

Dual Returns to Experience

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- Temporary employment is widespread (ter Weel 2018)
 - ▷ 19% of dependent employment in OECD countries
 - ▷ larger incidence in EU countries: **Spain (27%)**
- Extensive use due to employers' quest for **flexibility** in rigid labor markets (Aguirregabiria and Alonso-Borrego 2014)
- **Implications for human capital development?**
 - ▷ Workers might benefit since fixed-term (FT) contracts ease job finding rates (de Graaf-Zijl et al. 2011) and mitigate wage losses associated with skill depreciation during non-employment (Guvenen et al. 2017; Jarosch 2021) → accumulate experience (almost) continuously
 - ▷ Temporary employment could be detrimental if induces unstable careers (Blanchard and Landier 2002) and lower human capital accumulation (Dolado et al. 2010; Cabrales et al. 2017; Bratti et al. 2021) → worse quality of the experience due to poorer learning opportunities

The Spanish Dual Labor Market

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- FT represents more than 90% of the contracts signed each month. (Felgueroso et al. 2018)
- The existing duality attributable to large differences in employment protection legislation following the 1984 labor market reform that liberalized the use of FTC.
- The aim was to promote flexibility and stimulate job creation in a rigid labor market with unemployment. (Bentolila et al. 2008; Garcia-Perez et al. 2019)
- The spike in the use of FT contracts led the Spanish authorities to adopt several reforms in 1994, 1997, 2001, 2006, 2010, 2012 (and 2021), but they proved mostly unsuccessful in reducing labor market duality. (Conde-Ruiz et al. 2010; Garcia-Perez and Domenech 2019)

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- Administrative data to track workers since LM entry and compute precise measures of accumulated experience under different contractual arrangements
 - ▷ We estimate reduced-form wage regressions derived from a stylized framework: **dual returns**
 - ▷ We control for worker permanent heterogeneity and job-firm characteristics to take into account:
 - ▶ the selection of the best workers into the best jobs
 - ▶ the hysteresis of contracts along workers' careers
- We shed light on a human capital channel
 - ▷ job switchers
 - ▷ heterogeneity across ability distribution

Preview of the Results

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- **Lower returns** to past experience under FTC vs OEC
 - ▷ each additional year of experience in FTC relative to OEC is associated with 0.8 p.p. lower daily-wage
 - ▷ this corresponds to a 18.5% lower yearly return
- **Gap in returns** related to a human capital channel
 - ▷ the gap prevails among workers who switch jobs
 - ▷ it persists when workers move to jobs with similar skill requirements
 - ▷ it vanishes when they move to jobs where prior accumulated skills are less portable
- **Substantial heterogeneity** among workers
 - ▷ the gap widens along the ability distribution: negligible at the bottom while reaching 1.6 p.p. for high-ability workers (25% lower yearly return)
 - ▷ heterogeneous returns to experience translate into significant changes in the position of workers along the wage growth distribution 15 years after entry

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- Contemporaneous wage gaps between FTC and OEC
(Bentolila and Dolado 1994; Booth et al. 2002; De la Rica 2004; Mertens et al. 2007; Kahn 2016; Albanese and Gallio 2020)
 - ▷ impact accumulates over workers' careers
- Long-term career effects of labor market duality
(Amuedo-Dorantes and Serrano-Padial 2007; Guell and Petrongolo, 2007; Autor and Houseman 2010; Rebollo-Sanz 2011; Barcelo and Villanueva 2016; Garcia-Perez et al. 2019)
 - ▷ wage losses among equally experienced individuals
- Heterogeneous returns to experience
(Pesola 2011; de la Roca and Puga 2016; Jarosch et al. 2021; Arellano-Bover and Saltiel 2021)
 - ▷ heterogeneous returns based on type of contract
- Human capital accumulation and skill transferability
(Neal 1995; Gibbons and Waldman 2004; Lazear 2009; Kambourov and Manovskii 2009; Robinson 2018)
 - ▷ link skills' acquisition to their portability

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Earnings Trajectories in a Dual Labor Market

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Framework linking labor market duality to on-the-job human capital accumulation and wages.

