)	(70.6908)	(25.9086)
d_y2004			0.0161	-0.0719	-29.2518	-92.8033***
			(0.0242)	(0.0818)	(85.3414)	(30.5642)
d_y2005			-0.0009	-0.0818	-56.0160	-114.5512***
			(0.0289)	(0.0964)	(104.9215)	(36.2211)
d_y2006			-0.0117	-0.1070	-16.5626	-126.2454***
			(0.0340)	(0.1119)	(121.1634)	(41.2826)
d_y2007			-0.0170	-0.1288	4.0424	-132.1354***
			(0.0391)	(0.1307)	(140.5737)	(47.5882)
d_y2008			-0.0315	-0.1495	3.5323	-121.5956**
			(0.0453)	(0.1484)	(159.4959)	(54.3311)
d_y2009			-0.0187	-0.1670	-76.4815	-149.4521**
			(0.0505)	(0.1632)	(173.8986)	(58.7294)
d_y2010			-0.0378	-0.1970	-54.4050	-155.5810**
			(0.0565)	(0.1761)	(192.4969)	(64.9975)
lin_calend_year|trend>3	-0.0057	-0.0005				
	(0.0063)	(0.0059)				
lin_calend_year|trend>6	-0.0064	0.0073*				
	(0.0048)	(0.0043)				
lin_calend_year|trend>9	0.0027	-0.0025				
	(0.0045)	(0.0039)				
d_province2	-0.0448	0.0339	-0.0169	-0.0166	-33.2013	5.9581
	(0.0276)	(0.0262)	(0.0217)	(0.0526)	(92.8610)	(39.2545)
d_province3	-0.0710***	0.0677***	0.0423**	0.0635	156.8683**	-63.1090**
	(0.0228)	(0.0223)	(0.0206)	(0.0504)	(68.5089)	(30.5171)
d_province4	-0.0391**	0.0319**	0.0434***	0.0267	29.4486	-24.5258
	(0.0167)	(0.0155)	(0.0148)	(0.0412)	(56.6118)	(24.7125)
d_province5	-0.0382	0.0407	0.0201	0.1331**	198.9715**	-26.1553
	(0.0272)	(0.0262)	(0.0181)	(0.0598)	(76.9946)	(32.3431)
lin_calend_year_province2			-0.0052**	0.0035	14.3407*	-1.9295
			(0.0022)	(0.0050)	(7.3382)	(3.5427)

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Table S.6 – continued from previous page

	salaried	self-empl.	log wage	log hours§	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
lin_calend_year_province3			-0.0058***	-0.0115**	-14.5633**	6.0920*
			(0.0020)	(0.0052)	(6.0903)	(3.4753)
lin_calend_year_province4			0.0004	-0.0030	-5.0574	3.8559
			(0.0022)	(0.0046)	(4.8954)	(2.8497)
lin_calend_year_province5			-0.0028	-0.0121**	-11.7671*	-0.4693
			(0.0022)	(0.0058)	(6.7259)	(2.7682)
R-squared	0.9986		0.9999		0.9953	
WSSR (2nd step)	331		1289		1519	
Obs (2nd step)	375		756		754	
Parameters (2nd step)	54		88		86	
Test joint signif. all imposed restr.(p-val)	0.286		0.155		0.268	
P-value of chi2 test	0.341		0.000		0.000	
Level of clustering	no	no	$g*p$	$g*p$	$g*p$	$g*p$
Imposed Restrictions:						
effect URate at grad. symmetric up/downturn	yes	yes	yes	no	yes	yes
effect Current URate over exp=0	yes	yes	no	no	no	no
spline for calendar year FE	yes	yes	no	no	no	no
effect prov-time trends=0	yes	yes	no	no	no	no

Significance level: *** p<0.01, ** p<0.05, * p<0.1. Standard errors between parentheses. The table shows the estimates obtained by two-step FGLS on mentioned outcomes, as described in Section S.4. The data are weighted by the inverse of the cluster-robust variance matrix of $\hat{\mu}_{gpt}$ estimated in the first step. For discrete outcomes, the Moore-Penrose generalized inverse of this matrix is used as weight, to take into account the perfect serial correlation induced by the fact that, for specific clusters, the outcomes do not vary over time (see Section S.4 for details). Since the outcomes satisfy adding-up constraints (salaried+self-empl.=overall empl.; log wage+log hours=log earnings; FT hours+PT hours=total hours), a FGLS SUR is estimated on the first two outcomes in the sum and effects on the third outcome are obtained from the adding-up constraints. Depending on the outcome, we impose restrictions which cannot be jointly rejected at the 5% level: these restrictions are listed in the bottom panel of the table. If the χ^2 goodness-of-fit statistic rejects the model (p-value>0.05), standard errors clustered at the *gp* level are reported; otherwise conventional ones.
§ For log hours worked the following additional restriction (not mentioned in the table) is also imposed: $\beta_{g2} = 0$, i.e. the slope of the linear spline remains fixed after 6 years of experience. This restriction cannot be rejected.

