Dual Returns to Experience

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The views expressed here do not necessarily reflect the position of Banco de España, Bank of Lithuania, or the Eurosystem

Temporary Employment, Flexibility, and Human Capital

- Temporary employment is widespread
  - $\sim$12% of dependent employment in OECD countries
  - larger incidence in EU countries, $\sim$15%
    - France (16%), Italy (17%), Netherlands (20%), Portugal (21%), Spain (26%)
- Extensive use due to the quest of **flexibility** by employers in rigid labor markets (Aguirregabiria and Alonso-Borrego, 2014)
- **Implications for human capital accumulation and life-cycle wage trajectories?**
  - ease job finding rates (e.g., de Graaf-Zijl et al.,2011) & mitigate wage losses associated with skill depreciation during non-employment (e.g., Guvenen et al., 2021)
  - lower job stability (e.g., Blanchard and Landier, 2002) & on-the-job training (e.g., Bratti et al., 2021) may dampen skill acquisition

The Paper in a Nutshell

- Spanish labor market to study the effect of duality on life-cycle wage profiles
  - 90% of the contracts signed each month are fixed-term & 26% of the workforce is in temporary employment (Felgueroso et al., 2018)
  - administrative data to track workers since LM entry and compute precise measures of accumulated experience ($\sim$*human capital*) under different contractual arrangements
- Stylized framework of human capital acquisition and wage profiles in a dual labor market
  - estimate contract-specific returns to experience
  - document human capital channel
  - implications for life-cycle wage growth

Preview of the Results

- Returns to experience acquired under temporary contracts lower than that of permanent
  - 18.5% lower returns after accounting for worker heterogeneity and firm-job attributes
  - firm heterogeneity explains at most 15% of the gap
  - accounting for unobserved match quality yields a larger gap
- Lower returns consistent with poorer human capital development in temporary jobs
  - same level of experience: higher incidence of temporary employment implies higher losses
  - portability of human capital: wider gap among job switchers driven by within industry movers
  - learning-skill complementary: wider gap among high ability individuals

Literature and Contribution

- Contemporaneous wage gaps between temporary and permanent workers
  (Booth et al., 2002; De la Rica, 2004; Mertens et al., 2007; Kahn, 2016; Albanese and Gallio, 2020)
    - impact of temporary employment accumulates over workers' careers

- Long-term career effects of labor market duality
  (Booth et al., 2002; Autor and Houseman, 2010; Garcia-Perez et al., 2019)
    - wage losses among equally experienced individuals

- Heterogeneous returns to experience
  (Pesola, 2011; de la Roca and Puga, 2016; Gregory, 2020; Jarosch et al., 2021; Arellano-Bover and Saltiel, 2021)
    - heterogeneous returns based on type of contract

- Alternative work arrangements and labor market performance
  (Roman et al., 2011; Dolado et al., 2021; Ponczek and Ulyssea, 2021)
    - human capital accumulation as an additional dimension to consider

The Spanish Dual Labor Market

- The 1984 labor market reform
  - what: liberalized the use of fixed-term contracts without changes on permanent contracts ($\sim$ 3x higher firing costs)
  - goal: promote flexibility and stimulate job creation in a rigid labor market with high unemployment (Bentolila et al., 2008; Garcia-Perez et al., 2019)
  - consequence: $\sim$90% of the contracts signed each month are fixed-term & $\sim$26% of the workforce is in temporary employment (Felgueroso et al., 2018)
- Several compensatory reforms in 1994, 1997, 2001, 2006, 2010 and 2012, but they proved mostly unsuccessful in reducing labor market duality (Conde-Ruiz et al., 2010; Garcia-Perez and Domenech, 2019)
  - until the 2022 reform!