Adapts Arellano-Bover and Saltiel (2021) to a setting with dual labor market and two types of contracts (FTC vs. OEC).

Let the stock of human capital of individual i in period t be

$$H_{it} = \eta_i + h_{it} \quad (1)$$

where

η_i human capital before labor market entry (education level but also innate ability)

h_{it} human capital accumulated since entry up to t

Human capital accumulation

h_{it} varies depending on the type of contract c worker i is employed up to time t and evolves according to the law of motion

$$h_{it+1} = h_{it} + \mu_{it}^c \quad (2)$$

where μ_{it}^c is an i.i.d. draw from a contract-specific distribution F^c , such that $\mathbf{E}[\mu_{it}^c] = \gamma^c$.

The stock of human capital accumulated since entry depends on:

$$h_{it} = \sum_{k=1}^{t-1} \mu_{ik}^{c(i,k)} \quad (3)$$

and

$$\mathbf{E}[h_{it} | \mathbf{oec}_{it}, \mathbf{ftc}_{it}] = \sum_{k=1}^{t-1} \sum_{m \in \{\mathbf{ftc}, \mathbf{oec}\}} \mathbf{1}[c(i, k) = m] \gamma^m \quad (4)$$

where $\mathbf{oec}_{it}$ and $\mathbf{ftc}_{it}$ are the complete histories in OEC and FTC since entry up until t , while $\mathbf{1}[c(i, k) = m]$ equals 1 if worker i was employed under a FTC or OEC contract in period k .

The structure of expected (log) wages are thus given by

$$\mathbf{E}[\ln w_{it}|i, X_{it}, \mathbf{oec}_{it}, \mathbf{ftc}_{it}] = \eta_i + \gamma^{\text{oec}} \mathbf{oec}_{it} + \gamma^{\text{ftc}} \mathbf{ftc}_{it} + X_{it} \Omega \quad (5)$$

where

η_i is the individual FE

$\mathbf{oec}_{it}$ and $\mathbf{ftc}_{it}$ are measures of accumulated experience under OEC and FTC since labor market entry up to time t

X_{it} are contemporaneous job characteristics

The sum of $\mathbf{oec}_{it}$ and $\mathbf{ftc}_{it}$ represents the standard experience component in a Mincer regression (Mincer 1974).

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- 4% random sample of individuals affiliated to Social Security in 2005-2018
 - ▷ spell-level data: worker demographics, labor relationship (e.g. days worked, type of contract), and monthly labor income (SS contribution bases)
 - ▷ longitudinal design: for each sample member, all relationships with the Social Security are available since the date of the first job spell
- **Baseline sample**
 - ▷ Spanish-born individuals who graduated after 1996 (followed for up to 15 years)
 - ▷ Annual panel of employment observations (annual income $\geq 1.5 \times$ monthly MW)
 - ▷ 242,774 workers over 1,954,097 observations between 1997 and 2018

CENSORING CORRECTION

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Linear panel data model for the log of real daily wages of individual i and year t :

$$\ln w_{it} = \eta_i + \gamma^{\text{oec}} \text{oec}_{it} + \gamma^{\text{ftc}} \text{ftc}_{it} + X_{it}\Omega + \delta_e + \delta_t + \epsilon_{it} \quad (6)$$

- η_i pre-labor market (permanent) ability
- oec_{it} experience accumulated on open-ended contracts
- ftc_{it} experience accumulated on fixed-term contracts
- X_{it} contemporaneous job-firm characteristics
 - ▷ female, education, tenure, type of contract, part-time, skill, firm size and age, location, and sector
- δ_e potential experience dummies
- δ_t time dummies

Returns To Experience under Different Contracts

	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Experience	0.0294*** (0.0003)		0.0497*** (0.0005)	
Experience OEC		0.0351*** (0.0003)		0.0500*** (0.0005)
Experience FTC		0.0209*** (0.0004)		0.0421*** (0.0006)
Observations	1,954,097	1,954,097	1,954,097	1,954,097
R-squared	0.6330	0.6343	0.3058	0.3064