Table S.7: Second step FGLS estimation for the high-educated

Outcomes:	discrete		continuous			
	salaried	self-empl.	log wage	log hours	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
URate_grad	-0.0258	0.0087	-0.0184	-0.0565***	-132.7637***	31.0621**
	(0.0183)	(0.0165)	(0.0114)	(0.0207)	(28.4491)	(13.0104)
URate_grad*lin_exp	0.0096*	-0.0076*	-0.0046*	0.0214***	50.7776***	-7.7613*
	(0.0052)	(0.0045)	(0.0024)	(0.0067)	(8.1339)	(4.3468)
URate_grad*lin_exp|exp>3	-0.0089	0.0104*	0.0042	-0.0248***	-63.7346***	10.0000**
	(0.0061)	(0.0055)	(0.0031)	(0.0071)	(8.7159)	(4.9163)
URate_grad*lin_exp|exp>6	-0.0041	-0.0001	-0.0023	0.0046	20.5970**	-2.1085
	(0.0039)	(0.0038)	(0.0021)	(0.0066)	(8.5333)	(1.2834)
URate_grad*lin_exp*upturn				-0.0090**	-13.0287**	
				(0.0044)	(4.8606)	
URate_grad*lin_exp|exp>3*upturn				0.0186***	21.0758**	
				(0.0067)	(8.0703)	
URate_grad*lin_exp|exp>6*upturn				-0.0136**	-12.9939*	
				(0.0066)	(6.7360)	
d_exp1	0.9697***	0.0308	2.3992***	7.4988***	1,709.5018***	141.1729***
	(0.0568)	(0.0557)	(0.0334)	(0.0572)	(101.9240)	(31.5225)

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Table S.7 – continued from previous page

	salaried	self-empl.	log wage	log hours	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
d_exp2	0.9408***	0.0574	2.4429***	7.5401***	1,905.9920***	64.8359***
	(0.0553)	(0.0543)	(0.0333)	(0.0388)	(74.3620)	(21.5103)
d_exp3	0.9331***	0.0648	2.4848***	7.5086***	1,937.7451***	43.0083**
	(0.0540)	(0.0533)	(0.0334)	(0.0326)	(69.4179)	(20.7862)
d_exp4	0.9258***	0.0763	2.5181***	7.4682***	1,955.6993***	35.3342
	(0.0538)	(0.0532)	(0.0353)	(0.0502)	(95.3896)	(31.1004)
d_exp5	0.9079***	0.0945*	2.5499***	7.4050***	1,938.0647***	24.3331
	(0.0543)	(0.0535)	(0.0384)	(0.0764)	(136.8705)	(46.1787)
d_exp6	0.8982***	0.1083*	2.5708***	7.3546***	1,941.3592***	7.7160
	(0.0562)	(0.0554)	(0.0432)	(0.1034)	(183.4455)	(63.8553)
d_exp7	0.8877***	0.1167**	2.5894***	7.3062***	1,937.0128***	3.6514
	(0.0589)	(0.0579)	(0.0479)	(0.1339)	(230.4968)	(80.2243)
d_exp8	0.8613***	0.1369**	2.6090***	7.2465***	1,907.5481***	0.4558
	(0.0627)	(0.0613)	(0.0539)	(0.1630)	(281.2384)	(98.1468)
d_exp9	0.8377***	0.1579**	2.6192***	7.1994***	1,891.2816***	2.2098
	(0.0671)	(0.0653)	(0.0598)	(0.1911)	(330.2644)	(115.9887)
d_exp10	0.8150***	0.1707**	2.6230***	7.1421***	1,852.2196***	6.1605
	(0.0729)	(0.0709)	(0.0673)	(0.2196)	(381.8000)	(133.9872)
current_URate*lin_exp					-7.9607***	
					(2.4082)	
current_URate*lin_exp|exp>3					19.0362***	
					(4.8666)	
current_URate*lin_exp|exp>6					-13.7122***	
					(4.8368)	
lin_grad_year	-0.0169	0.0116	0.0353***	-0.0628**	-22.8865	-2.8056
	(0.0194)	(0.0191)	(0.0103)	(0.0306)	(53.1461)	(19.2831)
lin_grad_year|trend>3	-0.0042	0.0060	-0.0109	0.0256**	-6.0510	14.6038
	(0.0221)	(0.0221)	(0.0133)	(0.0122)	(25.7994)	(11.0858)
lin_grad_year|trend>6	-0.0362	0.0392	0.0104	0.0366**	80.7248**	-51.1515***
	(0.0284)	(0.0284)	(0.0109)	(0.0143)	(35.2520)	(15.2233)
d_y2000			0.0165*	0.0610	-26.6306	-9.5551
			(0.0093)	(0.0403)	(63.6992)	(26.7663)
d_y2001			0.0347*	0.1076	-33.6986	1.0926
			(0.0180)	(0.0690)	(118.5847)	(43.9962)
d_y2002			0.0544**	0.1799*	-6.4181	12.6021
			(0.0245)	(0.0998)	(168.1877)	(60.9035)
d_y2003			0.1253***	0.1695	-91.7889	33.3459
			(0.0322)	(0.1310)	(220.8156)	(79.5331)
d_y2004			0.1289***	0.2448	-70.6336	40.0388
			(0.0382)	(0.1595)	(271.2868)	(96.7843)
d_y2005			0.1344***	0.3112	-78.1185	43.9727
			(0.0458)	(0.1897)	(320.7529)	(115.4804)
d_y2006			0.1587***	0.3620	-60.0532	47.7650
			(0.0534)	(0.2216)	(372.7299)	(133.7550)
d_y2007			0.1873***	0.4257	-13.9987	46.8146
			(0.0607)	(0.2525)	(425.3406)	(152.0748)
d_y2008			0.1917***	0.4870*	14.9304	49.7238
			(0.0688)	(0.2821)	(476.3703)	(170.3990)
d_y2009			0.2328***	0.5344*	12.3347	61.1454
			(0.0772)	(0.3120)	(529.1195)	(188.3118)
d_y2010			0.2285**	0.5976*	40.1475	69.7336
			(0.0843)	(0.3412)	(581.2636)	(207.3524)
lin_calend_year|trend>3	0.0096	-0.0079				
	(0.0093)	(0.0081)				
lin_calend_year|trend>6	-0.0006	0.0044				
	(0.0050)	(0.0044)				
lin_calend_year|trend>9	0.0032	-0.0068*				