Contract-Specific Human Capital

- Human capital of individual i in period t

$$H_{it} = \eta_i + h_{it} = \eta_i + h_{it-1} + \mu^c$$

  - η_i is the human capital before labor market entry
  - h_{ik} is the stock of human capital accumulated since entry up to k
  - μ_{it}^c is an i.i.d. draw from a contract-specific distribution F^c, such that $\mathbf{E}[\mu_{it}^c] = \gamma^c$

- Differences in F^c govern human capital accumulation across contracts
  - Firms may invest less in training people due to (potential) finite nature of the relationship (Crawford, 1988; Poulissen et al., 2021)
  - Workers may put less effort into learning if the conversion probability is low (Sanchez and Toharia, 2000; Dolado et al., 2016)

Wage Profiles in a Dual Labor Market

- Current human capital depends on the entire past employment history across contracts

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

  - $\mathbf{1}[c(i,k) = m]$ equals to one if worker i was employed under a FTC or OEC in period k

- The structure of wages with contract-specific human capital (hc) equals

$$\mathbf{E}[\ln w_{it}|i, X_{it}, \mathbf{oec}_{it}, \mathbf{ftc}_{it}] =$$

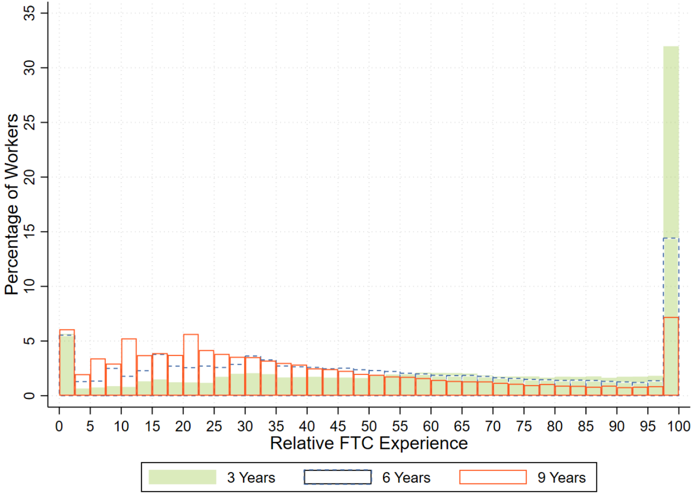
$$= \underbrace{\eta_i}_{\text{pre-labor market hc}} + \underbrace{\sum_{k=1}^{t-1} \mathbf{1}[c(i,k) = oec]\gamma^{oec}}_{\text{hc in permanent contracts}} + \underbrace{\sum_{k=1}^{t-1} \mathbf{1}[c(i,k) = ftc]\gamma^{ftc}}_{\text{hc in temporary contracts}} + \underbrace{X_{it}\Omega}_{\text{observables}}$$

Muestra Continua de Vidas Laborales

- 4% random sample of individuals linked to Social Security between 2005-2018
  - spell-level data: worker demographics, labor relationship (e.g. days worked, type of contract), and labor income (top-coded 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 $\rightarrow$ reconstruct labor histories
- **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**] [**SUMMARY STATISTICS**]

Distribution of Workers by Relative FTC Experience



Notes: Relative FTC experience is the share of experience accumulated under fixed-term contracts relative to overall experience.

Econometric Model

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

- w_{it} real daily wages
- η_i pre-labor market ability/human capital
- oec_{it} and ftc_{it} experience accumulated on open-ended and fixed-term contracts
  - oec_{it} + ftc_{it} = standard experience component in a Mincer equation (Mincer, 1974)
- X_{it} contemporaneous job-firm characteristics
  - tenure, **type of contract**, part-time, skill, firm size and age, location, and sector
- δ_e and δ_t potential experience and year fixed effects

Dual Returns to Experience

	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Current FTC	-0.0463***	-0.0320***	-0.0327***	-0.0359***
	(0.0011)	(0.0010)	(0.0009)	(0.0009)
Experience	0.0294***		0.0497***	
	(0.0003)		(0.0005)	
Experience OEC		0.0351***		0.0500***
		(0.0003)		(0.0005)
Experience FTC		0.0209***		0.0421***
		(0.0004)		(0.0006)
Gap in Returns (%)		68.31***		18.52***
		(2.74)		(1.05)
Observations	1,954,097	1,954,097	1,954,097	1,954,097
R-squared	0.6330	0.6343	0.3057	0.3064

Notes: Gap in returns is computed as $100 \times (\frac{\gamma^{oec}}{\gamma^{ftc}} - 1)$ and standard errors are obtained using the Delta method. The R-squared reported in Columns (3) and (4) is within workers.