Notes: Experience is measured in days and then it is transformed into years. OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively. All specifications include controls for contemporaneous job-firm characteristics (inc. current FTC), potential experience dummies and year dummies. OLS regressions include additional controls for education levels and female. Standard errors clustered at the individual level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

WAGE CONCEPT

LIFE CYCLE

COHORTS

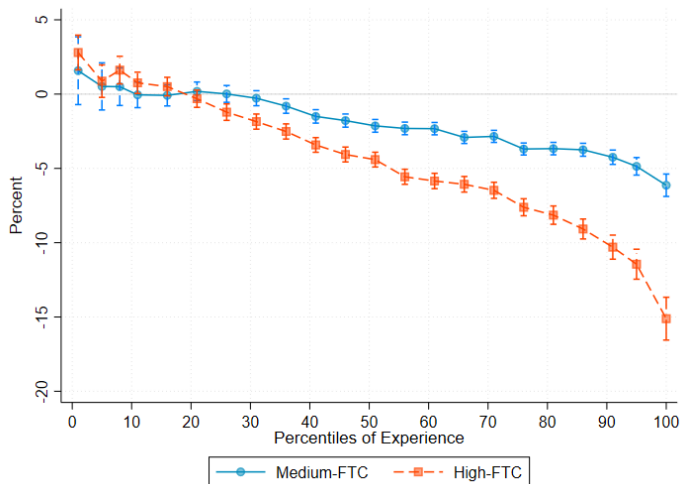
Heterogeneity in Experience

We extend our benchmark model and consider:

$$\ln w_{it} = \eta_i + \sum_{m=1}^3 \sum_{q=0}^Q \beta_{m(q)} \mathbf{1}\{\text{exp}_{it} = q\} \times \mathbf{1}\{\text{ftc}_{it} = m\} + X_{it}\Omega + \delta_e + \delta_t + \epsilon_{it}$$

- Each year, we discretize total experience into Q-bins
 $Q = \{\{0\}, (0, 4], (4, 7], (7, 10], (10, 15], \dots, (95, 97], (97, 100]\}$.
- We create three groups of workers based on the incidence of temporary employment: low (ratio lower than 0.3), medium (between 0.3 and 0.9) and high incidence (above 0.9).
- Notice that the parameters $\beta_{m(q)}$ are only identified up to a normalization (impact set to zero for the first observation).
- $\beta_{2(q)}$ and $\beta_{3(q)}$ capture the wage gap between individuals who have been employed for the same amount of time since entry but have had a higher incidence of FTC in the past.

Dual wage gap by Experience and FT incidence



FTC INCIDENCE

HETEROGENEITY BY GENDER

HETEROGENEITY BY EDUCATION

Threats to Identification

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Individual wages are determined by who the worker is, but also by:

- the firm where she works
- the success of the idiosyncratic job match

The omission of either component could result into biased estimates for the gap in returns to experience.

Formally:

$$\epsilon_{it} = \gamma_{j(i)} + \nu_{ij(i)} + \xi_{ij(i)t}$$

where

- $\gamma_{j(i)}$ unobserved firm-specific FE
- $\nu_{ij(i)}$ unobserved match-specific FE
- $\xi_{ij(i)t}$ transitory uncorrelated error disturbances

Ignoring the sorting of workers across firms could threaten the correct identification of the gap (Card et al. 2018):

1. We create an annual panel of employment observations that includes all workers observed btw 1997-2018
2. We select firms for which we observe at least 10 workers each year
3. We fit linear wage models that include both individual and establishment FE as in (Abowd et al. 1999), further controlling for workers' part-time status, age dummies and time effects
4. We recover the firm FE from the estimation and match them with our baseline sample
5. We use the estimated firm FE as an additional control in our estimation using the matched sample

Dual Returns to Experience: Firm Heterogeneity

	Baseline Sample (1)	Matched Sample (2)	Matched Sample (3)
Experience OEC	0.0500*** (0.0005)	0.0575*** (0.0011)	0.0541*** (0.0009)
Experience FTC	0.0421*** (0.0006)	0.0440*** (0.0013)	0.0431*** (0.0011)
Gap in Returns (%)	18.52*** (1.05)	30.50*** (2.21)	25.71*** (1.83)
Observations	1,954,097	456,364	456,364
R-squared	0.3064	0.2372	0.3067
Estimated firm FE	No	No	Yes