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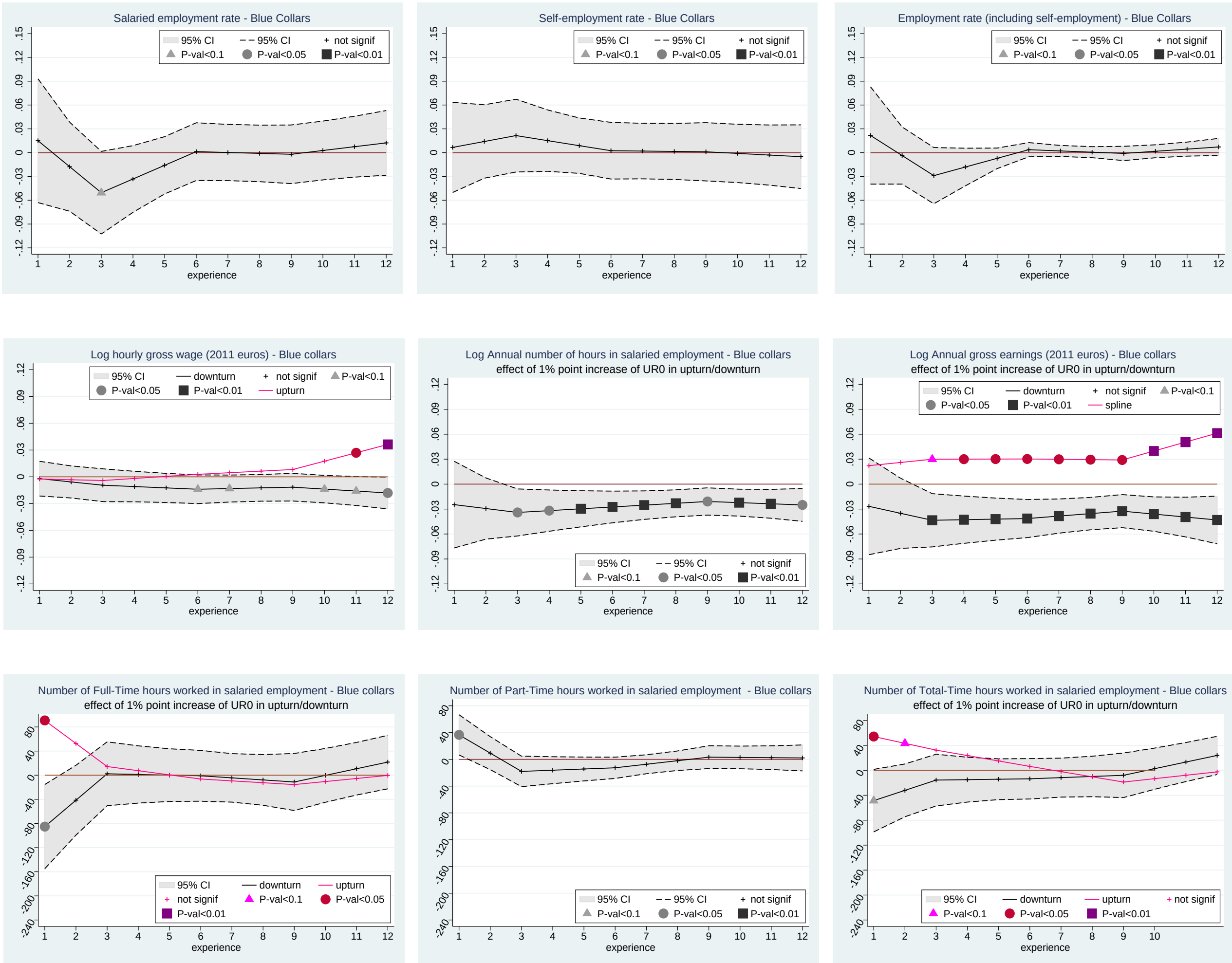
Table S.7 – continued from previous page

	salaried	self-empl.	log wage	log hours	FT hours	PT hours
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0041)	(0.0040)				
d_province2	0.0302	-0.0306	-0.0594*	0.0563	116.7313**	-36.1011**
	(0.0260)	(0.0260)	(0.0345)	(0.0390)	(51.7205)	(15.2201)
d_province3	-0.0221	0.0208	-0.0293	0.0256	-32.9023	-10.5819
	(0.0280)	(0.0280)	(0.0217)	(0.0351)	(60.0183)	(16.2143)
d_province4	0.0016	-0.0023	-0.0053	0.0567	157.2709***	-39.6587**
	(0.0206)	(0.0205)	(0.0208)	(0.0369)	(56.3724)	(15.3425)
d_province5	-0.0184	0.0186	0.0081	0.0642*	83.7151	-14.2460
	(0.0279)	(0.0278)	(0.0237)	(0.0343)	(56.5859)	(17.6747)
lin_calend_year_province2			0.0009	-0.0055	-11.1725*	4.3444**
			(0.0035)	(0.0037)	(5.5786)	(2.0338)
lin_calend_year_province3			-0.0072***	-0.0024	7.9390	-1.8570
			(0.0025)	(0.0033)	(5.9834)	(1.8436)
lin_calend_year_province4			0.0013	-0.0045	-10.7012*	0.8637
			(0.0030)	(0.0037)	(5.6221)	(1.6140)
lin_calend_year_province5			-0.0034	-0.0042	0.5409	-3.3208*
			(0.0028)	(0.0035)	(5.3448)	(1.7501)
R-squared	1.0000		0.9999		0.9988	
WSSR (2nd step)	272		1084		1059	
Obs (2nd step)	310		646		646	
Parameters (2nd step)	48		75		78	
Test joint signif. all imposed restr.(p-val)	0.494		0.309		0.390	
P-value of chi2 test	0.329		2.89E-34		4.48E-32	
Level of clustering	no	no	$g*p$	$g*p$	$g*p$	$g*p$
Imposed Restrictions:						
effect URate at grad. symmetric up/downturn	yes	yes	yes	no	no	yes
effect Current URate over exp=0	yes	yes	yes	yes	no	yes
spline for calendar year FE	yes	yes	no	no	no	no
effect prov-time trends=0	yes	yes	no	no	no	no