Missing Unobserved Heterogeneity

- Structure of wage residuals:

$$\epsilon_{it} = \nu_{ij(it)} + \varphi_{f(it)} + \xi_{it}$$

  - $\varphi_{f(it)}$ unobserved firm-specific effects $\equiv$ where the individual works (Card et al., 2018)
  - $\nu_{ij(it)}$ unobserved match-specific components $\equiv$ the success of the match (Woodcock, 2015)
  - ξ_{it} transitory error disturbances

- Experience (and tenure) potential correlated with omitted permanent heterogeneity

The Role of Firm Heterogeneity and Match Quality

- Firm heterogeneity: explains at most 15% of the gap [AKM]
  - estimate AKM firm fixed effect in the full dataset (Abowd, Kramarz, and Margolis, 1999)
  - use firm permanent components as additional controls in the baseline sample

- Match quality: wider gap due to larger upward bias of returns to FTC [AS]
  - deviation from averages within contract or firm-contract (experience) and within firm (tenure) (Altonji and Shakotko, 1987)
  + availability of OEC-hiring subsidies by region/year (Garcia-Perez and Rebollo-Sanz, 2009)

Robustness Checks

- Life-cycle controls: no potential experience, cubic polynomial, or age effects [R1]
- Non-parametric contract-specific experience: 2×22 indicators [R2]
- Wage concept: censored labor income, income from all employers, tax data [R3]
- Contract-specific returns to tenure [R4]
- Cohorts fully observed, i.e., graduates from 1996 to 1999 [R5]
- Impact of 2012 EPL reform [R6]
- Firm-cluster fixed-effects (Bonhomme, Lamadon, and Manresa, 2021) [R7]
- Accounting for level of accumulated experience [R8]

Human Capital Transferability

- Human capital is (partly) recyclable across jobs (Gathmann and Schoenberg, 2010)
  $\rightarrow$ gap in returns should remain when switching jobs
- A large component of on-the-job learning is industry specific (Neal, 1995; Sullivan, 2010)
  $\rightarrow$ gap in returns should be larger for within-industry movements

Human Capital Channel: Job Switchers

	Fixed-Effects		FE+Heckman	
	(1)	(2)	(3)	(4)
Experience	0.0492***		0.0438***	
	(0.0008)		(0.0008)	
Experience OEC		0.0495***		0.0447***
		(0.0008)		(0.0008)
Experience FTC		0.0380***		0.0364***
		(0.0010)		(0.0010)
Inverse Mills Ratio			0.0553***	0.0482***
			(0.0022)	(0.0022)
Gap in Returns (%)		30.19***		22.91***
		(2.35)		(2.32)

Notes: Job switchers = 167, 702.

Human Capital: Portability of Acquired Skills

	Within industries			Across industries		
	(FE)	(FE + Heckman)		(FE)	(FE + Heckman)	
	(1)	(2)	(3)	(4)	(5)	(6)
Experience OEC	0.0501***	0.0457***	0.0487***	0.0435***	0.0390***	0.0379***
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0015)
Experience FTC	0.0341***	0.0326***	0.0337***	0.0392***	0.0378***	0.0376***
	(0.0016)	(0.0016)	(0.0016)	(0.0019)	(0.0019)	(0.0019)
Inverse Mills Ratio		0.0491***			0.0417***	
(job switching)		(0.0034)			(0.0040)	
Inverse Mills Ratio			0.0337***			0.1027***
(industry/job switching)			(0.0050)			(0.0050)
Gap in Returns (%)	46.97***	40.38***	44.74***	11.01***	3.15	0.92
	(4.35)	(4.29)	(4.33)	(3.72)	(3.67)	(3.59)

[INVOLUNTARY MOVERS] [DISTANCE IN SKILL COMPOSITION ACROSS INDUSTRIES]