Notes: See previous table. Firm FE recovered from a standard AKM model using *all* workers employed by firms for which we observe at least 10 workers each year. Column (1) replicates benchmark specification. Columns (2) and (3) estimate our model in a restricted sample for which we can match the estimated *out-of-sample* firm FE. SE clustered at the individual level and, in Column (3), bootstrapped with 100 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Omitting match effects could bias the estimated returns to experience (Altonji and Shakotko 1987; Topel 1991; Moscarini 2005).

Unobserved match quality to be correlated with:

- experience, since more experienced workers have had more time to locate themselves into good matches
- tenure, since a worker employed in a good match is more likely to keep that job longer

Importantly, the strength of these correlations may vary between OEC and FTC experience.

Two instrumental variables approaches:

- deviation from averages computed within each contract spell or within each match-contract spell
- availability of hiring subsidies for hiring workers under OECs by region/year

Dual Returns to Experience: Match Quality

	Altonji and Shakotko (1987)		(1) & Subsidies availability	(2)
	(1)	(2)	(3)	(4)
Experience OEC	0.044*** (0.001)	0.046*** (0.004)	0.043*** (0.001)	0.047*** (0.004)
Experience FTC	0.035*** (0.001)	0.030*** (0.004)	0.035*** (0.001)	0.031*** (0.004)
Gap in Returns (%)	26.14*** (1.96)	55.40*** (8.46)	26.08*** (1.95)	52.73*** (7.70)
Observations	1,954,097	1,954,097	1,954,097	1,954,097
R-squared	0.479	0.478	0.479	0.478

Notes: See previous tables. In Column 1, we de-mean experience at the contract-individual level. In Column 2, we de-mean experience at the match-contract-individual level. Columns 3 and 4 add the instrument based on availability of subsidies for hiring under OEC.

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Dual Returns to Experience: Job Switchers

	All		Within Industries			Across Industries		
	FE (1)	FE + Heckman (2)	FE (3)	FE + Heckman (4)	FE + Heckman (5)	FE (6)	FE + Heckman (7)	FE + Heckman (8)
Experience OEC	0.0495*** (0.0008)	0.0447*** (0.0008)	0.0501*** (0.0013)	0.0457*** (0.0013)	0.0487*** (0.0013)	0.0435*** (0.0014)	0.0390*** (0.0015)	0.0379*** (0.0015)
Experience FTC	0.0380*** (0.0010)	0.0364*** (0.0010)	0.0341*** (0.0016)	0.0326*** (0.0016)	0.0337*** (0.0016)	0.0392*** (0.0019)	0.0378*** (0.0019)	0.0376*** (0.0019)
Inverse Mills Ratio (job switching)		0.0482*** (0.0022)		0.0491*** (0.0034)			0.0417*** (0.0040)	
Inverse Mills Ratio (industry/job switching)					0.0337*** (0.0050)			0.1027*** (0.0050)
Gap in Returns (%)	30.19*** (2.35)	22.91*** (2.32)	46.97*** (4.35)	40.38*** (4.29)	44.74*** (4.33)	11.01*** (3.72)	3.15 (3.67)	0.92 (3.59)
Observations	447,098	447,098	235,882	235,882	235,882	211,216	211,216	211,216
R-squared	0.3197	0.3208	0.2968	0.2982	0.2971	0.3357	0.3364	0.3387

Notes: See previous tables. Heckman correction in Columns (2), (4), and (7) uses household composition for the job switching equation as exclusion restriction. Columns (5) and (8) estimate a simultaneous job-industry switching equation where the exclusion restriction for job switching is household composition, whereas past wage is used for the industry switching equation. In these specifications we use only the first re-employment observation after a job change. Job switchers = 167,702.