Notes as in Table S.6

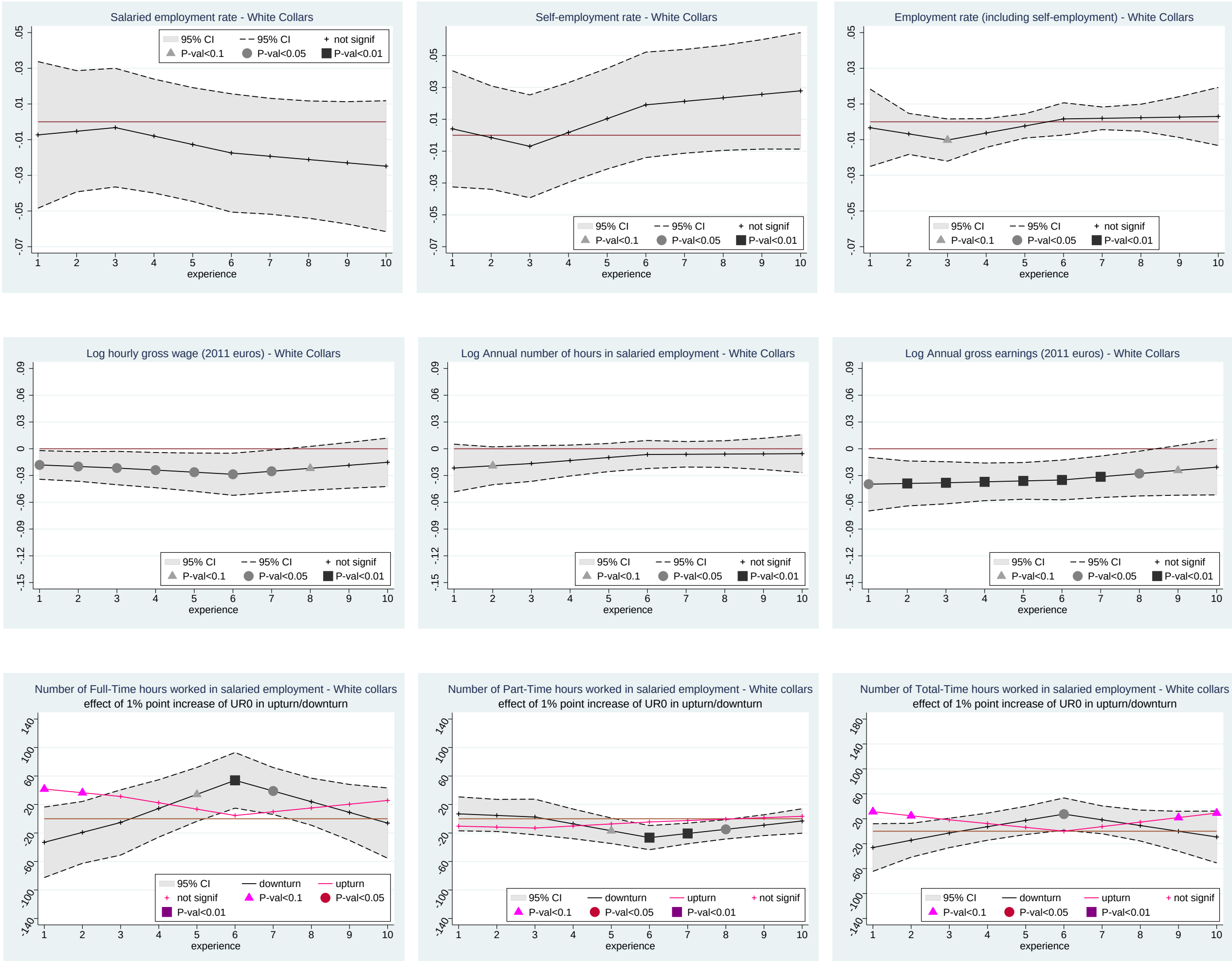
S.6 Analysis by Blue- and White-Collar Workers

Figure S.1: Effect of one *pp* Increase in the Provincial URate at Graduation: Blue-Collars



The figure displays for blue-collar workers the effect of one *pp* increase (decrease in case of an upturn) of the provincial unemployment rate at graduation on mentioned outcomes. The reported estimates are obtained by two-step FGLS, as described in Section S.4.

Figure S.2: Effect of one *pp* Increase in the Provincial URate at Graduation: White-Collars



Depicts similar effects as in Figure S.1 but for white-collar workers.

