Urban Elevators and the Geography of Labor Market Polarization

Fabio Cerina* Elisa Dienesch†
Alexander Monge-Naranjo‡ Alessio Moro§

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Abstract

Large cities gain abstract jobs and shed routine jobs faster than small ones. Whether this divergence arises because workers move across locations or because workers' labor market careers differ across locations matters for welfare and policy, and cross-sectional data cannot tell the two apart. Using the French administrative panel DADS–EDP (1984–2021), we decompose the change in each occupation's employment share, by city size, into within-city occupational switches, cross-city relocation, combined moves, and non-employment flows. The divergence is produced inside cities. We find that large cities move workers from routine to abstract jobs at twice the rate of small cities, and this flow more than accounts for the urban gap in abstract employment. The routine decline is absorbed by upgrading into abstract work, not by downgrading into manual services. This urban elevator predates the 1994 onset of French polarization and operates within occupations: holding worker characteristics and the occupation of origin fixed, staying in a large city raises the rate of upgrading by about 40%, for college and non-college workers alike. The evidence places the burden of explanation on agglomeration forces that act on occupational mobility within cities rather than on the sorting of heterogeneous workers across them.

Keywords: *Spatial polarization; Urban elevator; Worker flows; Spatial sorting; Occupational mobility; Longitudinal data.*

JEL Codes: J62, J24, R11, R23.

* University of Cagliari and CRENoS.
† University of Cagliari, CRENoS, and AMSE.
‡ Federal Reserve Bank of Atlanta, Emory University, and CEPR.
§ University of Cagliari, CEPR and IZA@LISER.

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1 Introduction

Large cities polarize faster than small ones. In the United States, large metropolitan areas have lost middle-paid jobs faster and gained upper-tier jobs faster than smaller labor markets (Moretti, 2012; Autor, 2019; Cerina et al., 2023; Eeckhout et al., 2026), and Davis et al. (2026) document the same divergence for France over 1994–2015. This cross-sectional evidence, however, is silent about the spatial mechanics behind it. This divergence is known as the 'urban elevator,' and it can arise through two mechanisms. One mechanism is that workers move across space: high-skill workers relocate into large cities, low-skill service workers follow, and the occupational mix of each city changes with who lives there, as in models in which a city's skill and occupational composition is determined by the sorting of workers across locations (Eeckhout et al., 2014; Diamond, 2016; Davis and Dingel, 2020; Parkhomenko, 2025; Eeckhout et al., 2026). An alternative mechanism is that workers switch occupations: routine workers in large cities upgrade into abstract jobs, or downgrade into manual ones, at a higher rate than in small cities, and the mix changes with what residents do, as in routinization accounts (Autor and Dorn, 2013; Autor, 2019).[1] These two mechanisms are not mutually exclusive, but their relative weight matters for welfare and for policy. If the gap is produced by occupation switching, the relevant margins are the pace and composition of occupational transitions within exposed cities: training, transition assistance, and local skill formation. If it is produced by spatial reallocation, the central issues are housing access in destination cities, regional inequality, and the amenity gap between large and small labor markets.

Separating these two mechanisms requires following the same workers across occupations and across cities. We use the French administrative panel DADS–EDP, which tracks about 1.9 million salaried workers, in the private and public sectors, over 1984–2021. Building on the worker-flow accounting of Cerina et al. (2026), we decompose the change in each occupation's employment share, separately in large and small cities, into four channels: (i) net flows between occupations within the same city group; (ii) relocation across city groups within the same occupation; (iii) combined moves that change both occupation and city group; and (iv) net flows in and out of non-employment. The decomposition is exact: the four channels exhaust the change in every occupation-by-city share in every year. The sorting account predicts that channels (ii) and (iii) carry the urban divergence; the switching account predicts that channel (i) does.

We find that occupational switching within cities accounts for most of the observed spatial divergence. Between 1984 and 2021, over the years covered by the decomposition, the gap between the abstract shares of large and small cities widened by 7.6 percentage points. Occupational switches by workers who stay in the same group of cities contribute

[1] The polarization literature is surveyed in Acemoglu and Autor (2011); see also Autor et al. (2006) and Goos et al. (2014).

10.6 points, more than the whole gap; non-employment flows offset 2.9 points, and the relocation of employed workers, with or without a change of occupation, contributes essentially nothing. Within-city switches also contribute more than the whole gap in the routine share. Within cities, one flow makes the difference: large cities move workers from routine to abstract jobs at roughly twice the rate of small cities, 0.63 against 0.35 percentage points of employment a year, and this flow drives the gap in both shares. We call this amplification of within-city occupational upgrading by city size the *urban elevator*. Its direction matters as much as its size. The urban routine decline is absorbed by upgrading into abstract work, not by downgrading into manual services. This runs counter to the US narrative in Autor (2019), in which the within-commuting-zone decline of middle-skill routine work is absorbed by the reallocation of non-college workers down to low-paid services. In France, the elevator runs up.

However, these data do not rule out sorting across cities. It happens before careers begin, and it leaves unchanged the occupational mix of the cities workers join, the margin through which the sorting account produces the divergence. The decomposition follows workers from age 25, when the annual cross-city move rate has fallen to 5.4%, from a peak of 8.9% at ages 19 and 20. Before then, workers do sort: one fifth of those entering employment in a large city held their first job in a small one, against about one in seven of those entering a small city in the opposite direction, and they are drawn disproportionately from the educated. What they do not bring is a different occupational mix. They enter in the occupational proportions of the city they join, matching it more closely than its other entrants do, so that their arrival changes the city's size and not its composition. Their subsequent advantage, moreover, comes mostly from the large city itself. With worker-level controls and year effects, routine workers who stay in a small city move into abstract jobs at 2.24% a year, and staying in a large city raises this rate by 1.36 percentage points. Workers who moved from a small to a large city before 25 gain a further 0.47 points: of their 1.83-point advantage over small-city stayers, three quarters come from the city and a quarter from the move.

Two further results characterize the elevator. First, it is a long-standing feature of the French urban system rather than a product of the polarization era. Cerina et al. (2026) date the onset of French polarization to 1994, when the routine share, flat over the previous decade, begins to fall. The break arrives in large and small cities alike, and the within-city routine-to-abstract flow already runs at 2.4 times the small-city rate in the decade before it, against 1.6 times afterwards. Second, the elevator works within occupations and for college and non-college workers alike. Holding gender, age and tenure fixed, staying in a large city raises the annual probability of a routine-to-abstract move from 6.2% to 9.3% for college workers and from 2.0% to 3.3% for non-college workers. However, about two fifths of the urban premium is explained by the different mix of routine occupations in large cities: among workers who start from the same occupation, the large city raises the

rate of upgrading by about 40% in both education groups.

Three qualifications are in order. First, the decomposition identifies the channel, not the force behind it. Thicker local labor markets, faster learning on the job (Baum-Snow and Pavan, 2012; De la Roca and Puga, 2017), and a denser supply of abstract-task employers are each consistent with the rates we observe, and a spatial-equilibrium model in which abstract jobs are created in large cities and filled locally predicts the within-city flow we document (Davis et al., 2026). What the evidence rules out is the relocation of employed workers after age 25 as the route through which the divergence is produced. Second, one might object that France is a low-mobility country, so that small cross-city channels are to be expected: only 5.9% of employed workers change *aire urbaine* in a given year, and 2.3% cross the large–small boundary. Low mobility alone, however, is unlikely to deliver the result. The occupational composition of movers is not distinctive, so that, as long as it does not change with the rate of mobility, flows twice as large would still leave the abstract share of either city group essentially unchanged. Third, our results concern France. Whether the US routine decline is absorbed by upgrading rather than downgrading remains open, and settling it would require a comparable worker-level panel.

Our contribution lies at the intersection of three literatures. The first documents the urban divergence in polarization (Moretti, 2012; Autor, 2019; Cerina et al., 2023; Parkhomenko, 2025; Davis et al., 2026; Eeckhout et al., 2026). We complement the cross-sectional evidence for France in Davis et al. (2026) by identifying the worker flows behind it; our longer sample and broader occupational coverage, which includes the public sector, reproduce their routine and abstract patterns.[2] The second is the flows approach to routine-job decline (Cortes, 2016; Cortes et al., 2017, 2020). We extend the worker-flow accounting of Cerina et al. (2026) to a city-size dimension, integrating cross-city relocation and combined occupation-and-city switches alongside within-city switches and non-employment flows into a single decomposition that exhausts the change in each occupation-by-city share. The third asks whether the advantages of large cities reflect the sorting of workers or the experience of working there. Combes et al. (2008) attribute most of the French spatial wage gap to sorting on worker ability, while Gould (2007), De la Roca and Puga (2017), and Eckert et al. (2022) document a return to big-city experience that workers carry with them. Our evidence places the occupational dimension of the urban divergence in the second camp: large cities are escalators for occupation as well as for wages, in the sense of Fielding (1992), and the escalator belongs to the city.

The remainder of the paper proceeds as follows. Section 2 describes the DADS–EDP sample and the large/small classification by city size. Section 3 formalizes the decomposition. Section 4 reports the aggregate spatial shares, the eight-state flow decomposition,

[2]The two samples diverge on the manual margin over sub-periods, plausibly because their DADS-Postes data exclude public-sector employment. Appendix D compares their wage-ranked classification with our task-based one; all qualitative results are robust to reclassifying the two CS2 codes on which the schemes differ.

the 1994 break, the *aire urbaine*-level mobility analysis, and the education cut. Section 5 concludes.

2 Data and Definitions

We use the Déclaration Annuelle des Données Sociales – Échantillon Démographique Permanent (DADS–EDP), a French matched employer–employee administrative panel covering both private- and public-sector salaried employment (*tous salariés*). Restricting the sample to workers aged 25–64, the panel covers roughly 1.9 million workers over 1984–2021. Each worker is observed annually with main occupation (two-digit PCS code, hereafter CS2),[3] employer location, gross and net wages and, from 2002 onward, education.

We classify employed workers into three task-based occupation groups: *Manual* (M; CS2 $\in \{10, 53, 55, 56, 64, 68, 69\}$), *Routine* ($R$; CS2 $\in \{42, 43, 45, 46, 48, 52, 54, 62, 63, 65, 67\}$) and *Abstract* ($A$; CS2 $\in \{23, 31, 33, 34, 35, 37, 38, 47\}$); workers without a recorded employment spell are classified as non-employed (NE).[4] The mean-wage ranking $A > R > M$ holds in every benchmark year (Appendix A.4).

We classify each worker's *aire urbaine* (AU) into Large (L) or Small (S) by a median-employment split, applied as a time-invariant indicator to all years: AUs are ranked by their 2003 employment, and the Large group is the smallest set of top-ranked AUs accounting for at least half of employment. We rank AUs in 2003, the first year after the 2002 doubling of the panel, so that the boundary of the Large group is set on the largest available cross-section; the fifteen largest AUs (Paris, Lyon, Marseille, Lille, Toulouse, Bordeaux, Strasbourg, Nantes, Nice, Grenoble, Rennes, Rouen, Avignon, Orléans, Douai-Lens) are Large under any reference year, and the choice of year only moves a handful of boundary AUs, each about one percent of Large-group employment (Appendix A.1). The resulting Large group contains 21 AUs, and its employment share stays within 50.2–53.1% throughout 1984–2021 (Appendix A.2). During non-employment spells, the AU is imputed by forward and then backward fill from the worker's records with an observed employer location, with priority to the most recent pre-spell location, so that every worker-year in the sample carries a city group (Appendix A.6). The Large/Small split is therefore defined on employment and inherited, not imposed, for NE.

Two features of the data require special treatment. First, the 2002 and 2006 EDP expansions introduce discontinuities in year-to-year flow counts; the transition pairs $(2001, 2002)$ and $(2005, 2006)$ are excluded from all flow decompositions. Second, because 1990 is absent

[3] For worker-years with positive wage but no recorded CS2 code (concentrated in the civil service before 2009), we use the layered imputation procedure of Cerina et al. (2026), summarized in Appendix A.5: 97.8% of cases are resolved from the worker's own occupation history and the remainder by a classifier; the imputed occupation group matches the observed one in 90% of a holdout sample.

[4] DADS records salaried employment only, so non-employment also includes self-employment. For France as a whole, Cerina et al. (2026) show that flows into and out of self-employment cannot by themselves account for the behavior of the non-employment channel.

from DADS, the year-pair $(1989, 1991)$ spans two years; its flow contribution is halved to obtain annual-equivalent rates. Full sample restrictions, demographic-imputation rules, and the AU classification mapping are documented in Appendix A.

3 Empirical Framework

We adopt the accounting framework of Cerina et al. (2026), extended to track cross-city flows alongside within-city occupational switches and non-employment transitions.

We classify workers each year along two dimensions: occupation ($k \in \{M, R, A, NE\}$) and city size ($g \in \{S, L\}$). The cross of the two dimensions defines an eight-state space, with six employed states (the 3×2 occupation-by-city-size employed cells) and two non-employed states (NES and NEL). The city-group assignment g for a worker-year in non-employment is inherited from the AU imputation rule of Section 2: each NE year takes the L/S classification of the worker's nearest observed employment spell. For each year-pair $(t-1, t)$, $N_{(j,h),(k,g)}(t)$ denotes the number of workers in state (j, h) at $t-1$ and in state (k, g) at t. Cross-sectional counts $N_{k,g}(t)$ and $N_{\text{emp},g}(t) = \sum_k N_{k,g}(t)$ are computed on all workers aged 25–64 observed in year t, not only on those matched across the two dates. The within-employment share of occupation k in city group g is

$$E_{k,g}(t) \;=\; \frac{N_{k,g}(t)}{N_{\text{emp},g}(t)}, \qquad k \in \{M, R, A\}, \;\; g \in \{S, L\}, \tag{1}$$

with $\sum_k E_{k,g}(t) = 1$ for each g.

Employed-to-employed transitions $N_{(j,h),(k,g)}$ for $(j, h), (k, g)$ both employed and exits to non-employment $N_{(k,g),0}$ are observed directly in the matched panel. Entries from non-employment $N_{0,(k,g)}$ are instead recovered from the cross-sectional accounting identity, because a worker's first appearance in a job cannot be distinguished from a genuine transition out of non-employment: a worker observed for the first time in occupation k may have been non-employed, or simply outside the panel, in the previous year. Since the stocks are computed on the full cross-section, the identity attributes to entries whatever part of the change in $N_{k,g}$ is not explained by observed employed-to-employed flows and observed exits:

$$N_{0,(k,g)}(t) \;=\; \Big[N_{k,g}(t) - N_{k,g}(t-1)\Big] \;-\; \mathcal{F}_{(k,g)}(t) \;+\; N_{(k,g),0}(t), \tag{2}$$

where $\mathcal{F}_{(k,g)}(t) = \sum_{(j,h)\neq(k,g),\,(j,h)\in\mathcal{E}} \Big[N_{(j,h),(k,g)} - N_{(k,g),(j,h)}\Big]$ is the net employed-to-employed inflow into (k, g) from all other employed states. Boundary flows for workers aging in at 25 and aging out at 65 are treated on the same footing as entries from and exits to non-employment.