SIMILARITY IN SKILL INTENSITY

Dual Returns to Experience: Observed Ability

	Education		Occupation	
	Non-College	College	Low-Skill	High-Skill
Experience OEC	0.0421*** (0.0005)	0.0590*** (0.0009)	0.0461*** (0.0005)	0.0540*** (0.0015)
Experience FTC	0.0428*** (0.0007)	0.0438*** (0.0011)	0.0420*** (0.0006)	0.0368*** (0.0017)
Gap in Returns (%)	-1.67 (1.08)	34.83*** (1.95)	9.77*** (1.09)	46.84*** (3.55)
Observations	1,180,999	773,098	1,523,962	430,135
R-squared	0.3051	0.3052	0.3060	0.2873

Notes: See previous tables. Non-college includes both high-school dropouts and high-school graduates. Low-Skill includes both medium and low-skill occupations. A worker is considered high-skill (low-skill) if she has been employed more than 50% of her career in a high-skill (low-skill) occupation.

$$\ln w_{it} = \eta_i + \sum_{c \in \{\text{ftc}, \text{oec}\}} \gamma^c c_{it} + \sum_{c \in \{\text{ftc}, \text{oec}\}} \varphi^c \eta_i c_{it} + X_{it} \Omega + \delta_e + \delta_t + \epsilon_{it} \quad (7)$$

- φ^c captures whether higher-ability workers face larger returns to experience acquired at different contracts

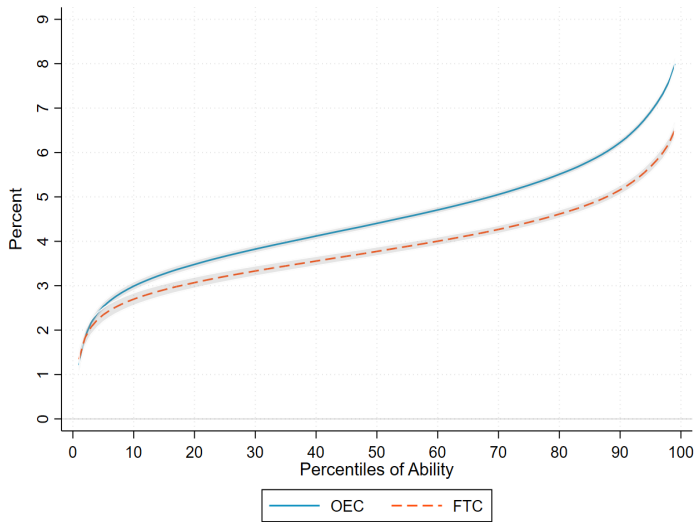
Estimation based on (de la Roca and Puga, 2016)'s algorithm

1. guess a set of individual fixed effects, η_i^0
2. estimate equation (7) by OLS
3. compute worker fixed effects as

$$\eta_i^1 = \frac{\ln w_{it} - \sum_{c \in \{\text{ftc}, \text{oec}\}} \gamma^c c_{it} - X_{it} \Omega - \delta_e - \delta_t}{\sum_{c \in \{\text{ftc}, \text{oec}\}} \varphi^c c_{it}}$$

4. iterate over previous steps until convergence

Returns to Experience by Ability



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- We assess how much dual returns to experience can affect earnings trajectories in the long run.
- We do this by comparing wage growth 15 years after entry for alternative labor market histories:
 - ▷ We use estimates from equation (7) to predict counterfactual wage growth for workers who spent 15 years in OEC and compare it to the alternative scenario where workers experienced 15 years in FTC.
 - ▷ Given the complementarity between ability and returns to experience, we look at low and high ability workers under the two scenarios.
 - ▷ To put these values in context, we compare them to the observed wage growth after 15 years of potential experience and report the associated percentile in the distribution.

Counterfactual Wage Profiles

Unobserved Ability	Employment Trajectory	Counterfactual Wage Growth, %	Actual Wage Growth, Percentiles
10th Percentile	Always in FTC	40.45	43
10th Percentile	Always in OEC	44.85	46
90th Percentile	Always in FTC	77.37	67
90th Percentile	Always in OEC	93.37	77

Notes: Wage growth calculated as the log difference between entry-level daily wages and daily wages observed 15 years after. Counterfactual wage growth is computed for alternative employment trajectories based on the continuous incidence of OEC or FTC and using (unobserved) ability-specific returns from equation (7). Actual wage growth stands for wage growth for workers observed during 15 years in the labor market.