S.7 Tables of the Sensitivity Analysis

Table S.8: Individual discrete labor market outcomes: low-educated

		sensitivity tests:			
	baseline	education†	aggregate§	probit‡	blue-collars
Imposed Restrictions:§§					
effect URate at grad. symmetric up/downturn	yes	yes	-	yes	yes
effect Current URate over exp=0	yes	yes	yes	yes	yes
spline for calendar year FE	yes	yes	-	yes	no
effect prov-time trends=0	yes	yes	yes	yes	yes
level of clustering††	no	no	no	no	no
Potential experience	(1)	(2)	(3)	(4)	(5)
Salaried employment					
1	-0.017	-0.016	0.004	0.000	0.015
	(0.018)	(0.018)	(0.020)	(0.023)	(0.040)
2	-0.011	-0.008	-0.001	0.009	-0.018
	(0.015)	(0.015)	(0.020)	(0.021)	(0.028)
3	-0.005	0.000	-0.007	0.017	-0.050

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Table S.8 – continued from previous page

Potential experience	baseline (1)	sensitivity tests: education† (2)	aggregate§ (3)	probit‡ (4)	blue-collars (5)
	(0.015)	(0.015)	(0.020)	(0.018)	(0.026)
4	-0.002	0.003	-0.011	0.018	-0.033
	(0.015)	(0.014)	(0.019)	(0.017)	(0.021)
5	0.000	0.006	-0.014	0.019	-0.016
	(0.014)	(0.014)	(0.020)	(0.017)	(0.018)
6	0.002	0.009	-0.018	0.018	0.001
	(0.015)	(0.015)	(0.021)	(0.017)	(0.018)
7	0.002	0.007	-0.010	0.018	0.000
	(0.014)	(0.014)	(0.020)	(0.016)	(0.018)
8	0.002	0.005	-0.003	0.016	-0.001
	(0.014)	(0.014)	(0.021)	(0.016)	(0.018)
9	0.002	0.003	0.005	0.013	-0.002
	(0.015)	(0.015)	(0.022)	(0.014)	(0.019)
10	0.003	0.005	0.013	0.014	0.003
	(0.015)	(0.014)	(0.022)	(0.013)	(0.019)
11	0.004	0.007	0.020	0.019	0.007
	(0.015)	(0.015)	(0.024)	(0.016)	(0.019)
12	0.006	0.009	0.027	0.019	0.012
	(0.015)	(0.015)	(0.028)	(0.015)	(0.021)
Self-employment					
1	0.036	0.048	0.015	0.021	0.007
	(0.018)	(0.018)	(0.016)	(0.031)	(0.029)
2	0.021	0.024	0.022	0.006	0.014
	(0.015)	(0.014)	(0.016)	(0.026)	(0.023)
3	0.007	0.001	0.028	-0.008	0.021
	(0.015)	(0.015)	(0.017)	(0.022)	(0.023)
4	0.001	-0.004	0.024	-0.016	0.015
	(0.014)	(0.014)	(0.017)	(0.021)	(0.020)
5	-0.005	-0.009	0.020	-0.024	0.009
	(0.014)	(0.014)	(0.017)	(0.022)	(0.018)
6	-0.010	-0.013	0.015	-0.029	0.002
	(0.014)	(0.014)	(0.018)	(0.021)	(0.018)
7	-0.009	-0.011	0.012	-0.026	0.002
	(0.014)	(0.013)	(0.018)	(0.020)	(0.018)
8	-0.007	-0.009	0.008	-0.021	0.002
	(0.014)	(0.013)	(0.018)	(0.020)	(0.018)
9	-0.005	-0.006	0.004	-0.014	0.001
	(0.014)	(0.014)	(0.019)	(0.017)	(0.019)
10	-0.009	-0.011	-0.002	-0.017	-0.001
	(0.014)	(0.014)	(0.020)	(0.017)	(0.019)
11	-0.013	-0.015	-0.008	-0.024	-0.003
	(0.014)	(0.014)	(0.022)	(0.021)	(0.019)
12	-0.017	-0.019	-0.014	-0.026	-0.005
	(0.014)	(0.014)	(0.024)	(0.019) (	0.020)
Overall employment					
1	0.018	0.031	0.019	0.021	0.022
	(0.015)	(0.015)	(0.014)	(0.023)	(0.031)
2	0.010	0.017	0.020	0.016	-0.004
	(0.009)	(0.009)	(0.012)	(0.015)	(0.018)
3	0.002	0.002	0.021	0.009	-0.029
	(0.009)	(0.009)	(0.012)	(0.012)	(0.018)
4	-0.001	0.000	0.013	0.002	-0.018
	(0.007)	(0.007)	(0.011)	(0.010)	(0.012)
5	-0.005	-0.003	0.005	-0.005	-0.007
	(0.006)	(0.006)	(0.010)	(0.010)	(0.007)

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Table S.8 – continued from previous page

Potential experience	baseline (1)	sensitivity tests: education† (2)	aggregate§ (3)	probit‡ (4)	blue-collars (5)
6	-0.008	-0.005	-0.003	-0.011	0.004
	(0.008)	(0.007)	(0.011)	(0.011)	(0.005)
7	-0.007	-0.004	0.001	-0.008	0.002
	(0.006)	(0.006)	(0.010)	(0.009)	(0.004)
8	-0.005	-0.004	0.005	-0.004	0.001
	(0.005)	(0.005)	(0.010)	(0.008)	(0.004)
9	-0.004	-0.003	0.009	-0.001	-0.001
	(0.006)	(0.006)	(0.011)	(0.008)	(0.005)
10	-0.006	-0.006	0.011	-0.003	0.002
	(0.005)	(0.005)	(0.011)	(0.007)	(0.004)
11	-0.009	-0.008	0.012	-0.005	0.004
	(0.006)	(0.005)	(0.013)	(0.009)	(0.004)
12	-0.011	-0.010	0.013	-0.007	0.007
	(0.007)	(0.007)	(0.016)	(0.009)	(0.005)