We split $\mathcal{F}_{(k,g)}$ according to whether each contributing transition keeps the city group,

keeps the occupation, or changes both:

$$F^{w}_{k,g}(t) \;=\; \sum_{j\neq k,\, j\in\{M,R,A\}} \Big[N_{(j,g),(k,g)}(t) - N_{(k,g),(j,g)}(t)\Big], \tag{3}$$

$$F^{r}_{k,g}(t) \;=\; N_{(k,h),(k,g)}(t) - N_{(k,g),(k,h)}(t), \quad h \neq g, \tag{4}$$

$$F^{c}_{k,g}(t) \;=\; \sum_{j\neq k,\, j\in\{M,R,A\}} \Big[N_{(j,h),(k,g)}(t) - N_{(k,g),(j,h)}(t)\Big], \quad h \neq g, \tag{5}$$

so that $\mathcal{F}_{(k,g)} = F^{w}_{k,g} + F^{r}_{k,g} + F^{c}_{k,g}$. $F^{w}_{k,g}$ is the within-city net flow (workers switching occupation but staying in the same city group); $F^{r}_{k,g}$ is the relocation net flow (workers keeping their occupation but changing city group, the margin emphasized by spatial-sorting accounts); $F^{c}_{k,g}$ is the combined net flow (workers who both switch occupation and change city group). The bilateral within-city contribution from occupation j to state (k,g) is the corresponding term in the $F^{w}_{k,g}$ sum,

$$F^{w,\,j}_{k,g}(t) \;=\; N_{(j,g),(k,g)}(t) - N_{(k,g),(j,g)}(t), \tag{6}$$

so that $F^{w}_{k,g} = \sum_{j\neq k} F^{w,\,j}_{k,g}$; Section 4.2 reports these bilateral pieces (M→R, R→A, M→A) separately to identify which occupational pair drives the spatial differential.

The non-employment channel for (k,g) captures the contribution of flows between (k,g) and non-employment, net of what would be expected if those flows maintained the existing share:

$$\text{Excess_NE}_{k,g}(t) \;=\; \Big[N_{0,(k,g)}(t) - N_{(k,g),0}(t)\Big] \;-\; E_{k,g}(t)\,\Delta N_{\text{emp},g}(t). \tag{7}$$

The benchmark term $E_{k,g}(t)\,\Delta N_{\text{emp},g}$ is the net NE inflow that would leave the share of (k,g) unchanged when the city group's employment grows or shrinks: a positive $\text{Excess_NE}_{k,g}$ therefore means non-employment flows are enlarging the share of (k,g) beyond what neutral scaling would deliver, and a negative value means they are eroding it.

The change in the within-employment share of (k,g) decomposes as

$$\Delta E_{k,g}(t) \;=\; \frac{F^{w}_{k,g}(t) + F^{r}_{k,g}(t) + F^{c}_{k,g}(t) + \text{Excess_NE}_{k,g}(t)}{N_{\text{emp},g}(t-1)}. \tag{8}$$

The relative magnitudes of the four channels across Large and Small cities are the central object of interest. F^{w} is the empirical signature of within-city occupational reallocation, while F^{r} and F^{c} jointly capture the spatial-sorting margin. All flow magnitudes in Section 4 are simple-year-averages of annual rates over the relevant year-pairs (to avoid overweighting the post-expansion years).

4 Spatial Flow Decomposition

We apply the framework of Section 3 and report the four-channel decomposition of $\Delta E_{k,g}$ for each occupation-by-city cell.

4.1 Employment Shares by City Group

Figure 1 displays within-employment occupation shares separately for Large and Small cities. The Abstract gap widens substantially: Large cities have a higher Abstract share throughout, and the gap roughly doubles from +7.2 pp in 1984 to +15.0 pp in 2021. The Routine gap widens in the opposite direction: Large cities start with a lower Routine share (−4.4 pp in 1984) and the gap reaches −11.0 pp by 2021, so the Routine decline, the defining feature of polarization, is spatially concentrated in large cities, mirroring the US pattern documented by Cerina et al. (2023). The 1994 break is more pronounced in small cities, where the Routine share was approximately flat before 1994 (71.4% in 1984, 71.0% in 1994), than in large cities, where the share was already declining over the same period (66.9% to 64.4%). The Manual gap remains negative throughout (−2.8 pp in 1984, −4.1 pp in 2021) but the pace of divergence differs across sub-periods: pre-1994 the Manual share fell faster in Large cities than in Small (gap widening from −2.8 to −3.7 pp), while from 1994 onward Manual expands in both groups with the gap widening only modestly (−3.7 to −4.1 pp over 27 years).[5]

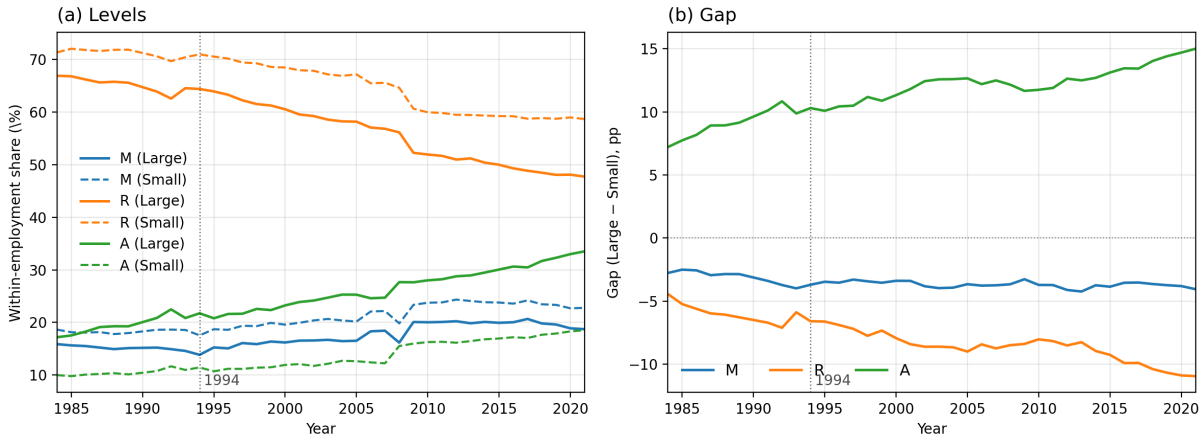


Figure 1: Within-employment occupation shares by city group, 1984–2021. Panel (a): solid lines for Large cities, dashed for Small. Panel (b): gap (Large − Small) in percentage points.

[5] Davis et al. (2026) report that Manual grows slower in Large cities over 1994–2015. In percentage points our extended sample agrees; in proportional terms Manual expands somewhat more in Large cities (+35% vs +30% over 1994–2021), plausibly because their DADS-Postes sample excludes the public-sector employment we include. Appendix D compares their wage-ranked occupational classification with our task-based one; all qualitative results are robust to reclassifying the two CS2 codes on which the schemes differ.

4.2 The Four-Channel Decomposition

Table 1 reports the four-channel decomposition of equation (8) for each of the six employed states (k, g), averaged over the full period. The columns report, in order, the within-city net flow $F^w_{k,g}$, the relocation net flow $F^r_{k,g}$, the combined net flow $F^c_{k,g}$, the Excess_NE channel $\text{Excess_NE}_{k,g}$, and the resulting $\Delta E_{k,g}$.

Table 1: Mean annual $\Delta E_{k,g}$ decomposition (pp/year), full period 1984–2021

State	**Within city group** $F^w_{k,g}$	**Relocation** $F^r_{k,g}$	**Combined** $F^c_{k,g}$	**Excess_NE**	$\boldsymbol{\Delta E}$
M-S	−0.12	−0.02	+0.00	+0.18	+0.04
M-L	−0.19	+0.02	−0.01	+0.20	+0.03
R-S	−0.26	+0.02	−0.02	−0.04	−0.30
R-L	−0.49	−0.02	−0.03	+0.05	−0.50
A-S	+0.38	−0.00	+0.04	−0.16	+0.26
A-L	+0.68	+0.00	+0.03	−0.24	+0.47

Notes: Values ×100 (pp/year). Within a city group the F^w column and the ΔE column each sum to zero by construction, as do the three remaining channels taken together. Channels are defined in equations (3)–(7).

The within-city net flow channel $F^w_{k,g}$ accounts for the bulk of $\Delta E_{k,g}$ outside the Manual states, and operates at roughly double intensity in large cities: it drives Routine down by −0.49 pp in Large cities versus −0.26 pp in Small (1.86×), and pushes Abstract up by +0.68 pp in Large versus +0.38 pp in Small (1.78×). The cross-city channels $F^r_{k,g}$ and $F^c_{k,g}$, by contrast, are below 0.05 pp in absolute value on every cell. The Large–Small gap in Abstract growth (+0.21 pp/year in ΔE) reflects a +0.30 pp/year gap in within-city flows, partly offset by a larger non-employment drain in Large cities (−0.08 pp/year), while the cross-city channels contribute essentially nothing (−0.01 pp/year): less than 5% of the Abstract urban divergence comes from the relocation of workers who are already employed. Summed over the year pairs the decomposition covers, the Large–Small gap in Abstract growth amounts to 7.6 percentage points: the within-city channel contributes 10.6 points, non-employment −2.9, and the cross-city channels essentially nothing. Across year pairs the within-city gap is about nine times its standard error, while the cross-city gap cannot be distinguished from zero (Appendix B.7). The conclusion does not rest on the annual horizon. Measured between endpoints three and five years apart, where a worker who moves and later switches occupation counts as a combined move, the within-city channel still accounts for the whole Large–Small gap in Abstract growth and the cross-city channels stay at or below zero (Appendix B.6). The spatial dimension of polarization is overwhelmingly local. Most moves between *aires urbaines* stay inside a city group and are therefore absorbed into F^w; Section 4.4 shows that they behave like same-AU transitions.

Bilaterally (Appendix B.4), the within-city $R \to A$ net flow runs at 0.63 pp/year in Large cities and 0.35 in Small, the dominant channel behind the spatial differential in both Routine and Abstract. The within-city $M \to R$ net flow is secondary (0.09 pp/year in Small, 0.14 in Large), and the direct $M \to A$ net flow is small (0.03 in Small, 0.05 in Large): large cities offer some direct upgrading paths that bypass Routine, but the magnitude is too small to alter the conclusion that the urban elevator runs predominantly through Routine-to-Abstract upgrading. The spatial pattern of the non-employment channel differs across occupations. Manual benefits from non-employment inflows in both city groups (+0.18 in Small, +0.20 in Large); Abstract loses to non-employment more than its share would predict, more so in large cities (−0.24 versus −0.16). Routine's full-sample Excess_NE is small in level but flips sign across groups (−0.04 in Small, +0.05 in Large): non-employment erodes Routine in Small cities while sustaining it in Large. The Large–Small differential on the Routine NE channel (about 0.08 pp) is in fact comparable in magnitude to Abstract's, even though the levels are several times smaller. As we show next, this Routine sign-flip masks a regime change at 1994 that runs in opposite directions before and after the break. Figure B.1 in Appendix B.4 displays the same decomposition graphically.

4.3 The Urban Elevator and the 1994 Break

Cerina et al. (2026) document that French labor-market polarization is concentrated in time: between 1984 and 1993 the Routine share is flat ("pre-polarization"), while from 1994 onward the Routine share falls sharply ("polarization"). The same paper identifies three flow-level components of the 1994 break: a sign flip in the non-employment channel for routine, a weakening of the within-city manual-to-routine buffer, and an acceleration of non-employment entry into manual. This raises two distinct questions for the spatial decomposition. First, is the 1994 break itself urban-driven, rural-driven, or both? Second, does the urban elevator on routine-to-abstract upgrading appear before the break, or is it a polarization-era phenomenon? Figure 2 applies the four-channel decomposition separately to the pre-polarization (1984–1993) and polarization (1994–2021) sub-samples.

The three components of the 1994 break each shift in both city groups, but with consistent and revealing asymmetries. The Excess_NE$_R$ sign flip, from positive (non-employment flows sustaining Routine) to negative (non-employment flows draining it), is more pronounced in Small cities: the swing between 1984–1993 and 1994–2021 is −0.39 pp in Small versus −0.29 pp in Large. The within-city manual-to-routine buffer weakens by a comparable amount in both groups (−0.08 pp in Small, −0.13 pp in Large), and the non-employment-to-manual entry channel accelerates by +0.23 pp in Small and +0.19 pp in Large. Taken together, Small cities are the more affected side of the 1994 break on every routine channel except the within-city manual-to-routine buffer.

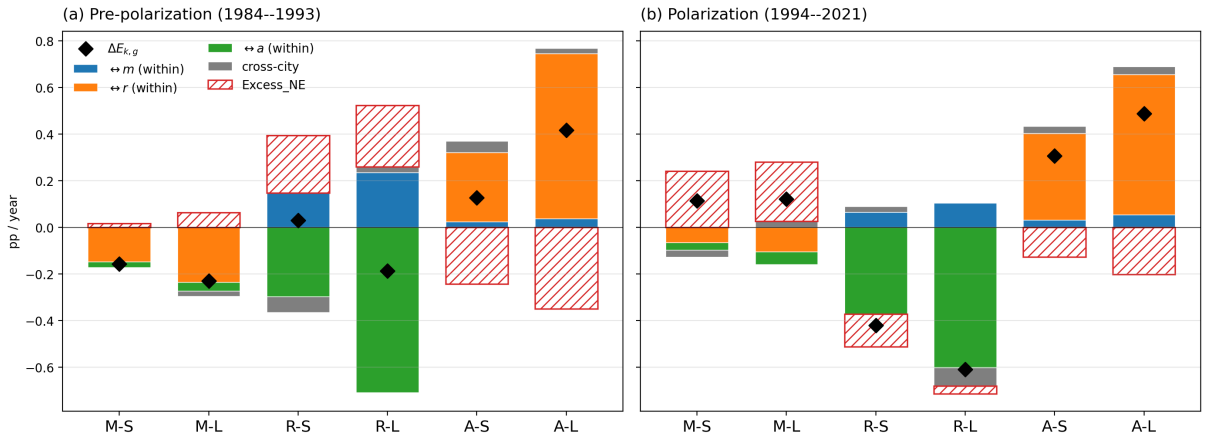


Figure 2: Spatial flow decomposition by sub-period, pre-polarization (1984–1993) and polarization (1994–2021), in pp/year. For each state (k, g), the stacked bar decomposes $\Delta E_{k,g}$ into the three within-city bilateral components of $F^w_{k,g}$, the aggregate cross-city contribution $F^r_{k,g} + F^c_{k,g}$, and the Excess_NE channel Excess_NE$_{k,g}$. Diamond: total $\Delta E_{k,g}$.