Human Capital and Workers' Ability

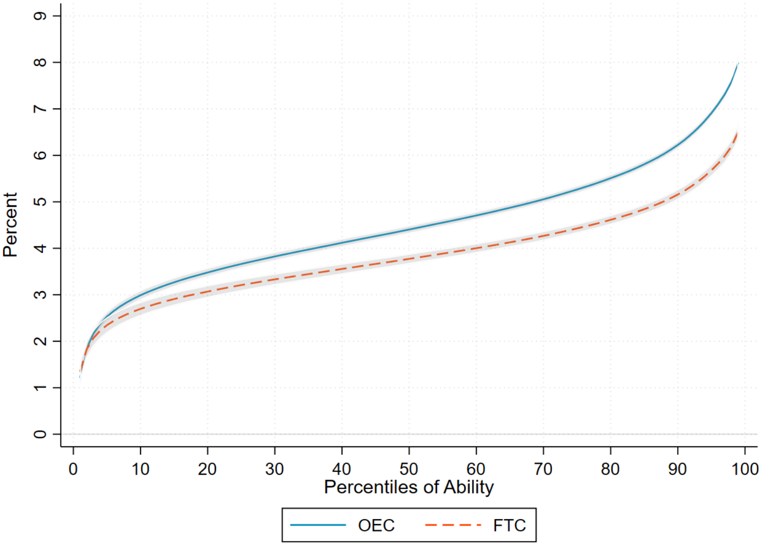
- Complementary between human capital and ability (Heckman et al., 2006)
  - → if gap is due to human capital, more able workers should be mostly penalized
  - → returns to human capital steeper for more able workers

Human Capital: Complementarity with Observed Ability

	Education		Occupation	
	Non-College	College	Low-Skill	High-Skill
Experience OEC	0.0421***	0.0590***	0.0461***	0.0540***
	(0.0005)	(0.0009)	(0.0005)	(0.0015)
Experience FTC	0.0428***	0.0438***	0.0420***	0.0368***
	(0.0007)	(0.0011)	(0.0006)	(0.0017)
Gap in Returns (%)	-1.67	34.83***	9.77***	46.84***
	(1.08)	(1.95)	(1.09)	(3.55)

Notes: A worker is considered high-skill (low-skill) if she is employed more than 50% of the time in a high-skill (low-skill) occupation.

Human Capital: Complementarity with Unobserved Abilities



[MODEL]

Counterfactual Wage Trajectories

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. Actual wage growth stands for wage growth for workers observed during 15 years in the labor market.

Taking Stock

- LM duality affects workers over and above the instability of employment histories
  - almost 20% lower annual returns to experience acquired under temporary contracts
  - within-industry job movers & complementarity with individual ability suggest a human capital channel
  - implications for life-cycle wage **inequality**
- Room for labor market policy
  - ? non-structural intervention: on-the-job training subsidies for workers in FTC
  - ? structural reform: single contract with increasing firing costs

THANK YOU

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APPENDIX

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 2×450 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).

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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.

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Actual experience, % of potential experience	$\geq$0%	$\geq$50%	$\geq$80%	$\geq$90%	=100%
	(1)	(2)	(3)	(4)	(5)
Current FTC	-0.0370***	-0.0418***	-0.0540***	-0.0611***	-0.0716***
	(0.0009)	(0.0012)	(0.0018)	(0.0024)	(0.0059)
Share of Experience FTC	-0.1984***	-0.1670***	-0.1348***	-0.1233***	-0.1001***
	(0.0023)	(0.0030)	(0.0041)	(0.0050)	(0.0076)
Observations	1,954,097	1,235,490	636,241	411,096	183,045
R-squared	0.3047	0.2899	0.2751	0.2621	0.2305

back

Firm Heterogeneity

	Baseline Sample	Matched Sample	
	(1)	(2)	(2) + Firm FE
Experience OEC	0.0500***	0.0575***	0.0541***
	(0.0005)	(0.0011)	(0.0009)
Experience FTC	0.0421***	0.0440***	0.0431***
	(0.0006)	(0.0013)	(0.0011)
Gap in Returns (%)	18.52***	30.50***	25.71***
	(1.05)	(2.21)	(1.83)

back

Match Quality

	Altonji and Shakotko (1987)		(1) (2) & Subsidies availability	
	(1)	(2)	(3)	(4)
Experience OEC	0.0435***	0.0462***	0.0434***	0.0474***
	(0.0009)	(0.0035)	(0.0009)	(0.0035)
Experience FTC	0.0345***	0.0297***	0.0345***	0.0311***
	(0.0012)	(0.0038)	(0.0011)	(0.0038)
Gap in Returns (%)	26.14***	55.40***	26.08***	52.73***
	(1.96)	(8.46)	(1.95)	(7.70)