Standard errors between parentheses. The table shows the effect of increasing the provincial unemployment rate at graduation by one *pp* on the mentioned outcomes. Since the outcomes satisfy adding-up constraints (salaried+self-empl.=overall empl.), a FGLS SUR is estimated on the first two outcomes in the sum and effects on the third outcome are obtained from the adding-up constraints. Estimates of Column 1 result from predictions based on estimates obtained by two-step FGLS, as described in Section S.4: this is the benchmark. The other estimates result from predictions based on estimates obtained by the following sensitivity analyses: two-step FGLS approach in which completed education fixed effects (FE) are included as individual controls in the first step (Col 2); two-step FGLS approach for the aggregate model (Col 3); two-step FGLS approach in which the first step is estimated by Probit rather than by a Linear Probability Model (Col 4); two-step FGLS approach for blue-collar workers (Col 5). Column 2 and 4 rely on the sub-sample retained for the benchmark (Col 1) and use the benchmark specification. In Col 5, sample selection on blue-collars and choice specification follow the same rules used for the benchmark on low-educated. Clustered (conventional) standard errors reported if the model is (not) rejected based on the χ^2 goodness-of-fit test at 5% level.
†Completed education is measured as the number of years of education successfully attained from the start of secondary education. Repeated grades are not included.
§In aggregate model cells need not be dropped, as always large enough (see selection rule in Table S.5). Only for this case, the variance of unobserved cluster-time shocks - as calculated by Eq. (5) in Cockx and Ghirelli (2015) - is strictly positive for salaried employment. Thus, the estimated variance of cluster-time shocks is added to the diagonal of the variance matrix of the measurement error and the inverse of the resulting matrix is used as weight in FGLS estimation.
‡The table shows partial effects on the probability of employment for each year of potential experience evaluating aggregate regressors at their sample mean.
§§The restrictions listed at the top of the table are imposed on both salaried and self-employment.

Table S.9: Individual continuous labor market outcomes: low-educated

	baseline	Sensitivity tests: education†	aggregate§	blue-collars
Log hourly wage				
Imposed Restrictions:				
effect URate at grad. symmetric up/downturn	yes	yes	yes	no
effect Current URate over exp=0	no	no	-	no
spline for calendar year FE	no	no	no	no
effect prov-time trends=0	no	no	-	no
level of clustering	$g*p$	$g*p$	no	$g*p$
Potential experience	(1)	(2)	(3)	(4)
1	0.005	0.004	-0.008	-0.002
	(0.013)	(0.013)	(0.017)	(0.010)
2	-0.001	-0.001	-0.005	-0.006
	(0.010)	(0.011)	(0.015)	(0.009)

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Table S.9 – continued from previous page

		sensitivity tests:		
	baseline	education†	aggregate§	blue-collars
Potential experience	(1)	(2)	(3)	(4)
3	-0.006	-0.006	-0.002	-0.009
	(0.009)	(0.010)	(0.015)	(0.009)
4	-0.008	-0.007	0.000	-0.011
	(0.008)	(0.009)	(0.015)	(0.008)
5	-0.009	-0.008	0.003	-0.012
	(0.008)	(0.008)	(0.015)	(0.008)
6	-0.011	-0.010	0.005	-0.014
	(0.007)	(0.008)	(0.016)	(0.008)
7	-0.008	-0.008	0.004	-0.013
	(0.007)	(0.008)	(0.016)	(0.007)
8	-0.006	-0.005	0.003	-0.012
	(0.007)	(0.008)	(0.017)	(0.007)
9	-0.003	-0.003	0.002	-0.012
	(0.008)	(0.009)	(0.017)	(0.008)
10	-0.006	-0.006	0.003	-0.014
	(0.008)	(0.009)	(0.018)	(0.008)
11	-0.009	-0.009	0.004	-0.016
	(0.009)	(0.009)	(0.019)	(0.008)
12	-0.012	-0.011	0.006	-0.018
	(0.010)	(0.010)	(0.022)	(0.009)
Log hours worked				
Imposed Restrictions:§§				
effect URate at grad. symmetric up/downturn	no	no	yes	yes
effect Current URate over exp=0	no	no	-	no
spline for calendar year FE	no	no	no	no
effect prov-time trends=0	no	no	-	no
level of clustering	$g*p$	$g*p$	$g*p$	$g*p$
Potential experience	(1)	(2)	(3)	(4)
1	-0.044	-0.044	-0.067	-0.025
	(0.022)	(0.022)	(0.049)	(0.026)
2	-0.035	-0.036	-0.045	-0.029
	(0.020)	(0.019)	(0.043)	(0.018)
3	-0.026	-0.028	-0.023	-0.034
	(0.022)	(0.021)	(0.044)	(0.014)
4	-0.026	-0.027	-0.021	-0.032
	(0.019)	(0.018)	(0.040)	(0.012)
5	-0.026	-0.026	-0.019	-0.030
	(0.016)	(0.015)	(0.037)	(0.011)
6	-0.025	-0.025	-0.017	-0.027
	(0.014)	(0.013)	(0.035)	(0.009)
7	-0.025	-0.024	-0.014	-0.025
	(0.012)	(0.012)	(0.034)	(0.008)
8	-0.025	-0.023	-0.012	-0.023
	(0.012)	(0.012)	(0.035)	(0.008)
9	-0.025	-0.021	-0.010	-0.021
	(0.013)	(0.013)	(0.036)	(0.008)
10	-0.027	-0.023	-0.007	-0.022
	(0.010)	(0.011)	(0.039)	(0.008)
11	-0.030	-0.026	-0.004	-0.024
	(0.010)	(0.010)	(0.049)	(0.009)
12	-0.033	-0.028	-0.001	-0.025
	(0.012)	(0.012)	(0.063)	(0.010)
Log earnings				
1	-0.039	-0.040	-0.075	-0.027