The within-city $R \to A$ flow in Figure 2 is present at substantial intensity in both panels but moves in opposite directions across 1994: it *rises* in Small cities, from 0.30 pp/year in 1984–1993 to 0.37 pp/year in 1994–2021, and *falls* in Large cities from 0.71 pp/year to 0.60 pp/year. The Large to Small ratio of the within-city routine-to-abstract flow therefore narrows across the break (from about 2.4× pre-polarization to about 1.6× afterwards), although the flow itself remains several times larger than any cross-city channel in either regime. This opposite-direction movement of the $R \to A$ flow across city groups is why the growth of the Abstract share speeds up by more in Small cities, +0.18 pp/year against +0.07 pp/year in Large: the urban gap in Abstract growth narrows across the break without closing. The urban elevator on routine-to-abstract upgrading is thus not a polarization-era phenomenon: it was already operating at full strength in the pre-polarization era, when the aggregate Routine share was flat, although its intensity in Large cities does adjust modestly downward at the break. Spatial heterogeneity adds a *level effect* to polarization (the urban elevator amplifies routine-to-abstract upgrading by a factor of 1.6 to 2.4 throughout the sample) and a mild directional asymmetry to the 1994 break in routine channels, but does not alter the timing of polarization.[6]

4.4 Mobility Across *Aires Urbaines*

The decomposition treats city size as a binary attribute: a move between two Small AUs, or between two Large AUs, is classified as within-city-group and absorbed into F^w. This subsection uses the finer AU identifier to ask how much spatial mobility the binary split actually collapses, and whether the collapsed moves behave differently. Among

[6]The full sub-period decomposition by city group, including a finer split of the polarization era into 1994–2008 and 2009–2021, is reported in Appendix B.5.

employed-to-employed transitions, 94.1% of workers remain in the same AU from one year to the next. Of the 5.9% who change AU, 44.7% move between two Small AUs, 15.7% between two Large AUs, and 39.7% cross the Small–Large boundary; even the largest within-group category (moves between Small AUs) affects only 2.6% of employed workers per year.

Decomposing each occupation switch into six spatial channels (Appendix B.8) shows that occupation transitions are overwhelmingly local. Of all $R \to A$ switches, 84.7% occur without a change of AU, 8.3% move between two AUs of the same size group, and 6.9% cross the Small–Large boundary; 55.3% of all upgrades take place inside a Large AU against 29.4% inside a Small one. The moves between AUs of the same size group are the ones the binary split absorbs into F^w, and they behave like same-AU transitions, so the binary treatment does not distort the channel. Boundary crossings are small and nearly offsetting, 3.6% of upgrades moving $S \to L$ against 3.3% moving $L \to S$.

Interestingly, what distinguishes Large cities is where their workers switch to, not how often they switch. Within the same AU, Routine workers move to Abstract at 4.25% a year in Large cities against 2.13% in Small ones, twice the rate and inside the 1.6–2.4 band the decomposition reports for F^w. The contrast is a gradient in city size rather than a Paris effect. Within the same AU, the Routine-to-Abstract rate falls from 5.4% a year in Paris to 3.3% in the other Large AUs, 2.5% in the next tier of urban areas, 1.9% in the smallest ones and 1.7% outside urban areas, and the ordering survives when every class is given the same mix of routine origin occupations (Table B.12). By contrast, their moves to Manual run at 2.81% within Large AUs against 2.43% within Small ones. Manual workers show the same asymmetry, and Abstract workers leave for Routine or Manual slightly less often in Large cities than in Small ones (Table B.11). These data confirm that the urban advantage falls on entry into abstract work rather than on occupational mobility at large. All in all, the urban elevator operates almost entirely *within* cities: very little between cities of the same group and even less *across* city groups.

The preceding conclusion is drawn from transitions among workers aged 25 to 64 and is silent on mobility at earlier ages. Should workers sort into Large cities before entering the labor market, the cross-city channels could remain small among the employed while sorting nonetheless accounted for the urban divergence. Mobility at those ages is indeed higher: the cross-city rate peaks near 9% at ages 19 and 20, falls to 5.4% at 25 and averages 2.4% between 30 and 45, and one fifth of the workers entering a Large city had held their first job in a Small one, against about one in seven of those entering a Small city in the opposite direction. Their occupational composition at entry, however, is not distinctive. They resemble the city they enter more closely than its other entrants do (Table 2), and their contribution to its non-employment channel does not exceed 0.03 pp on any cell. Appendix B.9 reports that, had they remained, their Abstract share would have stood below the Small-city average. Section 4.5 attributes the greater part of their subsequent

advantage to the city they enter rather than to the movers themselves.

Table 2: Young arrivals: workers who changed city group before 25

	Large cities			Small cities		
	Arrivals from other group	All entrants	Work-force	Arrivals from other group	All entrants	Work-force
Share of entrants (%)	22	100		14	100	
Occupation at entry (%)						
Manual	21	24	17	27	29	21
Routine	52	55	58	57	62	66
Abstract	26	21	25	16	9	14
Contribution to Excess_NE (pp/year), against the whole channel						
Abstract	-0.02	-0.24		+0.00	-0.16	
Routine	+0.01	+0.05		-0.02	-0.04	
Manual	+0.02	+0.20		+0.02	+0.18	

Notes: Young arrivals are workers whose first record inside the 25–64 window falls at age 25 or 26 and whose first job before 25 was in the other city group; apprenticeship positions count as a location but not as employment. Arrivals number about 1,653 a year into Large cities against 876 into Small ones, in sample workers. The contribution column is the arrivals' excess entry, $n_k - E_{k,g}(t)\, n$, expressed in the units of Table 1, beside the whole Excess_NE channel of that table.

4.5 Who Rides the Urban Elevator?

In this section we ask to what extent the faster upgrading in Large cities belongs to particular workers or is connected to the urban environment itself. For each one-year transition $j \to k$ we estimate, on workers observed in both years,

$$y_{it}^{j\to k} = \alpha + \beta_1 \,\text{college}_i + \beta_2 \,\text{female}_i + \beta_3 \,\text{age}_{it} + \beta_4 \,\text{tenure}_{it} + \gamma_{SL}\, SL_{it} + \gamma_{LS}\, LS_{it} + \gamma_{LL}\, LL_{it} + \lambda_t + \varepsilon_{it}, \tag{9}$$

where y equals one if the worker moves from j to k between t and $t+1$, college and female are indicators, age is measured from 40, tenure is the number of consecutive years in the current two-digit PCS code, λ_t are year effects, and SL, LS and LL indicate the worker's city group at the two dates (Small then Large, Large then Small, Large at both), with Small at both dates as the omitted category. The model is estimated by weighted least squares with each year weighted equally, the conventions of the individual-level analysis in Cerina et al. (2026). The coefficient of interest is γ_{LL}, the premium of a Large-city stayer over a Small-city stayer with the same characteristics. The cross-city coefficients γ_{SL} and γ_{LS} are large and similar in both directions of the move, which we read as the self-selection of movers rather than as an effect of the destination (Appendix C). Table 3 reports γ_{LL} for the seven margins, over the full period and over 1994–2021, from the pooled sample and

from the same equation estimated separately on college and non-college workers, where the college term drops out. Beside each premium the table reports the transition rate of Small-city stayers in the same sample, and we call $1 + \gamma_{LL}/\text{rate}$, the factor by which the city multiplies that rate, the multiplier. A further column adds fixed effects for the two-digit PCS code of the origin occupation; they are not defined for workers coming from non-employment.

Table 3: Conditional within-Large premia by transition (linear probability model)

	All workers				**Non-college**			**College**			**Arrived young**
Transition	Small-stayer rate	College	γ_{LL}	γ_{LL} origin FE	Small-stayer rate	γ_{LL}	γ_{LL} origin FE	Small-stayer rate	γ_{LL}	γ_{LL} origin FE	Moved $S \to L$ before 25
1984–2021											
Upgrading to Abstract											
R → A	2.24	+8.09***	+1.54***	+0.92***	1.96	+1.36***	+0.77***	6.16	+3.10***	+2.46***	—
M → A	0.70	+5.64***	+0.27***	+0.26***	0.62	+0.26***	+0.24***	4.46	+0.63	+0.58	—
NE → A	1.59	+6.74***	+1.07***	—	1.06	+0.86***	—	7.09	+3.23***	—	—
Downgrading from Abstract											
A → R	6.84	−6.39***	−1.10***	−0.93***	8.93	−1.41***	−1.19***	3.36	−0.48***	−0.46**	—
Entry into Routine											
M → R	7.49	+3.67***	+0.03	−0.15	7.36	+0.01	−0.18	12.90	+1.39	+1.34	—
NE → R	8.64	−4.54***	+0.32***	—	8.73	+0.22***	—	7.68	+0.77***	—	—
Entry into Manual from Non-Employment											
NE → M	5.59	−4.40***	−0.35***	—	5.96	−0.44***	—	1.75	+0.07	—	—
1994–2021											
Upgrading to Abstract											
R → A	2.24	+6.76***	+1.36***	+0.83***	1.95	+1.18***	+0.67***	6.08	+3.19***	+2.61***	+0.47***
M → A	0.70	+5.15***	+0.25***	+0.25***	0.62	+0.22***	+0.22***	4.42	+1.72***	+1.64***	+0.32**
NE → A	1.60	+6.82***	+0.95***	—	1.06	+0.78***	—	7.14	+2.79***	—	+0.53***
Downgrading from Abstract											
A → R	6.71	−5.19***	−0.94***	−0.70***	8.77	−1.23***	−0.92***	3.33	−0.50***	−0.45***	−1.06***
Entry into Routine											
M → R	7.34	+4.37***	−0.08	−0.20**	7.21	−0.11	−0.22***	12.88	+0.88	+0.79	−0.48
NE → R	8.54	−3.68***	−0.25***	—	8.62	−0.36***	—	7.76	+0.09	—	−2.35***
Entry into Manual from Non-Employment											
NE → M	5.64	−4.60***	−0.50***	—	6.02	−0.63***	—	1.78	0.00	—	−2.17***

Notes: Coefficients in percentage points; Small-stayer rates in percent. Dashes mark estimates not defined for that block or origin. HC3-robust standard errors; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Standard errors and full estimates in Appendix C.

The premium survives the controls. Over 1984–2021, Small-city stayers, college and non-college together, move from Routine to Abstract at 2.24% a year. A Large-city stayer with the same education, gender, age and tenure as a given Small-city stayer is 1.54 pp more likely to make the move, about 70% of the Small-city rate. For comparison, a college degree raises the same probability by 8.1 pp for a worker in either city group. Education is therefore the first-order determinant of upgrading, as in Cerina et al. (2026), and the city effect is about a fifth of it. The city also protects against downgrading: Large-city stayers fall back from Abstract to Routine 1.10 pp less often than Small-city stayers, whose rate

is 6.84%. Over 1994–2021 the upgrading premium is somewhat smaller, 1.36 pp on an unchanged Small-city rate of 2.24%. The faster upgrading in Large cities is thus not fully explained by the observable characteristics of their workers.[7]

Part of the premium reflects the occupations from which Large-city workers start. The Routine group pools two-digit codes with very different rates of upgrading to Abstract work, and among stayers the Large cities hold a much larger share of one of the codes with the highest rates, the intermediate administrative and commercial occupations of firms, and a smaller share of industrial workers, whose rates are below the routine average (Table C.3). With fixed effects for the origin code, so that Large- and Small-city stayers are compared within the same occupation, the premium on $R \to A$ falls to 0.92 pp on the same Small-city rate of 2.24%, a multiplier of 1.41 instead of 1.69. About three fifths of the premium therefore survives within occupations, and the Large-city rate exceeds the Small-city rate in every routine code. The protective margin depends less on composition: on $A \to R$ the premium moves from -1.10 to -0.93 pp.

Estimated separately by education group, the premium is larger for college workers, 3.10 against 1.36 pp on $R \to A$, and the multiplier is larger for non-college workers: Small-city stayers without a degree upgrade at 1.96% a year, so their multiplier is 1.69, against 1.50 for college workers, whose rate is 6.16%. The difference rests on the origin occupation. With fixed effects for the origin code the premium falls to 0.77 pp for non-college and to 2.46 pp for college workers, and the two multipliers become almost equal, 1.39 and 1.40; over 1994–2021 they are 1.34 and 1.43. On entry into Abstract work from non-employment, where no origin code is defined, the multiplier is again larger for non-college workers, 1.81 against 1.46; on the direct Manual-to-Abstract route the college premium is imprecisely estimated over the full period, so the two multipliers cannot be compared. The protection against downgrading is present in both groups and in similar proportion. On the Manual–Routine margins, and on re-entry from non-employment into Routine or Manual work, there is no consistent urban premium for either group. Both education groups therefore ride the urban elevator, and within the same origin occupation they ride it in about the same proportion.

Nor does the premium belong to workers who arrived in the Large city young. Two further dummies, added to equation (9), mark workers whose first job before 25 was in the other city group; they are defined for workers entering the sample from 1994, which is why the lower block of Table 3 is estimated on 1994–2021, and the table reports the one for a move from a Small to a Large city. On $R \to A$ the premium for having arrived young is 0.47 pp against a within-Large premium of 1.36: about three quarters of the advantage of a young mover over a worker who started and stayed in a Small city is

[7] The interaction specification of Appendix C shows how the premium varies with them: it declines with tenure in the current occupation, halving after about eight years, is somewhat lower for women and varies little with age.

associated with the city rather than with the move. The city's share is about two thirds on entry from non-employment and about half on the protective $A \to R$ margin, and on the Manual-to-Abstract route the premium for having arrived young is the larger of the two, 0.32 against 0.25 pp.

In sum, the faster upgrading in Large cities is not fully accounted for by the observable characteristics of their workers, nor by when they arrived. About two fifths of the premium reflects the routine occupations from which Large-city workers start, and the rest is present within each occupation. The premium reaches both education groups, in about the same proportion once the origin occupation is held fixed, and it is confined to entry into abstract work and to remaining in it. What remains is connected to the urban environment rather than to the workers' observable characteristics.

5 Conclusion

Using French administrative panel data, we show that the spatial dimension of labor-market polarization is produced inside cities rather than between them. Large cities move routine workers into abstract jobs at roughly twice the rate of small ones, and that margin alone more than accounts for the urban gap in how the routine and abstract shares evolve. The relocation of workers who are already employed contributes little: the flows are small, and they leave the occupational composition of either group of cities unchanged. The urban elevator predates the polarization onset, dated around 1994: it runs at full strength in the decade before the break, which itself arrives in large and small cities alike.