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- Experience acquired under fixed-term contracts yields **lower** wage returns compared to permanent contracts:
 - ▷ a difference that is neither due to unobserved firm heterogeneity nor idiosyncratic job match quality
 - ▷ our results are consistent with limited on-the-job learning during episodes of temporary employment, which **mainly penalizes high-skilled workers**
- Labor market duality affects workers' early careers over and above the instability of employment histories:
 - ▷ Experience accumulated in FTC is less valuable
 - ▷ Poorer learning opportunities in temporary employment have implications for wage inequality over the life cycle
- Policies aimed at increasing human capital accumulation in temporary contracts could be beneficial in reducing wage differentials in the long run

THANK YOU!



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Censoring Correction

- Fit cell-by-cell Tobit models to daily wages
(Dustmann et al., 2009; Card et al., 2013; Bonhomme and Hospido, 2017)
- Gender-specific cells defined by occupational groups (3 categories), age groups (5 categories), and years (39) for a total of 2×585 cells
- Top-coded observations replaced stochastically using estimated parameters

$$\ln w_{ijt} = X_{ijt}\hat{\beta}_c + \hat{\sigma}_c \Phi^{-1} \left[\Phi \left(\frac{\ln \bar{w} - X_{ijt}\hat{\beta}_c}{\hat{\sigma}_c} \right) + u_{ijt} \times \left(1 - \Phi \left(\frac{\ln \bar{w} - X_{ijt}\hat{\beta}_c}{\hat{\sigma}_c} \right) \right) \right]$$

where $(\hat{\beta}_c, \hat{\sigma}_c)$ are the maximum likelihood estimates of each cell, Φ denotes the standard normal cdf, and u represents a random draw from the uniform distribution, $U[0, 1]$

Comparison of Original and Corrected Wage Distributions

Percentiles	Censored	Corrected
5th	3.00	3.00
10th	3.33	3.33
25th	3.70	3.70
50th	4.04	4.04
75th	4.43	4.45
90th	4.74	5.17
95th	4.78	5.68

Notes: Wages refer to log real daily wages earned by workers in a given employer each month. Moments of the the log daily wage distribution are computed over month-worker-firm observations (93,407,145). [\(back\)](#)

Summary Statistics

	Mean	Std. Dev
Female	0.523	-
Age at Entry	22.30	3.16
Wage at Entry	39.51	22.59
Days Worked at Entry	189.56	105.18
under OEC	33.71	85.48
under FTC	155.85	106.45
Experience (yrs)	5.82	4.49
under OEC	3.22	3.87
under FTC	2.60	2.56
Annual Wage Growth	0.065	0.172
Workers		242,774
Observations		1,954,097

Notes: Entry refers to the first year of employment after the predicted year of graduation. Accumulated experience refers to the last individual observation. Experience is measured using daily information and transformed into years. Annual wage growth corresponds to year-on-year wage growth averaged over all observations. Wages are in 2018 euros. [\(back\)](#)

Robustness to Wage Concept

	Censored	Tax Data	Pooled Income
Experience OEC	0.0398*** (0.0004)	0.0474*** (0.0006)	0.0495*** (0.0005)
Experience FTC	0.0371*** (0.0006)	0.0410*** (0.0007)	0.0439*** (0.0006)
Observations	1,954,097	1,508,948	1,954,097
R-squared	0.3112	0.2306	0.2685

(back)

Robustness to Life Cycle

	Cubic Potential Exp. (1)	Excl. Potential Exp (2)	Age Effects (3)
Experience OEC	0.0514*** (0.0005)	0.0456*** (0.0005)	0.0481*** (0.0005)
Experience FTC	0.0433*** (0.0006)	0.0394*** (0.0006)	0.0414*** (0.0006)
Observations	1,954,097	1,954,097	1,954,097
R-squared	0.3152	0.3080	0.3089