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Table S.9 – continued from previous page

Potential experience	baseline (1)	sensitivity tests: education† (2)	aggregate§ (3)	blue-collars (4)
	(0.026)	(0.026)	(0.052)	(0.029)
2	-0.036	-0.037	-0.050	-0.035
	(0.023)	(0.021)	(0.046)	(0.021)
3	-0.033	-0.034	-0.025	-0.043
	(0.022)	(0.021)	(0.048)	(0.016)
4	-0.034	-0.034	-0.021	-0.043
	(0.019)	(0.019)	(0.045)	(0.014)
5	-0.035	-0.034	-0.016	-0.042
	(0.017)	(0.017)	(0.043)	(0.012)
6	-0.036	-0.035	-0.011	-0.041
	(0.015)	(0.015)	(0.041)	(0.011)
7	-0.033	-0.031	-0.010	-0.038
	(0.014)	(0.015)	(0.040)	(0.010)
8	-0.031	-0.028	-0.009	-0.035
	(0.014)	(0.016)	(0.040)	(0.010)
9	-0.028	-0.024	-0.008	-0.032
	(0.016)	(0.017)	(0.042)	(0.010)
10	-0.033	-0.029	-0.004	-0.036
	(0.014)	(0.016)	(0.044)	(0.010)
11	-0.039	-0.034	0.000	-0.040
	(0.014)	(0.016)	(0.052)	(0.012)
12	-0.045	-0.039	0.004	-0.043
	(0.017)	(0.018)	(0.065)	(0.014)

Notes as in Table S.8, but applied to the following continuous outcomes: log wage+log hours=log earnings.
§§For log hours the following additional restriction (not mentioned in the table) is imposed: $\beta_{g2} = 0$, i.e. the slope of linear spline remains fixed after 6 years of experience. This restriction cannot be rejected.

Table S.10: Individual discrete labor market outcomes: high-educated

	baseline	sensitivity tests: education†	aggregate§	probit‡	white-collars
Imposed Restrictions:§§					
effect URate at grad. symmetric up/downturn	yes	yes	yes	yes	yes
effect Current URate over exp=0	yes	yes	-	yes	yes
spline for calendar year FE	yes	yes	yes	yes	no
effect prov-time trends=0	yes	yes	-	yes	yes
level of clustering††	no	no	no	no	no
Potential experience	(1)	(2)	(3)	(4)	(5)
Salaried employment					
1	-0.016	-0.021	-0.012	-0.011	-0.007
	(0.015)	(0.015)	(0.013)	(0.023)	(0.021)
2	-0.006	-0.012	-0.010	0.001	-0.005
	(0.013)	(0.013)	(0.011)	(0.022)	(0.017)
3	0.003	-0.004	-0.009	0.012	-0.003
	(0.014)	(0.013)	(0.013)	(0.019)	(0.017)
4	0.004	-0.003	-0.003	0.008	-0.008
	(0.013)	(0.013)	(0.012)	(0.017)	(0.016)
5	0.005	-0.002	0.003	0.005	-0.013
	(0.013)	(0.013)	(0.012)	(0.019)	(0.016)
6	0.005	-0.002	0.009	0.002	-0.017
	(0.014)	(0.013)	(0.013)	(0.022)	(0.017)

Continued on next page

Table S.10 – continued from previous page

Potential experience	baseline (1)	sensitivity tests: education† (2)	national§ (3)	probit‡ (4)	white-collars (5)
7	0.002	-0.004	0.000	0.000	-0.019
	(0.013)	(0.013)	(0.012)	(0.016)	(0.016)
8	-0.001	-0.005	-0.009	-0.001	-0.021
	(0.014)	(0.013)	(0.012)	(0.017)	(0.017)
9	-0.005	-0.007	-0.018	-0.002	-0.023
	(0.014)	(0.013)	(0.014)	(0.016)	(0.017)
10	-0.008	-0.009	-0.027	-0.003	-0.025
	(0.015)	(0.014)	(0.016)	(0.015)	(0.019)
Self-employment					
1	0.001	0.007	0.007	-0.013	0.004
	(0.014)	(0.014)	(0.009)	(0.026)	(0.019)
2	-0.007	-0.001	0.005	-0.020	-0.001
	(0.013)	(0.013)	(0.009)	(0.023)	(0.016)
3	-0.014	-0.008	0.003	-0.025	-0.007
	(0.014)	(0.013)	(0.010)	(0.021)	(0.016)
4	-0.011	-0.005	0.002	-0.018	0.002
	(0.013)	(0.013)	(0.010)	(0.019)	(0.016)
5	-0.009	-0.002	0.002	-0.014	0.010
	(0.013)	(0.013)	(0.010)	(0.021)	(0.016)
6	-0.006	0.001	0.001	-0.010	0.019
	(0.014)	(0.013)	(0.011)	(0.023)	(0.017)
7	-0.003	0.002	0.008	-0.006	0.021
	(0.013)	(0.013)	(0.011)	(0.018)	(0.017)
8	0.000	0.003	0.016	-0.004	0.023
	(0.014)	(0.013)	(0.011)	(0.019)	(0.017)
9	0.002	0.004	0.023	-0.002	0.026
	(0.014)	(0.013)	(0.012)	(0.018)	(0.017)
10	0.005	0.005	0.031	0.001	0.028
	(0.015)	(0.015)	(0.013)	(0.017)	(0.019)
Overall employment					
1	-0.015	-0.014	-0.005	-0.025	-0.003
	(0.006)	(0.006)	(0.009)	(0.011)	(0.011)
2	-0.013	-0.013	-0.005	-0.020	-0.007
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)
3	-0.011	-0.012	-0.005	-0.013	-0.010
	(0.004)	(0.004)	(0.008)	(0.006)	(0.006)
4	-0.007	-0.008	0.000	-0.010	-0.006
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)
5	-0.004	-0.004	0.005	-0.009	-0.002
	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)
6	0.000	-0.001	0.010	-0.008	0.002
	(0.003)	(0.003)	(0.008)	(0.005)	(0.005)
7	-0.001	-0.002	0.008	-0.006	0.002
	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)
8	-0.002	-0.002	0.007	-0.005	0.002
	(0.002)	(0.002)	(0.006)	(0.003)	(0.004)
9	-0.002	-0.003	0.006	-0.004	0.003
	(0.003)	(0.003)	(0.007)	(0.004)	(0.006)
10	-0.003	-0.004	0.004	-0.003	0.003
	(0.005)	(0.005)	(0.010)	(0.005)	(0.008)