Notably, sorting is not absent from these data. It happens before careers begin, and it does not work in the way the sorting account requires. A fifth of the workers who enter employment in a large city held their first job in a small one, and they are drawn disproportionately from the educated. What they do not bring is a different occupational mix: they take jobs in the proportions of the city they enter, so that their arrival changes its size and not its composition. Their subsequent advantage, moreover, is mostly associated with the large city itself rather than with their having arrived from elsewhere. The elevator reaches college and non-college workers alike and is confined to entry into abstract work and to remaining in it. About two fifths of it reflects the routine occupations from which large-city workers start; once these, education, gender, age, tenure and the age at arrival are accounted for, the premium that remains, about 40% of the small-city rate, is associated with the city rather than with the observable characteristics of its workers.

All in all, the margin that moves the urban gap is occupational mobility inside cities, not movement between them. Thicker local labor markets, faster learning on the job and a denser supply of upper-tier employers are each consistent with the rates we observe, and a decomposition of flows cannot distinguish them. That distinction calls for a model in which workers choose an occupation and a location jointly, and in which the two choices

are made at different stages of a career, as they appear to be in these data.

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Appendix

A Sample Description

This appendix supplements Section 2 with six pieces of evidence on the constructed panel: the full list of *aires urbaines* that belong to the Large group under alternative reference years; the temporal stability of the resulting 50/50 split; the age-window treatment used in the decomposition; the underlying wage hierarchy of the two-digit PCS occupation codes that motivates the M/R/A classification; the layered CS2 imputation procedure for worker-years with missing occupation codes; and the rule for assigning a city group to worker-years spent in non-employment.

A.1 The Large/Small AU classification

Table A.1 lists every *aire urbaine* (AU) that belongs to the Large group under at least one of four candidate reference years (1984, 1989, 1994, 2003), together with the 1984 DADS sample employment count and the 2017 INSEE census population. Fifteen AUs form a stable core that is classified as Large regardless of reference year: Paris, Lyon, Marseille–Aix-en-Provence, Toulouse, Lille, Bordeaux, Strasbourg, Nice, Nantes, Grenoble, Rennes, Rouen, Avignon, Orléans, and Douai–Lens. These are unambiguously France's largest metropolitan labor markets. Boldface rows mark the 21 AUs of the 2003 split used in the paper: the stable core plus Tours, Saint-Étienne, Nancy, Montpellier, Clermont-Ferrand and Valenciennes. The reference year only moves the boundary: the 1984 split would include Le Mans and exclude Montpellier, Clermont-Ferrand and Valenciennes.

Employment is steeply concentrated across AUs: just 21 of the more than 750 AUs in France account for half of all employed workers in our sample. Paris alone represents roughly 45% of the Large group's employment. The Large AUs correspond closely to the largest AUs by 2017 census population, with one notable exception: Toulon (2017 census rank 13, population $\approx$ 617,000) never appears in any sample-based split because its economy is dominated by the military (naval base) and retirees, both under-represented in DADS-EDP *tous salariés* data.

Table A.1: Classification of *aires urbaines* into Large and Small groups

AU	City	DADS 1984	INSEE 2017 (k)	1984	1989	1994	2003
1	**Paris**	**14,849**	**12,628**	✓	✓	✓	✓
2	**Lyon**	**2,282**	**2,323**	✓	✓	✓	✓
3	**Marseille–Aix**	**1,534**	**1,760**	✓	✓	✓	✓
5	**Lille**	**1,374**	**1,191**	✓	✓	✓	✓
6	**Bordeaux**	**857**	**1,248**	✓	✓	✓	✓
4	**Toulouse**	**823**	**1,360**	✓	✓	✓	✓
9	**Nantes**	**781**	**972**	✓	✓	✓	✓
8	**Nice**	**780**	**1,006**	✓	✓	✓	✓
12	**Rouen**	**772**	**663**	✓	✓	✓	✓
7	**Strasbourg**	**742**	**790**	✓	✓	✓	✓
10	**Grenoble**	**684**	**687**	✓	✓	✓	✓
17	**Tours**	**548**	**500**	✓	✓		✓
20	**Orléans**	**510**	**437**	✓	✓	✓	✓
11	**Rennes**	**508**	**733**	✓	✓	✓	✓
18	**Saint-Étienne**	**453**	**515**	✓	✓		✓
21	**Douai–Lens**	**450**	**539**	✓	✓	✓	✓
14	**Nancy**	**400**	**435**	✓			✓
19	**Avignon**	**397**	**518**	✓	✓	✓	✓
24	**Valenciennes**	**350**	**370**				✓
15	**Montpellier**	**328**	**607**			✓	✓
16	**Clermont-Ferrand**	**312**	**485**		✓		✓
25	Le Mans	392	344	✓		✓	
	Total Large AUs			19	18	17	21

Notes: A checkmark indicates that the AU belongs to the Large group under the median-employment split computed in the column's reference year. DADS 1984: sample employment count (multiply by ≈ 24 for approximate actual employment). INSEE 2017: total population in thousands from the 2017 census. Boldface rows mark the 21 AUs of the 2003 split used in the paper. AUs 997, 998 and 999 (non-urban areas) are always classified as Small and are omitted.

A.2 Temporal Stability of the Split

Because the classification is defined on the 2003 cross-section but applied to all years, the Large-group employment share could in principle drift away from one half over time. Table A.2 reports stability diagnostics for the adopted split and, for comparison, for the 1984 split, with and without replacing Le Mans by Montpellier (the swap that stabilizes the 1984 boundary). Under the adopted split the Large share is 50.5% in 2003 and 51.8% in 1984, ranges between 50.2% (2002) and 53.1% (1994), and drifts by +0.5 pp over 1984–2021; its standard deviation across years is 0.8 pp, the same as under the 1984 split. The reference year shifts the level of the Large share by about one percentage point, through the boundary AUs, without affecting its stability. The four-channel decomposition is equally insensitive to the reference year. Under the 1984 split the Large–Small gap in Abstract growth is 0.22 pp/year, against 0.21 under the adopted split, with a within-city gap of 0.29 and a cross-city gap of −0.02; replacing Le Mans by Montpellier gives 0.22, 0.30 and −0.01.

Table A.2: Stability of the Large-group employment share over time, by classification variant

	2003 split (used in the paper)	**1984 split**	**1984 split** + Montpellier
Number of Large AUs	21	19	19
Share in 1984 (%)	51.8	50.8	50.6
Share in 2003 (%)	50.5	48.9	49.0
Minimum (%)	50.2	48.6	48.7
Maximum (%)	53.1	51.9	51.8
Spread (pp)	3.0	3.3	3.1
Std. dev. (pp)	0.8	0.8	0.8
Drift 1984–2021 (pp)	+0.5	−0.3	+0.2

Notes: Each column applies a fixed set of Large AUs to all years 1984–2021. The share is the fraction of employed workers located in Large AUs; drift is the change from the 1984 value to the 2021 value.

A.3 Age Window and Boundary-Flow Treatment

The framework of Section 3 requires careful handling of workers who cross the boundary of the 25–64 prime working-age window. This appendix gives the formal definitions and shows that the resulting accounting identity holds with zero residual.

The framework uses two distinct sample restrictions, applied independently:

- Cross-sectional employment counts $N_{k,g}(t)$ at year t are computed on workers aged 25–64 *at year* t. Call this set $\mathcal{P}(t)$.
- Flow counts $N_{(j,h),(k,g)}(t)$ between $t-1$ and t are computed on workers aged 25–64 *at year* $t-1$, tracked via birth year forward to their state at t. Call this set

$\mathcal{P}_{\text{flow}}(t-1,t) \equiv \mathcal{P}(t-1)$ (the population frozen at the earlier date).

The two sets differ at exactly two age boundaries. Workers aged 24 at $t-1$ and 25 at t belong to $\mathcal{P}(t)$ but not to $\mathcal{P}(t-1)$; we call them *aging-in* workers, denoted $\mathcal{A}_{\text{in}}(t)$. Workers aged 64 at $t-1$ and 65 at t belong to $\mathcal{P}(t-1)$ but not to $\mathcal{P}(t)$; we call them *aging-out* workers, denoted $\mathcal{A}_{\text{out}}(t)$. Workers in $\mathcal{P}(t-1) \cap \mathcal{P}(t)$, i.e., aged 26–64 at $t-1$ and 25–63 at t, are in both sets.

Workers in $\mathcal{A}_{\text{in}}(t)$ have no observed state at $t-1$ within the 25–64 window (they were 24). If such a worker is observed in employed state (k,g) at t, we code her as a flow $0 \to (k,g)$, an entry from non-employment. This is consistent with the convention that the framework's "non-employed" state collects everyone outside the window of analysis, whether the reason is genuine non-employment or non-membership in the prime-age sample. Symmetrically, workers in $\mathcal{A}_{\text{out}}(t)$ have no observed state at t within the window (they are 65 or older). If such a worker is in employed state (j,h) at $t-1$, we code her as a flow $(j,h) \to 0$, an exit to non-employment. Workers in $\mathcal{A}_{\text{out}}(t)$ who are non-employed at $t-1$ leave the sample without contributing to any flow.

The accounting identity $\Delta N_{k,g} = \mathcal{F}_{(k,g)} + N_{0,(k,g)} - N_{(k,g),0}$ (Section 3, equation 2) requires that the left-hand side, the difference between two cross-sections computed on different populations $\mathcal{P}(t)$ and $\mathcal{P}(t-1)$, match the right-hand side, a sum of flows defined on the population $\mathcal{P}(t-1)$ followed forward to t. Without the boundary-flow coding, the two sides differ by exactly the count of aging-in workers in (k,g) at t and the count of aging-out workers in (k,g) at $t-1$:

$$\underbrace{N_{k,g}(t)}_{\text{cohort } \mathcal{P}(t)} - \underbrace{N_{k,g}(t-1)}_{\text{cohort } \mathcal{P}(t-1)} = \mathcal{F}^{\text{interior}}_{(k,g)}(t) + N^{\text{interior}}_{0,(k,g)}(t) - N^{\text{interior}}_{(k,g),0}(t) + |\mathcal{A}_{\text{in}}(t) \cap (k,g)| - |\mathcal{A}_{\text{out}}(t) \cap (k,g)|,$$

where the "interior" superscripts denote flows restricted to workers in $\mathcal{P}(t-1) \cap \mathcal{P}(t)$, $|\mathcal{A}_{\text{in}}(t) \cap (k,g)|$ is the number of aging-in workers observed in state (k,g) at t, and $|\mathcal{A}_{\text{out}}(t) \cap (k,g)|$ the number of aging-out workers in state (k,g) at $t-1$. Treating aging-in workers as $0 \to (k,g)$ entries adds the $|\mathcal{A}_{\text{in}}(t) \cap (k,g)|$ count to $N_{0,(k,g)}$; treating aging-out workers as $(k,g) \to 0$ exits adds the $|\mathcal{A}_{\text{out}}(t) \cap (k,g)|$ count to $N_{(k,g),0}$. After this absorption the identity holds with zero residual for every cell (k,g) and every year-pair $(t-1,t)$.

Aging-in cohorts (workers turning 25) and aging-out cohorts (workers turning 65) each represent roughly 1/40 of the working-age population per year, since the 25–64 window spans 40 birth-year cohorts. In our DADS-EDP sample this translates to approximately 25,000–40,000 workers per cohort year. The boundary flows are quantitatively modest relative to interior flows but are essential for the identity to be exact; without them the residual would accumulate to the order of 1 percentage point per year on $\Delta E_{k,g}$, easily large enough to overwhelm the sub-period differences the paper documents.

A.4 Wage Hierarchy of the M/R/A Classification

The task-based occupational classification of Section 2 groups CS2 codes into Manual, Routine and Abstract. Table A.3 ranks CS2 codes by their mean daily net wage, expressed relative to the Manual-group average ($\bar{w}_M = 1$), in four benchmark years. Within each broad group the codes are listed in descending order of wage.

The wage hierarchy is perfectly stable across the sample period: Abstract earns roughly 3× the Manual average, Routine roughly 1.5×. Within-Routine heterogeneity is sizable (CS2 codes from 0.9 to 2.1× the Manual benchmark) but the group as a whole sits cleanly between Abstract and Manual in every benchmark year. This stable ordering motivates the M/R/A classification used throughout the paper.

A.5 CS2 imputation for missing-CS2 worker-years

Some worker-years in DADS–EDP record positive wage but no two-digit CS2 occupation code, concentrated in the civil-service (FPE) sector pre-2009 (about 156,000 worker-years). Without imputation these observations could not be classified into the M/R/A scheme of Section 2. We adopt the layered procedure documented in Cerina et al. (2026), summarized here for self-containment.

The first layer is a within-worker temporal fill: for each worker with a missing CS2 at year t, we fill from the nearest observed CS2 in the same worker's panel (forward fill, then backward fill for residual gaps). This resolves 97.8% of missing cases, with 91.5% 4-state accuracy at gap one (validated against post-2009 observed CS2). For the remaining 2.2%, a second layer applies a multi-class gradient-boosted classifier, trained on observed CS2 in the full panel, which predicts the missing code from log(wage), sex, age, contract type, sector, region, diploma and year. Worker-years whose predicted top-class probability falls below 0.30 (0.1% of all missing cases) are dropped from the analysis. The combined pipeline achieves 90.0% 4-state and 88.0% 5-state accuracy on a 1.7M-observation holdout.

A.6 AU imputation during non-employment spells

The eight-state framework of Section 3 assigns each worker-year to a city group $g \in \{S, L\}$, including during non-employment. The DADS-EDP records an employer location (and hence an AU) only for years with a recorded job position; non-employed worker-years carry no AU and must be imputed before the worker can enter the NES or NEL state.

For each worker-year with $occ_0 = NE$ (i.e. no recorded employment spell at year t), we assign the AU and the implied L/S classification through a two-step rule:

1. *Forward fill from the most recent pre-spell AU.* If the worker has any observed employment spell at year $t' < t$, the imputed AU at t is the AU of the latest such t'.