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Robustness to Life-Cycle Controls

	Cubic Potential Exp.	Excl. Potential Exp	Age Effects
	(1)	(2)	(3)
Experience OEC	0.0513***	0.0456***	0.0481***
	(0.0005)	(0.0005)	(0.0005)
Experience FTC	0.0432***	0.0393***	0.0414***
	(0.0006)	(0.0006)	(0.0006)
Observations	1,954,097	1,954,097	1,954,097
R-squared	0.3152	0.3080	0.3089

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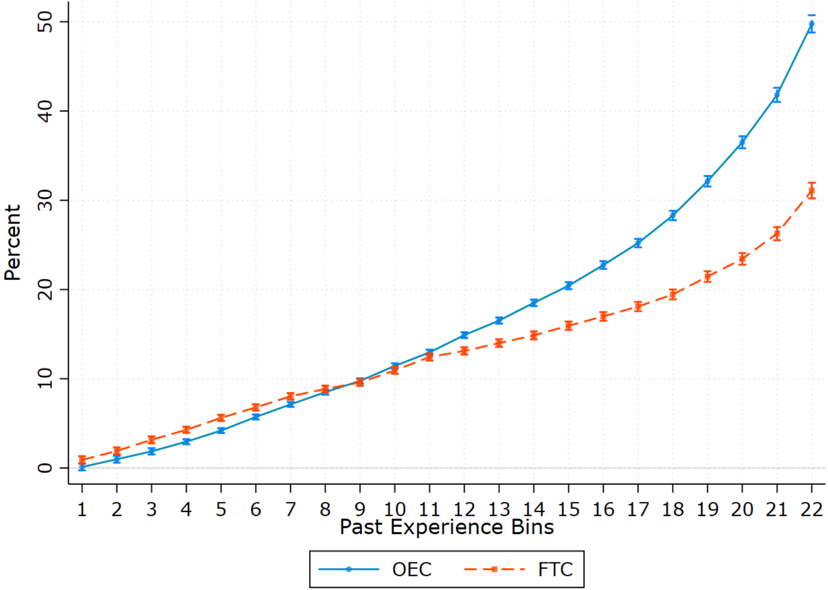
Robustness to Non-Parametric Experience



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Robustness to Wage Concept

	Censored	Tax Data	Pooled Income
Experience OEC	0.0398***	0.0474***	0.0495***
	(0.0004)	(0.0006)	(0.0005)
Experience FTC	0.0370***	0.0410***	0.0439***
	(0.0006)	(0.0007)	(0.0006)
Observations	1,954,097	1,508,948	1,954,097
R-squared	0.3112	0.2306	0.2685

back

Robustness to Contract-Specific Return to Tenure

	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Experience OEC	0.0355***	0.0355***	0.0498***	0.0502***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Experience FTC	0.0202***	0.0201***	0.0431***	0.0433***
	(0.004)	(0.0004)	(0.0006)	(0.0006)
Observations	1,954,097	1,954,097	1,954,097	1,954,097
R-squared	0.6338	0.6344	0.3038	0.3066

back

Robustness to Cohort Analysis

	Graduation year cohorts			
	1996	1997	1998	1999
Experience OEC	0.0487***	0.0513***	0.0522***	0.0537***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Experience FTC	0.0417***	0.0450***	0.0448***	0.0450***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Observations	153,943	157,732	159,666	160,648
R-squared	0.3053	0.2997	0.2991	0.3038

back

Robustness to Impact of 2012 EPL Reform

	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Experience	0.0295***		0.0540***	
	(0.0004)		(0.0005)	
Experience $\times$ $\mathbf{1}[t \geq 2012]$	-0.0003		-0.0050***	
	(0.0003)		(0.0003)	
Experience OEC		0.0350***		0.0527***
		(0.0005)		(0..0005)
Experience OEC $\times$ $\mathbf{1}[t \geq 2012]$		-0.0002		-0.0028***
		(0.0004)		(0.0003)
Experience FTC		0.0223***		0.0509***
		(0.0005)		(0.0007)
Experience FTC $\times$ $\mathbf{1}[t \geq 2012]$		-0.0024***		-0.0115***
		(0.0004)		(0.0004)
Observations	1,947,938	1,947,938	1,947,938	1,947,938
R-squared	0.6331	0.6344	0.3061	0.3071