Notes as in Table S.8.

Table S.11: Individual continuous labor market outcomes: high-educated

		Sensitivity tests		
	baseline	education†	aggregate§	white-collars
Log hourly wage				
Imposed Restrictions:				
effect URate at grad. symmetric up/downturn	yes	yes	yes	yes
effect Current URate over exp=0	yes	yes	-	yes
spline for calendar year FE	no	no	no	no
effect prov-time trends=0	no	no	-	no
level of clustering††	$g*p$	$g*p$	g	$g*p$
Potential experience	(1)	(2)	(3)	(4)
1	-0.023	-0.019	-0.013	-0.018
	(0.010)	(0.009)	(0.011)	(0.008)
2	-0.028	-0.023	-0.022	-0.020
	(0.009)	(0.009)	(0.010)	(0.008)
3	-0.032	-0.027	-0.031	-0.022
	(0.009)	(0.009)	(0.010)	(0.009)
4	-0.033	-0.027	-0.023	-0.024
	(0.008)	(0.009)	(0.014)	(0.010)
5	-0.033	-0.026	-0.015	-0.026
	(0.008)	(0.009)	(0.018)	(0.011)
6	-0.033	-0.026	-0.007	-0.029
	(0.009)	(0.009)	(0.022)	(0.012)
7	-0.036	-0.028	-0.008	-0.025
	(0.009)	(0.010)	(0.020)	(0.012)
8	-0.039	-0.029	-0.010	-0.022
	(0.010)	(0.010)	(0.018)	(0.012)
9	-0.042	-0.031	-0.012	-0.018
	(0.010)	(0.011)	(0.017)	(0.013)
10	-0.044	-0.032	-0.013	-0.015
	(0.011)	(0.012)	(0.015)	(0.013)
Log hours worked				
Imposed Restrictions:				
effect URate at grad. symmetric up/downturn	no	no	yes	no
effect Current URate over exp=0	yes	yes	-	yes
spline for calendar year FE	no	no	no	no
effect prov-time trends=0	no	no	-	no
level of clustering††	$g*p$	$g*p$	g	$g*p$
Potential experience	(1)	(2)	(3)	(4)
1	-0.035	-0.025	-0.120	-0.022
	(0.015)	(0.014)	(0.035)	(0.013)
2	-0.014	-0.007	-0.049	-0.019
	(0.011)	(0.010)	(0.027)	(0.010)
3	0.008	0.012	0.023	-0.017
	(0.009)	(0.010)	(0.027)	(0.010)
4	0.004	0.009	0.019	-0.013
	(0.009)	(0.009)	(0.019)	(0.009)
5	0.001	0.005	0.014	-0.010
	(0.009)	(0.009)	(0.013)	(0.008)
6	-0.003	0.002	0.010	-0.006
	(0.011)	(0.011)	(0.010)	(0.008)
7	-0.002	0.003	-0.005	-0.006
	(0.009)	(0.009)	(0.009)	(0.007)
8	-0.001	0.005	-0.020	-0.006
	(0.008)	(0.008)	(0.011)	(0.007)
9	0.001	0.006	-0.035	-0.006
	(0.009)	(0.009)	(0.015)	(0.009)

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Table S.11 – continued from previous page

Potential experience	baseline (1)	sensitivity tests: education† (2)	national§ (3)	white-collars (4)
10	0.002	0.007	-0.050	-0.005
	(0.011)	(0.012)	(0.019)	(0.010)
Log earnings				
1	-0.058	-0.044	-0.133	-0.040
	(0.019)	(0.018)	(0.034)	(0.015)
2	-0.041	-0.029	-0.071	-0.039
	(0.015)	(0.014)	(0.027)	(0.012)
3	-0.025	-0.015	-0.008	-0.038
	(0.013)	(0.014)	(0.026)	(0.012)
4	-0.029	-0.018	-0.004	-0.037
	(0.012)	(0.013)	(0.021)	(0.010)
5	-0.032	-0.021	-0.001	-0.036
	(0.013)	(0.013)	(0.021)	(0.010)
6	-0.036	-0.024	0.003	-0.035
	(0.014)	(0.014)	(0.026)	(0.011)
7	-0.038	-0.024	-0.013	-0.031
	(0.012)	(0.013)	(0.025)	(0.011)
8	-0.040	-0.025	-0.030	-0.028
	(0.011)	(0.012)	(0.024)	(0.012)
9	-0.041	-0.025	-0.047	-0.024
	(0.012)	(0.012)	(0.024)	(0.014)
10	-0.043	-0.025	-0.064	-0.021
	(0.014)	(0.013)	(0.025)	(0.015)

Notes as in Table S.8, but applied to the following continuous outcomes: log wage+log hours=log earnings.

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