Table A.3: CS2 codes ranked by mean daily wage relative to the Manual-group average

			1984		1994		2009		2019	
CS2	**Description**	**Group**	Rk	$w/\bar{w}_M$	Rk	$w/\bar{w}_M$	Rk	$w/\bar{w}_M$	Rk	$w/\bar{w}_M$
Abstract										
35	Prof. information/arts	A	1	6.29	7	2.37	9	2.05	4	2.42
37	Cadres admin./comm.	A	2	3.68	2	4.19	2	3.50	2	3.35
38	Ingénieurs/cadres tech.	A	3	3.52	4	3.62	3	3.33	3	3.00
23	Chefs entr. ≥10 sal.	A	4	3.28	1	5.01	1	5.43	1	3.81
33	Cadres fonc. publique	A	–	–	6	2.51	5	2.41	6	2.17
47	Techniciens	A	7	1.89	8	2.32	10	2.05	8	1.85
34	Prof. enseign./santé	A	8	1.76	3	3.71	6	2.39	5	2.37
	Abstract average	A		3.00		3.39		2.88		2.74
Routine										
46	Prof. int. admin./comm.	R	5	2.01	10	1.90	11	1.94	10	1.80
48	Contremaîtres	R	6	1.98	9	2.09	7	2.19	7	1.99
43	Prof. int. santé/social	R	9	1.58	5	2.74	12	1.78	13	1.56
65	Ouv. qual. manut./transp.	R	10	1.43	11	1.80	16	1.58	14	1.48
62	Ouv. qual. industriel	R	13	1.32	13	1.60	13	1.69	16	1.47
54	Empl. admin. entreprise	R	12	1.33	15	1.39	18	1.46	18	1.37
45	Prof. int. fonc. publ.	R	–	–	12	1.64	8	2.10	11	1.68
42	Instituteurs	R	14	1.26	21	0.90	14	1.65	15	1.48
52	Empl. civils fonc. publ.	R	15	1.19	14	1.44	20	1.40	21	1.22
63	Ouv. qual. artisanal	R	16	1.17	16	1.39	17	1.49	19	1.36
67	Ouv. non qual. industriel	R	18	1.05	19	1.29	22	1.27	22	1.17
	Routine average	R		1.41		1.62		1.60		1.46
Manual										
64	Chauffeurs	M	11	1.39	18	1.34	19	1.41	20	1.34
53	Policiers/militaires	M	17	1.13	17	1.36	15	1.59	12	1.58
55	Empl. de commerce	M	19	1.00	20	1.05	24	1.15	24	1.13
56	Pers. services partic.	M	20	0.84	24	0.78	26	0.66	26	0.71
68	Ouv. non qual. artisanal	M	21	0.78	23	0.80	25	0.89	25	0.83
69	Ouv. non qual. divers	M	22	0.68	22	0.89	23	1.21	23	1.15
	Manual average	M		1.00		1.00		1.00		1.00
Group rank summary			1984		1994		2009		2019	
	Abstract	A	1	3.00	1	3.39	1	2.88	1	2.74
	Routine	R	2	1.41	2	1.62	2	1.60	2	1.46
	Manual	M	3	1.00	3	1.00	3	1.00	3	1.00

Notes: Mean daily net wage by CS2 code, workers aged 25–64 with positive wages. Rk: rank among all CS2 codes within that year. $w/\bar{w}_M$: ratio of CS2 mean wage to the Manual-group average. Group averages are worker-weighted. Dashes indicate fewer than 10 observations. The group ranking $A > R > M$ is perfectly stable across all four benchmark years.

2. *Backward fill.* If no pre-spell AU exists (the NE year precedes the worker's first observed employment spell), the imputed AU is taken from the *earliest* subsequent employment spell at $t' > t$.

Forward fill therefore takes priority over backward fill; when both pre- and post-spell AUs exist (the standard case for an in-panel NE spell), the worker's L/S classification during the spell is the one she carried before becoming non-employed.

Every non-employed worker-year in the sample receives an AU through this rule. Workers with non-employment years in the 25–64 window but no employment spell within the window (3.6% of workers, 4.8% of non-employed worker-years) inherit their AU from spells observed outside the window, almost always before age 25. The few workers who never hold a job in the M/R/A classification at any age (0.6% of non-employed worker-years) still carry an employer location on records whose occupation code lies outside the classification, from which the AU is filled.

A worker who is employed in AU a_1, becomes non-employed, and re-enters employment in a different AU a_2 is by our rule classified as being in a_1's L/S group throughout the NE spell. At the moment of re-entry the worker is recorded as having moved from $(NE, g(a_1))$ to $(k, g(a_2))$, so a cross-group relocation during the spell shows up as an F^r or F^c entry in the year of re-entry, not as a within-NE relocation. Since the timing of the move within the spell is not observed, we attribute it to the year in which its destination is first observed.

Because the Large/Small classification is defined on employed workers, the Large share of employment is close to one half in the reference year (50.5% in 2003) and stays within 50.2–53.1% over 1984–2021 (Appendix A.2). The Large share of non-employed worker-years is instead inherited from employment spells and not pinned down by construction; empirically it ranges between 49.6% and 53.0%, and the Large share of all worker-years, employed and non-employed, between 50.2% and 52.4%.

B Detailed Spatial Matrices and Decomposition

This appendix collects the full 8×8 transition matrices and the bilateral within-city flow decomposition by sub-period that supports the discussion in Section 4. The classification of *aires urbaines* into Large and Small city groups is described in Section 2.

B.1 8×8 Full-Period Matrices

Tables B.1 and B.2 report the simple-average one-year transition matrices over the eight occupation×location states for the full sample 1984–2021. The expansion-boundary pairs 2001–02 and 2005–06 are excluded; the 1989→1991 gap pair enters as one pair observation. Table B.1 reports the *conditional* matrix: each row gives the probability of being in state (k, g) at $t + 1$ given (j, h) at t, and rows sum to one. Table B.2 reports the *unconditional*

(joint) matrix: each cell gives the share of the cohort following the $(j, h) \to (k, g)$ path, and all 64 cells sum to one.

Table B.1: Conditional transition matrix, full period 1984–2021

From / To	M-S	M-L	R-S	R-L	A-S	A-L	NE-S	NE-L
M-S	0.716	0.017	0.097	0.009	0.006	0.001	0.153	0.000
M-L	0.018	0.697	0.009	0.103	0.001	0.011	0.000	0.161
R-S	0.028	0.002	0.826	0.017	0.022	0.002	0.102	0.000
R-L	0.003	0.027	0.018	0.801	0.002	0.040	0.000	0.108
A-S	0.008	0.001	0.089	0.009	0.770	0.033	0.089	0.000
A-L	0.001	0.006	0.005	0.075	0.016	0.809	0.000	0.089
NE-S	0.043	0.005	0.085	0.009	0.014	0.003	0.841	0.001
NE-L	0.005	0.039	0.010	0.085	0.003	0.028	0.001	0.830

Notes: Rows sum to one.

Table B.2: Unconditional (joint) transition matrix, full period 1984–2021

From / To	M-S	M-L	R-S	R-L	A-S	A-L	NE-S	NE-L
M-S	0.046	0.001	0.006	0.001	0.000	0.000	0.010	0.000
M-L	0.001	0.040	0.000	0.006	0.000	0.001	0.000	0.009
R-S	0.006	0.000	0.167	0.004	0.005	0.000	0.021	0.000
R-L	0.001	0.005	0.004	0.153	0.000	0.008	0.000	0.021
A-S	0.000	0.000	0.003	0.000	0.032	0.001	0.003	0.000
A-L	0.000	0.000	0.000	0.006	0.001	0.067	0.000	0.007
NE-S	0.008	0.001	0.015	0.002	0.002	0.000	0.149	0.000
NE-L	0.001	0.007	0.002	0.016	0.000	0.005	0.000	0.153

Notes: All 64 cells sum to one.

B.2 8×8 Conditional Matrices by Sub-Period

Tables B.3 and B.4 report the simple-average conditional one-year transition matrices over the eight occupation×location states for the pre-polarization (1984–1993) and polarization (1994–2021) sub-periods. Each row gives the probability of being in state (k, g) at $t+1$ conditional on being in state (j, h) at t; rows sum to one. The expansion-boundary pairs 2001–02 and 2005–06 are excluded, and the 1989→1991 gap pair is excluded from the sub-period averages.

The cross-city off-diagonal entries are uniformly small (below 0.05 for every pre-polarization cell, and below 0.04 post-1994): most transitions are within-city. The NE→R entries on the diagonal of the bottom two rows fall sharply between the two regimes: NE-S→R-S drops from 0.107 to 0.076 and NE-L→R-L from 0.121 to 0.072. The entry-margin collapse documented in Cerina et al. (2026) is therefore visible in both city groups. As Section 4.3 reports, the swing in the routine Excess_NE channel across the break is somewhat larger in Small cities (−0.39 pp) than in Large (−0.30 pp).

Table B.3: Conditional transition matrix, pre-polarization (1984–1993)

From / To	M-S	M-L	R-S	R-L	A-S	A-L	NE-S	NE-L
M-S	0.628	0.017	0.148	0.012	0.007	0.001	0.186	0.000
M-L	0.019	0.608	0.012	0.155	0.001	0.012	0.001	0.193
R-S	0.036	0.003	0.777	0.024	0.025	0.002	0.133	0.000
R-L	0.003	0.032	0.023	0.751	0.003	0.047	0.000	0.140
A-S	0.010	0.001	0.144	0.016	0.651	0.041	0.136	0.001
A-L	0.001	0.007	0.007	0.124	0.021	0.712	0.000	0.128
NE-S	0.036	0.003	0.107	0.009	0.014	0.002	0.829	0.001
NE-L	0.003	0.035	0.008	0.121	0.002	0.031	0.001	0.799

Notes: Rows sum to one.

Table B.4: Conditional transition matrix, polarization (1994–2021)

From / To	M-S	M-L	R-S	R-L	A-S	A-L	NE-S	NE-L
M-S	0.749	0.017	0.079	0.007	0.006	0.001	0.140	0.000
M-L	0.017	0.730	0.008	0.084	0.001	0.011	0.000	0.148
R-S	0.025	0.002	0.844	0.015	0.021	0.002	0.090	0.000
R-L	0.003	0.025	0.017	0.819	0.002	0.038	0.000	0.097
A-S	0.007	0.001	0.071	0.007	0.812	0.030	0.073	0.000
A-L	0.001	0.005	0.004	0.058	0.014	0.842	0.000	0.075
NE-S	0.046	0.005	0.076	0.009	0.014	0.003	0.846	0.001
NE-L	0.006	0.040	0.010	0.072	0.003	0.027	0.001	0.841

Notes: Rows sum to one.

B.3 Bilateral Within-City Flows by Sub-Period

Table B.5 extends Figure 2 of the main text by reporting the three bilateral within-city flows (M↔R, R↔A, M↔A) separately by city group and sub-period. All values are net inflows to the second-listed occupation, expressed in pp/year, and each pair is symmetric: the corresponding outflow for the first occupation has the opposite sign.

Table B.5: Within-city bilateral flows, by city group and sub-period (pp/year, net inflow to second occupation)

Period	$M \to R$		$R \to A$		$M \to A$	
	S	*L*	*S*	*L*	*S*	*L*
Pre-polarization 1984–1993	+0.15	+0.23	+0.30	+0.71	+0.02	+0.04
Polarization 1994–2021	+0.07	+0.10	+0.37	+0.60	+0.03	+0.05
Acute pol. 1994–2008	+0.01	+0.07	+0.39	+0.62	+0.02	+0.03
Post-crisis 2009–2021	+0.12	+0.14	+0.35	+0.58	+0.05	+0.08
Full 1984–2021	+0.09	+0.14	+0.35	+0.63	+0.03	+0.05

Notes: Values ×100 (pp/year). Denominators are $N_{\text{emp},g}(t-1)$ of the relevant city group. The 1989→1991 gap pair is halved; expansion pairs 2001–02 and 2005–06 are excluded.

Three patterns reinforce the conclusions in Section 4.3. The $R \to A$ upgrading flow runs at substantially higher intensity in Large than in Small cities in every sub-period; the Large/Small ratio stays between 1.6× and 2.4× throughout (2.4× in pre-pol, 1.6× in pol, 1.6× acute, 1.6× post-crisis). The $M \to R$ replenishment channel, by contrast, collapses across the 1994 break (+0.15/ + 0.23 pre-pol to +0.01/ + 0.07 during 1994–2008) before partially recovering post-crisis (+0.12/ + 0.14), with no meaningful spatial heterogeneity in the collapse. The direct $M \to A$ channel remains small throughout but is consistently stronger in Large than in Small cities, pointing to some direct-upgrading capacity that bypasses Routine in the largest labor markets.

B.4 Bilateral Decomposition of the Within-City Channel

Table B.6 reports the bilateral decomposition referenced in Section 4.2 of the main paper: the within-city net flow channel $F^w_{k,g}$ is split into the three pairwise components corresponding to the three other employed states in the same city group, and the cross-city channels $F^r_{k,g}$ and $F^c_{k,g}$ are aggregated. Figure B.1 displays the same decomposition graphically, with the bilateral pieces stacked within each bar.

The within-city $R \to A$ net flow is the dominant channel in both city groups, running at 0.63 pp/year in Large and 0.35 pp/year in Small. The within-city $M \to R$ net flow is secondary; the direct $M \to A$ net flow is small but spatially differentiated. All cross-city components are below 0.05 pp in absolute value, an order of magnitude smaller than the

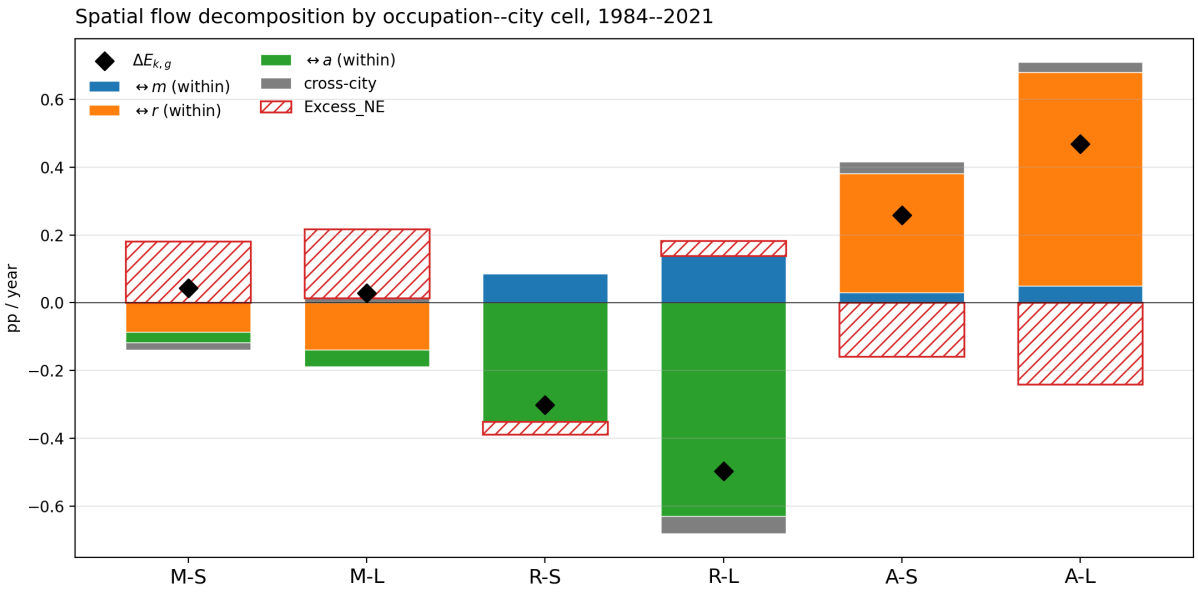


Figure B.1: Spatial flow decomposition, full period 1984–2021. For each state (k, g), the stacked bar decomposes $\Delta E_{k,g}$ into the three within-city bilateral components of $F^w_{k,g}$, the aggregate cross-city contribution $F^r_{k,g} + F^c_{k,g}$, and the Excess_NE channel $\text{Excess_NE}_{k,g}$. Diamond: total $\Delta E_{k,g}$.