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Firm-cluster fixed-effects as in BLM (2021)

	Baseline Sample	BLM Restricted Sample			
	(1)	(2)	(3)	(4)	(5)
Experience OEC	0.0500***	0.0575***	0.0570***	0.0562***	0.0564***
	(0.0005)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Experience FTC	0.0421***	0.0440***	0.0448***	0.0444***	0.0446***
	(0.0006)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Gap in Returns (%)	18.51***	30.50***	27.18***	26.45***	26.43***
	(1.05)	(2.21)	(2.05)	(2.05)	(2.03)
Observations	1,954,097	456,364	456,364	456,364	456,364
R-squared	0.3064	0.2372	0.2212	0.2180	0.2174
Firm-clusters	NO	NO	$K = 5$	$K = 50$	$K = 100$

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Econometric Model: Accounting for Experience Levels

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

- $Q = \{\{0\}, (0,4], (4,7], (7,10], (10,15], ..., (95,97], (97,100]\}$
- m are groups defined according to share of experience accumulated on FTC
  - *low* (ratio lower than 0.3), *medium* (between 0.3 and 0.9) and *high* (above 0.9)

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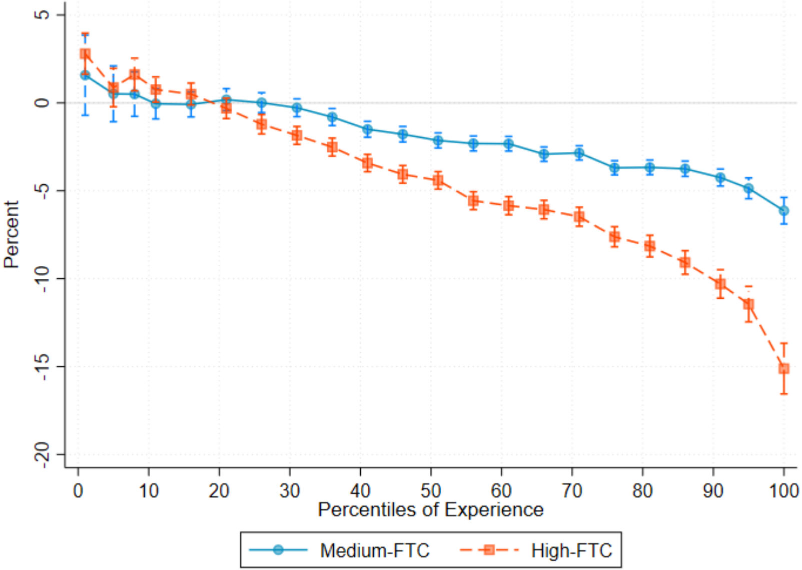
Human Capital Channel: Experience Level



[MODEL] [CONT. EMPLOYMENT] back

Portability of Human Capital and Skill Composition of Industries

	FE (1)	FE + Heckman (2)
Distance	-0.0651***	-0.0638***
	(0.0046)	(0.0046)
Experience OEC	0.0499***	0.0452***
	(0.0008)	(0.0009)
Experience FTC	0.0371***	0.0355***
	(0.0010)	(0.0010)
Experience OEC $\times$ Distance	-0.0067***	-0.0074***
	(0.0014)	(0.0014)
Experience FTC $\times$ Distance	0.0032**	0.0033**
	(0.0014)	(0.0014)
Inverse Mills Ratio		0.0477***
		(0.0022)
Average distance	0.1926	
Maximum distance	0.8277	

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Portability of Human Capital for Involuntary Movers

	All	Within Industries	Across Industries
	(1)	(2)	(3)
Experience OEC	0.0428***	0.0444***	0.0355***
	(0.0011)	(0.0017)	(0.0020)
Experience FTC	0.0353***	0.0323***	0.0357***
	(0.0013)	(0.0020)	(0.0023)
Gap in Returns (%)	21.17***	37.62***	-0.72
	(3.03)	(5.41)	(5.09)
Observations	307,637	161,468	146,169
R-squared	0.3238	0.3004	0.3381

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Econometric Model: Human Capital and Unobserved Ability

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

- 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 (42) 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

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