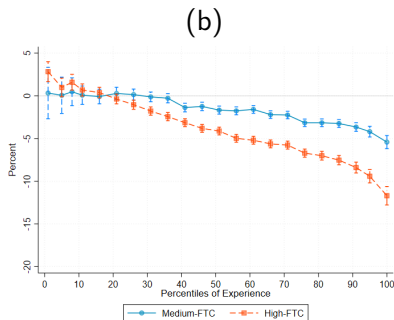
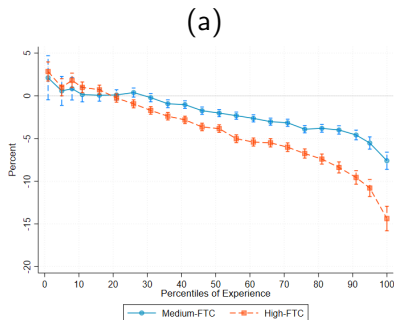
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Robustness to Cohort Analysis

	Graduation year cohorts			
	1996	1997	1998	1999
Experience OEC	0.0491*** (0.0018)	0.0513*** (0.0018)	0.0522*** (0.0018)	0.0537*** (0.0017)
Experience FTC	0.0421*** (0.0022)	0.0450*** (0.0022)	0.0448*** (0.0022)	0.0449*** (0.0022)
Observations	154,435	158,164	160,100	161,174
R-squared	0.3050	0.2993	0.2990	0.3039

(back)

Robustness to FTC Incidence Groups

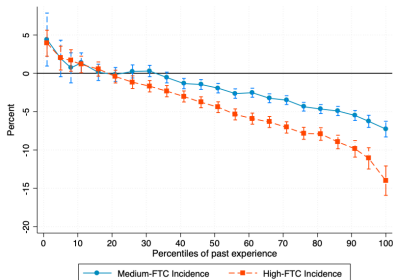


Notes: Medium(High)-FTC incidence refers to individuals whose actual experience on FTC relative to total experience is in graph (a) btw 0.5 and 0.9 (above 0.9) and in graph (b) btw 0.3 and 0.6 (above 0.6).

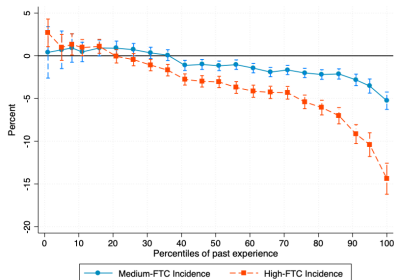
(back)

Dual wage gap by Experience, FT incidence and Gender

Men



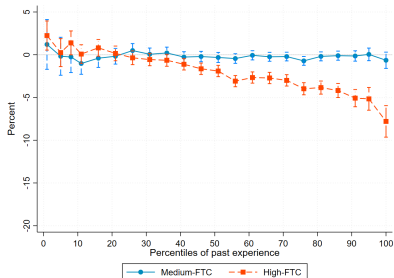
Women



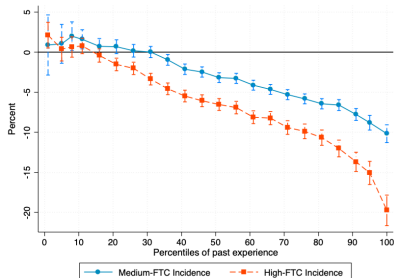
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Dual wage gap by Experience, FT incidence and Education

Non-college



College



(back)

Dual Returns to Experience: Industry Mobility and Skills

	FE (1)	FE + Heckman (2)
Distance	-0.0651*** (0.0046)	-0.0638*** (0.0046)
Experience OEC	0.0499*** (0.0008)	0.0452*** (0.0009)
Experience FTC	0.0371*** (0.0010)	0.0355*** (0.0010)
Experience OEC $\times$ Distance	-0.0067*** (0.0014)	-0.0074*** (0.0014)
Experience FTC $\times$ Distance	0.0032** (0.0014)	0.0033** (0.0014)
Inverse Mills Ratio		0.0477*** (0.0022)
Observations	447,098	447,098
R-squared	0.3214	0.3214
Gap in Returns (%)		
Minimum distance (= 0)	34.33*** (2.57)	27.42*** (2.54)
Maximum distance (= 0.7439)	13.64*** (3.98)	4.61 (3.94)

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