Table B.6: Bilateral decomposition of the net flow into each state (pp/year), full period 1984–2021

	Within city (F^w)			**Across city**		
State	$M \leftrightarrow R$	$R \leftrightarrow A$	$M \leftrightarrow A$	Reloc F^r	Combined F^c	$\boldsymbol{\mathcal{F}}$
M-S	−0.09	0	−0.03	−0.02	+0.00	−0.14
M-L	−0.14	0	−0.05	+0.02	−0.01	−0.18
R-S	+0.09	−0.35	0	+0.02	−0.02	−0.26
R-L	+0.14	−0.63	0	−0.02	−0.03	−0.54
A-S	0	+0.35	+0.03	−0.00	+0.04	+0.42
A-L	0	+0.63	+0.05	+0.00	+0.03	+0.71

Notes: Values ×100 (pp/year). Within a city group the bilateral within-city components sum to zero by construction, as do the cross-city and non-employment channels taken together. "Reloc" is the same-occupation relocation component ($F^r_{k,g}$); "Combined" is $F^c_{k,g}$. The last column reports the total net employed-to-employed inflow $\mathcal{F}_{(k,g)} = F^w + F^r + F^c$.

within-city $R \to A$ channel, confirming that the urban elevator runs predominantly through Routine-to-Abstract upgrading within cities.

B.5 Full Sub-period Decomposition by City Group

Table B.7 reports the full four-channel decomposition (F^w, F^r, F^c, Excess_NE, ΔE) for each of the six occupation-by-city cells, in each of the four sub-periods used in the paper: the pre-polarization era (1984–1993) and the polarization era (1994–2021), with the polarization era further split into the acute phase (1994–2008) and the post-crisis phase (2009–2021). Section 4.3 of the main paper uses the binary pre/post-1994 split visualized in Figure 2; the finer split is reported here for completeness.

The three components of the 1994 break (the sign flip in Excess_NE$_R$, the weakening of the within-city manual-to-routine buffer, and the acceleration of non-employment-to-manual entry) shift in both city groups by comparable magnitudes; the Large−Small gap on each component is small and switches sign across components. The acute phase (1994–2008) panel shows the largest absolute magnitudes for each of these shifts; the post-crisis phase (2009–2021) panel shows a partial reversal toward the pre-polarization levels for the routine non-employment channel, while the manual non-employment channel and the within-city $R \to A$ flow remain at polarization-era intensity.

B.6 Longer Transition Horizons

Table B.8 repeats the decomposition of Table 1 for endpoints three and five years apart. Each pair $(t, t+k)$ is treated as in Section 3 and divided by its length, so that the channels remain annual rates; a pair that would end in 1990 ends in 1991, and pairs that span the 2002 or 2006 sample expansions are dropped. Over longer horizons a worker who moves and later changes occupation is recorded in the combined channel rather than in the within-city channel of the destination. For Abstract the within-city channel accounts for the whole Large–Small gap at every horizon, and the cross-city channels stay at or below zero. For Routine the point estimates of the cross-city channels are larger, about a quarter of the gap at one year and about a third at three and five years, mostly a net relocation of routine workers out of Large cities, in the direction of the sorting of middle-skill workers that Cerina et al. (2023) infer for the United States; this flow, however, cannot be distinguished from zero across year pairs (Appendix B.7).

B.7 Sampling Dispersion and Cumulated Contributions

Table B.9 reports, for each channel, the Large–Small gap of Table 1 with its standard error across the 34 year pairs, and the gap summed over those pairs, which for ΔE equals the observed change in the share gap over the same years. The within-city gaps are precisely

Table B.7: Spatial flow decomposition by sub-period (pp/year)

State	F^w	F^r	F^c	Excess_NE	$\boldsymbol{\Delta E}$
Pre-polarization 1984–1993					
M-S	−0.17	+0.00	−0.01	+0.02	−0.16
M-L	−0.27	−0.00	−0.02	+0.06	−0.23
R-S	−0.15	−0.05	−0.02	+0.25	+0.03
R-L	−0.47	+0.05	−0.02	+0.26	−0.19
A-S	+0.32	+0.01	+0.04	−0.24	+0.13
A-L	+0.75	−0.01	+0.03	−0.35	+0.42
Polarization 1994–2021					
M-S	−0.10	−0.03	+0.00	+0.24	+0.11
M-L	−0.16	+0.03	−0.01	+0.25	+0.12
R-S	−0.31	+0.05	−0.02	−0.14	−0.42
R-L	−0.50	−0.04	−0.04	−0.03	−0.61
A-S	+0.40	−0.01	+0.04	−0.13	+0.31
A-L	+0.66	+0.01	+0.03	−0.20	+0.49
Polarization, acute phase 1994–2008					
M-S	−0.03	−0.08	+0.01	+0.36	+0.27
M-L	−0.09	+0.08	+0.00	+0.35	+0.34
R-S	−0.37	+0.06	−0.03	−0.31	−0.66
R-L	−0.56	−0.05	−0.04	−0.18	−0.82
A-S	+0.41	−0.04	+0.03	−0.00	+0.39
A-L	+0.65	+0.04	+0.02	−0.23	+0.48
Post-crisis 2009–2021					
M-S	−0.17	+0.01	−0.01	+0.11	−0.05
M-L	−0.23	−0.01	−0.02	+0.15	−0.11
R-S	−0.23	+0.03	−0.01	+0.05	−0.16
R-L	−0.43	−0.03	−0.03	+0.12	−0.38
A-S	+0.40	+0.03	+0.05	−0.26	+0.21
A-L	+0.66	−0.03	+0.03	−0.17	+0.49

Notes: Values ×100 (pp/year). Each panel's $F^w + F^r + F^c + \text{Excess_NE}$ column sums to zero across the six cells by construction. $\Delta E_{k,g} = (F^w + F^r + F^c + \text{Excess_NE})/N_{\text{emp},g}(t-1)$.

Table B.8: Large–Small difference in each channel at one-, three- and five-year horizons (pp/year)

	Within city group F^w	Relocation F^r	Combined F^c	Excess_NE	ΔE	Pairs
1984–2021						
Abstract						
$k = 1$	+0.30	0.00	−0.01	−0.08	+0.21	34
$k = 3$	+0.26	0.00	−0.01	−0.03	+0.22	28
$k = 5$	+0.22	0.00	0.00	0.00	+0.22	23
Routine						
$k = 1$	−0.23	−0.04	−0.01	+0.08	−0.20	34
$k = 3$	−0.21	−0.06	−0.01	+0.09	−0.19	28
$k = 5$	−0.18	−0.06	0.00	+0.06	−0.19	23
Manual						
$k = 1$	−0.07	+0.05	−0.01	+0.02	−0.01	34
$k = 3$	−0.05	−0.01	0.00	+0.04	−0.02	28
$k = 5$	−0.04	−0.01	−0.01	+0.03	−0.03	23
1994–2021						
Abstract						
$k = 1$	+0.25	+0.02	−0.01	−0.07	+0.18	25
$k = 3$	+0.21	−0.02	−0.01	0.00	+0.19	19
$k = 5$	+0.19	−0.02	−0.01	+0.05	+0.21	14
Routine						
$k = 1$	−0.19	−0.09	−0.02	+0.11	−0.19	25
$k = 3$	−0.17	−0.11	−0.01	+0.10	−0.19	19
$k = 5$	−0.15	−0.12	−0.02	+0.09	−0.20	14
Manual						
$k = 1$	−0.06	+0.07	−0.01	+0.01	+0.01	25
$k = 3$	−0.04	−0.01	−0.01	+0.06	0.00	19
$k = 5$	−0.04	−0.02	−0.02	+0.07	0.00	14

Notes: Each cell is the Large-city value minus the Small-city value of the channel in the units of Table 1, for endpoint pairs k years apart; $k = 1$ reproduces that table. Pairs: number of endpoint pairs.

estimated for all three occupations, while the cross-city gaps cannot be distinguished from zero; the routine relocation flow in particular is driven by a few year pairs with large swings in both directions. The Excess_NE gaps are also imprecise.

Table B.9: Large–Small gap in each channel: dispersion across year pairs and cumulated contributions

	Within city group F^w	Relocation F^r	Combined F^c	Excess_NE	ΔE
Abstract					
Annual (SE)	+0.30 (0.03)	0.00 (0.03)	−0.01 (0.01)	−0.08 (0.06)	+0.21 (0.06)
Cumulated	+10.6	+0.2	−0.3	−2.9	+7.6
Routine					
Annual (SE)	−0.23 (0.04)	−0.04 (0.11)	−0.01 (0.02)	+0.08 (0.13)	−0.20 (0.07)
Cumulated	−7.9	−1.4	−0.4	+2.8	−6.9
Manual					
Annual (SE)	−0.07 (0.02)	+0.05 (0.06)	−0.01 (0.01)	+0.02 (0.06)	−0.01 (0.04)
Cumulated	−2.7	+1.5	−0.4	+0.8	−0.8

Notes: Annual: the Large-city minus the Small-city value of each channel in Table 1 (pp/year), with its standard error across the year pairs in parentheses. Cumulated: the gap summed over the year pairs (pp); for ΔE it equals the observed change in the Large–Small gap of the employment share over those pairs.

B.8 Spatial Channels of Occupation Switches

Table B.10 supports the discussion in Section 4.4: each occupation switch is assigned to one of six spatial channels, according to whether the worker stays in the same *aire urbaine*, moves to another AU of the same size group, or crosses the Large/Small boundary.

Table B.10: Spatial channel decomposition of occupation switches (% of each transition type)

	Upgrading			**Downgrading**		
Move type	$M \to R$	$M \to A$	$R \to A$	$R \to M$	$A \to M$	$A \to R$
Same AU, Small	36.8	26.6	29.4	36.6	25.6	29.6
Same AU, Large	42.1	49.3	55.3	40.6	47.5	53.9
Within Small	10.2	7.5	4.8	11.0	9.0	5.4
Within Large	2.7	5.3	3.5	2.7	5.1	3.7
$S \to L$	4.3	6.5	3.6	4.2	4.7	3.5
$L \to S$	4.0	4.7	3.3	4.8	8.0	4.0
Sum	100	100	100	100	100	100

Notes: Each column reports the share of a given occupation switch occurring through each spatial channel, averaged across year-pairs. Mean annual switch counts: $R \to A \approx 8{,}600$; $M \to R \approx 7{,}900$; $R \to M \approx 7{,}500$; $A \to R \approx 6{,}200$; $M \to A \approx 1{,}000$; $A \to M \approx 730$.

Table B.11 reports the same transitions as rates rather than as shares. A share records where switches of a given type occur, and so mixes the propensity to switch with the number of workers available to switch; since Large cities hold proportionally fewer Routine and Manual workers and almost twice the Abstract share, the two objects answer different questions. Dividing by the origin population removes the composition and leaves the propensity, which is the object the urban elevator is about.

Table B.11: Annual occupation-switching rates by origin occupation and city group (%)

	All moves			**Within the same AU**		
Switch	Small	Large	L/S	Small	Large	L/S
Into Abstract work						
$R \to A$	2.71	4.76	1.76	2.13	4.25	2.00
$M \to A$	0.90	1.47	1.64	0.59	1.23	2.07
Between Manual and Routine						
$M \to R$	12.57	13.40	1.07	9.19	11.63	1.27
$R \to M$	3.36	3.30	0.98	2.43	2.81	1.15
Out of Abstract work						
$A \to R$	10.92	8.81	0.81	8.55	7.79	0.91
$A \to M$	0.99	0.76	0.76	0.66	0.60	0.91

Notes: Each rate divides the number of workers making the switch by the number of workers holding the origin occupation in that city group at t, so it is unaffected by the differing occupational composition of Large and Small cities. The right-hand block additionally requires the worker to remain in the same *aire urbaine*. Origin populations average about 127,000 Routine and 43,000 Manual workers a year in Small cities, against 115,000 and 38,000 in Large ones, and 32,000 against 62,000 Abstract workers.

Table B.12 splits the same-AU rates of Table B.11 by size class. The Routine-to-Abstract and Manual-to-Abstract rates fall monotonically with size, also when every class is given the same mix of routine origin occupations, so the urban contrast is not specific to Paris and survives without the non-urban areas. Exit from Abstract to Routine follows no such gradient: it is lowest in Paris and in the non-urban areas.

Table B.13 gives the same-AU rates by education group. Its Large/Small multipliers include the composition of each group by gender, age and tenure, which differs across city groups; the comparison that holds these fixed is in Section 4.5.

B.9 Sorting Before 25

The decomposition of Section 4.2 follows workers from age 25, so a worker who changed city group earlier enters it as an entry from non-employment in the destination. This appendix asks what those workers carry with them. We call *young arrivals* the workers whose first record inside the 25–64 window falls at age 25 or 26 and whose first job before 25, apprenticeships included as a location, was in the other city group.

Table B.12: Annual switching rates within the same AU, by AU size class (%)

	$R \to A$		$M \to A$	$A \to R$	$R \to M$	$M \to R$
	Rate	Common origin mix				
1984–2021						
Paris	5.43	4.72	1.61	7.47	2.93	12.40
Other Large AUs	3.32	3.36	0.94	8.24	2.73	11.04
Intermediate urban AUs	2.51	2.66	0.69	8.87	2.52	9.96
Smallest urban AUs	1.93	2.25	0.53	8.54	2.32	8.82
Non-urban areas	1.71	2.14	0.55	7.67	2.48	8.43
1994–2021						
Paris	4.99	4.36	1.52	5.61	2.76	9.99
Other Large AUs	3.12	3.11	0.89	6.24	2.39	8.69
Intermediate urban AUs	2.35	2.49	0.64	6.60	2.18	7.75
Smallest urban AUs	1.76	2.03	0.50	6.41	2.02	6.83
Non-urban areas	1.64	2.04	0.57	6.50	2.12	6.33

Notes: Rates as in the right-hand block of Table B.11. Size classes are fixed on 2003 employment: Paris (AU 1, 23% of 2003 employment), the other 20 Large AUs (27%), the remaining urban AUs split into two halves of their 2003 employment (61 intermediate AUs, 20%; 687 smallest AUs, 20%), and the non-urban areas (9%). Common origin mix: each class's rates by two-digit origin code weighted by the code mix of all Routine origins.

Figure B.2 motivates the age at which the window opens. Apprenticeships fall from 24% of paid positions at 18 to 4% at 25 and under 1% at 30, and the annual rates of occupational switching, of cross-city movement and of exit to non-employment all fall steeply through the early twenties before settling onto the gentle life-cycle decline that continues thereafter. The cross-city move rate peaks at 8.9% at age 20 and is 5.4% at 25 and 2.1% at 40. Age 25 is where the transition from school to work gives way to the career mobility the decomposition is about.

Table 2 in Section 4.4 reports what the young arrivals look like; the remainder of this appendix gives the evidence behind it.

Nor do the arrivals bring Abstract jobs with them. Of those entering a Large city in an Abstract job, only 10% held an Abstract job in the Small city they left, against 54% for the natives entering in the same occupation; the rest were Routine, Manual or apprentices, in jobs held on average at age 21.5. Applying the entry rates of the Small-city stayers, cell by cell on pre-move occupation and eventual education, the movers would have reached an Abstract share at entry of 9.7% had they stayed, against 21.2% observed in the Large city and a Small-city employment share of 13.6%. The Small cities did not lose Abstract workers to the Large ones.

Table B.14 gives the unconditional counterpart of the early-career column of Table 3. Large-city natives upgrade from Routine to Abstract at about twice the rate of Small-city

Table B.13: Transition rates by education and city group, same-AU stayers (%)

	Non-college			College		
Switch	Small	Large	L/S	Small	Large	L/S
1984–2021						
Into Abstract work						
$R \to A$	1.79	3.14	1.75	5.10	8.79	1.72
$M \to A$	0.52	0.87	1.68	4.29	5.40	1.26
Between Manual and Routine						
$M \to R$	10.21	11.78	1.15	15.39	19.42	1.26
$R \to M$	2.87	3.20	1.12	1.02	1.41	1.39
Out of Abstract work						
$A \to R$	13.07	12.30	0.94	6.54	5.84	0.89
$A \to M$	1.19	1.07	0.90	0.39	0.32	0.82
1994–2021						
Into Abstract work						
$R \to A$	1.63	2.79	1.71	4.09	7.18	1.76
$M \to A$	0.48	0.75	1.58	2.82	4.63	1.64
Between Manual and Routine						
$M \to R$	7.51	8.84	1.18	13.03	15.88	1.22
$R \to M$	2.53	2.93	1.16	1.04	1.41	1.35
Out of Abstract work						
$A \to R$	10.27	9.54	0.93	4.97	4.45	0.90
$A \to M$	1.13	0.99	0.87	0.31	0.31	1.00

Notes: One-year transition probabilities conditional on the origin occupation, for workers who remain in the same *aire urbaine*. The destination set includes non-employment, so the rates for a given origin do not sum to one across the columns shown. L/S is the ratio of the Large-city rate to the Small-city rate.

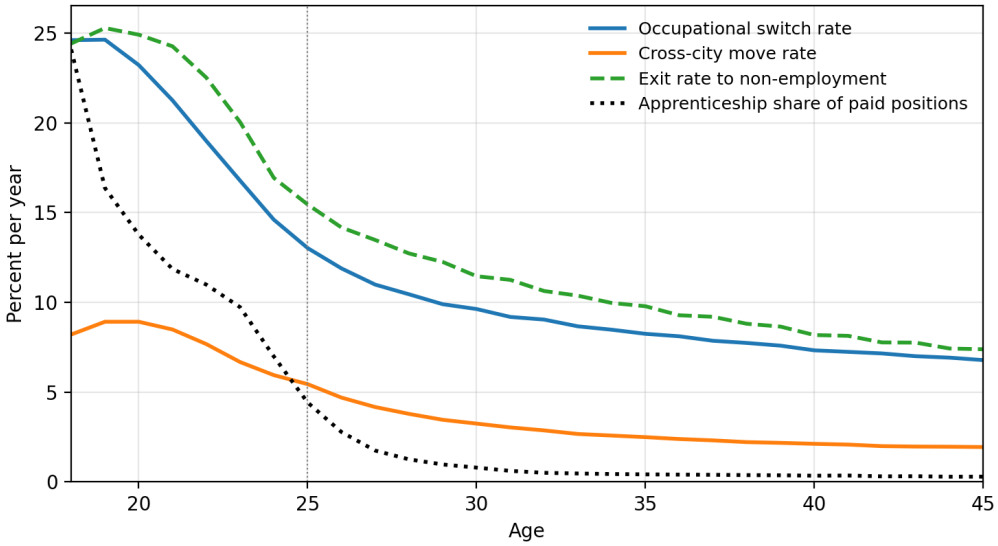


Figure B.2: Annual mobility rates and the apprenticeship share of paid positions, by single year of age, in-panel worker-years 1984–2021.

stayers with no mover involved, and the young movers exceed the natives by a margin that all but disappears within education groups.

Table B.14: Annual $R \to A$ upgrading rate at 25–64 by early-career group and education (%)

	All workers	College	Non-college
Small-city stayers	2.4	7.4	2.0
Large-city natives	4.8	13.4	3.4
Young movers, $S \to L$	6.1	14.0	3.9

Notes: Unconditional annual transition rates over 1984–2021 for the workers classified in Table 2, by the city group they occupy at t: stayers and natives in their own group, movers in the destination. Education is the worker-level highest diploma.

C The Linear Probability Model

Equation (9) of Section 4.5 is estimated by weighted least squares with each calendar year weighted equally and HC3-robust standard errors. For non-employed origins, tenure is the length of the current spell. Four variants are reported. The level specification is estimated on the pooled sample and separately on the college and non-college samples, where the college term drops out; for every fit we report the mean transition rate of within-Small stayers in that sample, the base to which γ_{LL} is to be compared, and for the split fits the difference between the two premia with its standard error. The interaction specification adds the four terms $LL \times$ college, $LL \times$ female, $LL \times$ age and $LL \times$ tenure jointly, so that its LL is the premium of the baseline worker (non-college, male, age 40, tenure 0) and each

interaction the shift from it. The early-career specification adds two dummies for workers whose first job before 25 was in the other city group, defined for those entering the sample from 1994 so that the whole 18–24 history is observed, and a third for workers whose early career is not observed; workers who did not change city group before 25 are the omitted category. The origin-occupation specification adds fixed effects for the two-digit PCS code at t to the level and early-career specifications, for transitions out of employment, where the code is defined. SL and LS are not interacted with worker characteristics: cross-city movers are self-selected on unobservables (Sections 4.2 and 4.4), and such terms would conflate a spatial effect with selection.

The transition indicator is built from the recorded states at t and $t+1$ for workers present at both dates. Rows originating in non-employment therefore exclude panel-entry first observations, which enter the aggregate inflow of Section 3 through the accounting identity but are not transitions in the micro sense. College is education observed at the origin date, carried forward and back within worker; workers never observed with education drop out. For non-employed origins the city at t is imputed from the nearest employment spell, which can inflate γ_{SL} and γ_{LS} but not γ_{LL}.

Two results are not discussed in the text. The within-Large premium on $R \to A$ is larger in 1984–1993, +1.95 pp, than over 1994–2021, +1.37 pp, though the earlier estimate rests on 244,964 observations against 8.0 million, because education is recorded only from 2002 and earlier years enter only for workers observed after that date. And a non-employed worker who had changed city group before 25 is 4.0 to 4.7 pp less likely to be in a job the following year than one who had not, a quarter to three tenths of the rate at which non-employed Small-city stayers return to work, with the shortfall concentrated in Routine and Manual jobs and of similar size in both directions of the move. Since non-employment in these data is absence from covered salaried employment, and the city at t for non-employed origins is imputed, we do not interpret this result.

Table C.1 reports the split-sample estimates for all margins and both windows; Table C.2 the premia with and without fixed effects for the origin occupation, and Table C.3 the origin composition of stayers and the transition rates by code behind that comparison; Tables C.4–C.10 the full pooled estimates, one per margin.

C.1 Full regression tables

Tables C.4–C.10 report the full pooled regressions behind Table 3: the level specification on the whole period and split at the 1994 break, the interaction specification, and the early-career specification. The last two columns are estimated on 1994–2021; the two early-career dummies are defined for workers entering the sample from 1994, so that the whole 18–24 history lies inside the panel, and the corresponding pre-1994 cells are empty by construction. The Small-stayer rate is the mean transition rate (%) of within-Small

Table C.1: Within-Large premium γ_{LL} by education group (level specification estimated separately on each sample)

Transition	Non-college γ_{LL} (SE)	Non-college Small-stayer rate	Non-college N	College γ_{LL} (SE)	College Small-stayer rate	College N	Difference (SE)
1984–2021							
Upgrading to Abstract							
R → A	+1.36*** (0.02)	1.96	7,582,626	+3.10*** (0.25)	6.16	705,546	+1.74*** (0.25)
M → A	+0.26*** (0.02)	0.62	2,800,185	+0.63 (0.60)	4.46	99,306	+0.37 (0.60)
NE → A	+0.86*** (0.02)	1.06	5,664,727	+3.23*** (0.12)	7.09	817,347	+2.37*** (0.12)
Downgrading from Abstract							
A → R	−1.41*** (0.12)	8.93	1,648,216	−0.48*** (0.15)	3.36	1,337,309	+0.92*** (0.19)
Entry into Routine							
M → R	+0.01 (0.10)	7.36	2,800,185	+1.39 (0.79)	12.90	99,306	+1.37 (0.79)
NE → R	+0.22*** (0.05)	8.73	5,664,727	+0.77*** (0.11)	7.68	817,347	+0.55*** (0.12)
Entry into Manual from Non-Employment							
NE → M	−0.44*** (0.03)	5.96	5,664,727	+0.07 (0.04)	1.75	817,347	+0.51*** (0.05)
1994–2021							
Upgrading to Abstract							
R → A	+1.18*** (0.02)	1.95	7,345,655	+3.19*** (0.15)	6.08	697,553	+2.01*** (0.15)
M → A	+0.22*** (0.02)	0.62	2,744,790	+1.72*** (0.34)	4.42	98,411	+1.50*** (0.34)
NE → A	+0.78*** (0.02)	1.06	5,498,000	+2.79*** (0.09)	7.14	799,474	+2.01*** (0.09)
Downgrading from Abstract							
A → R	−1.23*** (0.08)	8.77	1,611,375	−0.50*** (0.08)	3.33	1,321,659	+0.74*** (0.11)
Entry into Routine							
M → R	−0.11 (0.06)	7.21	2,744,790	+0.88 (0.54)	12.88	98,411	+0.99 (0.54)
NE → R	−0.36*** (0.04)	8.62	5,498,000	+0.09 (0.09)	7.76	799,474	+0.45*** (0.10)
Entry into Manual from Non-Employment							
NE → M	−0.63*** (0.03)	6.02	5,498,000	0.00 (0.04)	1.78	799,474	+0.63*** (0.05)

Notes: Coefficients in percentage points, HC3-robust standard errors in parentheses; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Each column group is equation (9) without the college term, estimated on that education sample; the Small-stayer rate is the mean transition rate (%) of within-Small stayers in that sample. The difference is the college minus the non-college premium, with the standard error of two independent estimates.

Table C.2: Within-Large premium γ_{LL} with and without fixed effects for the origin occupation

Transition	All workers		Non-college		College	
	Baseline	Origin FE	Baseline	Origin FE	Baseline	Origin FE
1984–2021						
R → A	+1.54*** (0.02)	+0.92*** (0.02)	+1.36*** (0.02)	+0.77*** (0.02)	+3.10*** (0.25)	+2.46*** (0.25)
M → A	+0.27*** (0.03)	+0.26*** (0.03)	+0.26*** (0.02)	+0.24*** (0.03)	+0.63 (0.60)	+0.58 (0.60)
A → R	−1.10*** (0.10)	−0.93*** (0.10)	−1.41*** (0.12)	−1.19*** (0.12)	−0.48*** (0.15)	−0.46** (0.15)
M → R	+0.03 (0.10)	−0.15 (0.10)	+0.01 (0.10)	−0.18 (0.10)	+1.39 (0.79)	+1.34 (0.80)
1994–2021						
R → A	+1.36*** (0.02)	+0.83*** (0.02)	+1.18*** (0.02)	+0.67*** (0.02)	+3.19*** (0.15)	+2.61*** (0.15)
M → A	+0.25*** (0.02)	+0.25*** (0.02)	+0.22*** (0.02)	+0.22*** (0.02)	+1.72*** (0.34)	+1.64*** (0.34)
A → R	−0.94*** (0.06)	−0.70*** (0.06)	−1.23*** (0.08)	−0.92*** (0.08)	−0.50*** (0.08)	−0.45*** (0.08)
M → R	−0.08 (0.06)	−0.20** (0.06)	−0.11 (0.06)	−0.22*** (0.06)	+0.88 (0.54)	+0.79 (0.55)
Moved S→L before 25, R→A						
All workers	+0.47*** (0.08)	+0.23** (0.08)				

Notes: Coefficients in percentage points, HC3-robust standard errors in parentheses; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. In the 1994–2021 block the All-workers estimates include the early-career dummies, as in Table 3.

stayers in the estimation sample. Coefficients are in percentage points; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

D Comparison with Davis et al. (2026)

Davis et al. (2026) document the urban divergence in France over 1994–2015 using DADS-Postes, the exhaustive annual declarations of job positions by privately incorporated companies. Their data cover the universe of private-sector positions but exclude public-sector employment, carry no education or tenure information and cannot follow workers over time, whereas DADS-EDP is a longitudinal sample of the same declarations (one worker in twenty-four before 2002 and one in twelve thereafter) that includes the public sector. A second difference is the occupational classification: they group CS2 codes by wage rank into high-, middle- and low-paid categories, while our task-based classification groups them into Abstract, Routine and Manual. The two classifications agree on most CS2 codes but differ in two substantive places.

First, CS2=47 (technicians) is classified as Abstract here but middle-paid in their scheme. Wages for CS2=47 sit at the top of the middle range, about 85–130% of the Manual-group average; their boundary is drawn by wage rank, while our boundary is drawn by the task content of the occupation (technicians perform predominantly non-routine cognitive tasks).

Second, CS2=64 (drivers) is classified as Manual here but middle-paid there. Driver wages cluster just above the Manual average (130–140%), placing them near the boundary between the two schemes. Driving is a routine-manual task in the task content literature but its compensation places it in the middle of the wage distribution in France.

Table C.3: Origin occupation of within-city stayers and transition rates by two-digit code, 1984–2021

		Share of stayers (%)		**Transition rate (%)**		
CS2	**Description**	Small	Large	Small	Large	L/S
Routine origins, transition $R \to A$						
62	Ouv. qual. industriel	17.6	11.2	1.94	3.00	1.55
52	Empl. civils fonc. publ.	17.2	16.1	0.66	1.02	1.55
54	Empl. admin. entreprise	13.5	18.1	2.26	3.60	1.59
63	Ouv. qual. artisanal	10.6	8.7	1.28	2.36	1.84
67	Ouv. non qual. industriel	9.2	5.7	0.88	1.74	1.98
46	Prof. int. admin./comm.	8.9	16.1	6.63	8.66	1.31
43	Prof. int. santé/social	8.7	8.5	1.43	2.05	1.43
42	Instituteurs	5.0	5.0	2.58	4.42	1.71
48	Contremaîtres	3.5	3.9	7.74	8.77	1.13
65	Ouv. qual. manut./transp.	3.4	3.3	1.28	1.81	1.41
45	Prof. int. fonc. publ.	2.4	3.4	4.52	5.24	1.16
	All stayers	100.0	100.0	2.24	3.83	1.71
	Large rates, Small composition				3.27	1.46
Abstract origins, transition $A \to R$						
47	Techniciens	26.1	17.3	10.51	9.94	0.95
37	Cadres admin./comm.	22.6	32.3	7.19	5.50	0.77
38	Ingénieurs/cadres tech.	17.2	26.5	4.74	2.92	0.62
34	Prof. enseign./santé	16.7	10.5	3.04	4.17	1.37
33	Cadres fonc. publique	10.7	7.2	6.42	4.48	0.70
23	Chefs entr. $\geq$10 sal.	3.4	2.2	4.13	4.20	1.02
35	Prof. information/arts	2.1	3.5	12.45	8.75	0.70
31	Professions libérales	1.1	0.6	5.11	6.81	1.33
	All stayers	100.0	100.0	6.84	5.47	0.80
	Large rates, Small composition				5.92	0.87

Notes: Stayers are workers in the same city group at both dates. The last row of each panel applies the Large-city rates by code to the Small-city composition.

Table C.4: LPM: Routine → Abstract

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	$+8.09^{***}$	$+16.82^{***}$	$+6.76^{***}$	$+5.70^{***}$	$+6.76^{***}$
Female	-2.21^{***}	-2.74^{***}	-1.97^{***}	-1.77^{***}	-1.97^{***}
Age	$+0.04^{***}$	$+0.13^{***}$	$+0.02^{***}$	$+0.03^{***}$	$+0.03^{***}$
Tenure	-0.27^{***}	-0.55^{***}	-0.25^{***}	-0.20^{***}	-0.25^{***}
SL	$+6.86^{***}$	$+5.25^{***}$	$+7.64^{***}$	$+7.87^{***}$	$+7.63^{***}$
LS	$+6.03^{***}$	$+5.14^{***}$	$+6.31^{***}$	$+6.53^{***}$	$+6.28^{***}$
LL	$+1.54^{***}$	$+1.95^{***}$	$+1.37^{***}$	$+2.09^{***}$	$+1.36^{***}$
$LL\times$Age	—	—	—	-0.02^{***}	—
$LL\times$Female	—	—	—	-0.43^{***}	—
$LL\times$College	—	—	—	$+1.84^{***}$	—
$LL\times$Tenure	—	—	—	-0.13^{***}	—
Moved $S\to L$ before 25	—	—	—	—	$+0.47^{***}$
Moved $L\to S$ before 25	—	—	—	—	$+0.03$
Year FE	Yes	Yes	Yes	Yes	Yes
N	8,288,172	244,964	8,043,208	8,043,208	8,043,208
R^2	0.0267	0.0399	0.0245	0.0251	0.0245
$\bar{y}$	3.11	3.82	3.09	3.09	3.09
Small-stayer rate	2.24	2.50	2.24	2.24	2.24

Table C.5: LPM: Manual → Abstract

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	$+5.64^{***}$	$+8.40^{***}$	$+5.16^{***}$	$+4.78^{***}$	$+5.15^{***}$
Female	-0.81^{***}	-0.79^{***}	-0.81^{***}	-0.76^{***}	-0.81^{***}
Age	$+0.00$	$+0.01$	-0.00^{*}	$+0.00$	$+0.01^{***}$
Tenure	-0.11^{***}	-0.18^{***}	-0.11^{***}	-0.09^{***}	-0.11^{***}
SL	$+2.96^{***}$	$+2.87^{***}$	$+2.98^{***}$	$+3.03^{***}$	$+2.99^{***}$
LS	$+2.24^{***}$	$+2.58^{***}$	$+2.06^{***}$	$+2.10^{***}$	$+2.04^{***}$
LL	$+0.27^{***}$	$+0.30^{**}$	$+0.26^{***}$	$+0.50^{***}$	$+0.25^{***}$
$LL\times$Age	—	—	—	-0.01^{**}	—
$LL\times$Female	—	—	—	-0.12^{**}	—
$LL\times$College	—	—	—	$+0.60^{*}$	—
$LL\times$Tenure	—	—	—	-0.05^{***}	—
Moved $S\to L$ before 25	—	—	—	—	$+0.32^{**}$
Moved $L\to S$ before 25	—	—	—	—	-0.09
Year FE	Yes	Yes	Yes	Yes	Yes
N	2,899,491	56,290	2,843,201	2,843,201	2,843,201
R^2	0.0158	0.0166	0.0160	0.0162	0.0162
$\bar{y}$	0.97	1.05	0.97	0.97	0.97
Small-stayer rate	0.70	0.73	0.70	0.70	0.70

Table C.6: LPM: Non-Employed → Abstract

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	$+6.74^{***}$	$+6.41^{***}$	$+6.81^{***}$	$+6.80^{***}$	$+6.82^{***}$
Female	-2.00^{***}	-2.67^{***}	-1.74^{***}	-1.57^{***}	-1.73^{***}
Age	$+0.01^{***}$	$+0.13^{***}$	$+0.00^{***}$	$+0.02^{***}$	$+0.02^{***}$
Tenure	-0.37^{***}	-1.63^{***}	-0.32^{***}	-0.22^{***}	-0.31^{***}
SL	$+12.98^{***}$	$+10.26^{***}$	$+13.45^{***}$	$+13.63^{***}$	$+13.37^{***}$
LS	$+11.08^{***}$	$+10.88^{***}$	$+10.91^{***}$	$+11.07^{***}$	$+10.85^{***}$
LL	$+1.07^{***}$	$+1.28^{***}$	$+0.96^{***}$	$+1.98^{***}$	$+0.95^{***}$
$LL\times$Age	—	—	—	-0.03^{***}	—
$LL\times$Female	—	—	—	-0.35^{***}	—
$LL\times$College	—	—	—	$+0.01$	—
$LL\times$Tenure	—	—	—	-0.21^{***}	—
Moved $S\to L$ before 25	—	—	—	—	$+0.53^{***}$
Moved $L\to S$ before 25	—	—	—	—	-0.34^{**}
Year FE	Yes	Yes	Yes	Yes	Yes
N	6,482,074	184,600	6,297,474	6,297,474	6,297,474
R^2	0.0475	0.0437	0.0510	0.0516	0.0513
$\bar{y}$	2.56	2.58	2.56	2.56	2.56
Small-stayer rate	1.59	1.48	1.60	1.60	1.60

Table C.7: LPM: Abstract → Routine

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	-6.39^{***}	-10.25^{***}	-5.20^{***}	-6.02^{***}	-5.19^{***}
Female	$+2.61^{***}$	$+4.11^{***}$	$+2.08^{***}$	$+2.08^{***}$	$+2.08^{***}$
Age	-0.10^{***}	-0.19^{***}	-0.08^{***}	-0.10^{***}	-0.08^{***}
Tenure	-0.78^{***}	-2.36^{***}	-0.71^{***}	-0.84^{***}	-0.71^{***}
SL	$+9.91^{***}$	$+9.42^{***}$	$+10.11^{***}$	$+10.01^{***}$	$+10.11^{***}$
LS	$+11.64^{***}$	$+7.87^{***}$	$+13.62^{***}$	$+13.49^{***}$	$+13.65^{***}$
LL	-1.10^{***}	-1.63^{***}	-0.95^{***}	-2.45^{***}	-0.94^{***}
$LL\times$Age	—	—	—	$+0.03^{***}$	—
$LL\times$Female	—	—	—	$+0.04$	—
$LL\times$College	—	—	—	$+1.28^{***}$	—
$LL\times$Tenure	—	—	—	$+0.20^{***}$	—
Moved $S\to L$ before 25	—	—	—	—	-1.06^{***}
Moved $L\to S$ before 25	—	—	—	—	-0.32
Year FE	Yes	Yes	Yes	Yes	Yes
N	2,985,525	52,491	2,933,034	2,933,034	2,933,034
R^2	0.0570	0.0534	0.0403	0.0407	0.0403
$\bar{y}$	6.26	13.86	6.13	6.13	6.13
Small-stayer rate	6.84	14.98	6.71	6.71	6.71

Table C.8: LPM: Manual → Routine

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	$+3.67^{***}$	-0.88	$+4.37^{***}$	$+4.34^{***}$	$+4.37^{***}$
Female	-3.61^{***}	-6.15^{***}	-2.77^{***}	-3.02^{***}	-2.77^{***}
Age	-0.11^{***}	-0.03	-0.12^{***}	-0.11^{***}	-0.08^{***}
Tenure	-1.02^{***}	-3.32^{***}	-0.88^{***}	-0.89^{***}	-0.88^{***}
SL	$+19.94^{***}$	$+24.06^{***}$	$+17.99^{***}$	$+17.99^{***}$	$+18.04^{***}$
LS	$+18.72^{***}$	$+16.67^{***}$	$+19.37^{***}$	$+19.36^{***}$	$+19.38^{***}$
LL	$+0.03$	$+0.29$	-0.10	-0.46^{***}	-0.08
$LL\times$Age	—	—	—	-0.02^{**}	—
$LL\times$Female	—	—	—	$+0.55^{***}$	—
$LL\times$College	—	—	—	$+0.04$	—
$LL\times$Tenure	—	—	—	$+0.02$	—
Moved $S\to L$ before 25	—	—	—	—	-0.48
Moved $L\to S$ before 25	—	—	—	—	-0.69^{*}
Year FE	Yes	Yes	Yes	Yes	Yes
N	2,899,491	56,290	2,843,201	2,843,201	2,843,201
R^2	0.0571	0.0523	0.0433	0.0433	0.0436
$\bar{y}$	8.11	16.85	7.93	7.93	7.93
Small-stayer rate	7.49	15.54	7.34	7.34	7.34

Table C.9: LPM: Non-Employed → Routine

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	-4.54^{***}	-7.71^{***}	-3.74^{***}	-4.44^{***}	-3.68^{***}
Female	-0.70^{***}	-2.35^{***}	$+0.03$	-0.43^{***}	$+0.07$
Age	-0.21^{***}	$+0.13^{***}$	-0.23^{***}	-0.24^{***}	-0.18^{***}
Tenure	-1.46^{***}	-7.34^{***}	-1.23^{***}	-1.25^{***}	-1.18^{***}
SL	$+42.49^{***}$	$+43.47^{***}$	$+41.08^{***}$	$+41.01^{***}$	$+40.97^{***}$
LS	$+41.83^{***}$	$+41.70^{***}$	$+40.87^{***}$	$+40.82^{***}$	$+40.79^{***}$
LL	$+0.32^{***}$	$+1.57^{***}$	-0.26^{***}	-1.17^{***}	-0.25^{***}
$LL\times$Age	—	—	—	$+0.03^{***}$	—
$LL\times$Female	—	—	—	$+0.96^{***}$	—
$LL\times$College	—	—	—	$+1.20^{***}$	—
$LL\times$Tenure	—	—	—	$+0.06^{***}$	—
Moved $S\to L$ before 25	—	—	—	—	-2.35^{***}
Moved $L\to S$ before 25	—	—	—	—	-2.57^{***}
Year FE	Yes	Yes	Yes	Yes	Yes
N	6,482,074	184,600	6,297,474	6,297,474	6,297,474
R^2	0.0758	0.0782	0.0828	0.0829	0.0842
$\bar{y}$	9.32	13.66	9.20	9.20	9.20
Small-stayer rate	8.64	11.91	8.54	8.54	8.54

Table C.10: LPM: Non-Employed → Manual

Variable	Level 1984–2021	Level 1984–1993	Level 1994–2021	Interaction 1994–2021	Early career 1994–2021
College	-4.40^{***}	-3.60^{***}	-4.62^{***}	-5.81^{***}	-4.60^{***}
Female	$+1.54^{***}$	$+0.40^{***}$	$+1.96^{***}$	$+2.45^{***}$	$+1.96^{***}$
Age	-0.12^{***}	-0.01	-0.13^{***}	-0.13^{***}	-0.13^{***}
Tenure	-0.50^{***}	-1.87^{***}	-0.44^{***}	-0.46^{***}	-0.44^{***}
SL	$+20.70^{***}$	$+15.08^{***}$	$+21.90^{***}$	$+22.00^{***}$	$+22.01^{***}$
LS	$+22.88^{***}$	$+15.71^{***}$	$+24.39^{***}$	$+24.47^{***}$	$+24.49^{***}$
LL	-0.35^{***}	$+0.01$	-0.51^{***}	-0.40^{***}	-0.50^{***}
$LL\times$Age	—	—	—	-0.00	—
$LL\times$Female	—	—	—	-1.01^{***}	—
$LL\times$College	—	—	—	$+1.99^{***}$	—
$LL\times$Tenure	—	—	—	$+0.05^{***}$	—
Moved $S\to L$ before 25	—	—	—	—	-2.17^{***}
Moved $L\to S$ before 25	—	—	—	—	-1.75^{***}
Year FE	Yes	Yes	Yes	Yes	Yes
N	6,482,074	184,600	6,297,474	6,297,474	6,297,474
R^2	0.0384	0.0228	0.0432	0.0436	0.0434
$\bar{y}$	5.71	4.13	5.75	5.75	5.75
Small-stayer rate	5.59	3.85	5.64	5.64	5.64

The two classification choices are independent, and all qualitative results in the present paper are robust to reclassifying CS2=47 and CS2=64 into the Davis-Mengus-Michalski categories; the changes shift point estimates by at most 0.02–0.04 pp/year and do not alter signs. The Davis-Mengus-Michalski spatial-equilibrium model predicts the within-city upgrading flow that dominates our decomposition in Large cities, so the two pieces of evidence are best read as complementary: their aggregate-share long differences reveal the urban divergence pattern, our flow-level decomposition identifies the underlying within-city upgrading channel that produces it.