The Great Separation:
Top Earner Segregation at Work in Advanced Capitalist Economies†

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[1]French data; [2]Hungarian data; [3]Danish data; [4]Norwegian data; [5]Canadian data; [6]South Korean data; [7]Japanese data; [8]Czech data; [9]Duch data; [10]German data; [11]Spanish data; [12]Swedish data

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Abstract

Earnings segregation at work is an understudied topic in social science, despite the workplace being an everyday nexus for social mixing, cohesion, contact, claims-making, and resource exchange. It is all the more urgent to study as workplaces, in the last decades, have undergone profound reorganizations that could impact the magnitude and evolution of earnings segregation. Analyzing linked employer-employee panel administrative databases, we estimate the evolving isolation of higher earners from other employees in twelve countries: Canada, Czechia, Denmark, France, Germany, Hungary, Japan, the Netherlands, Norway, Spain, South Korea, and Sweden. We find in almost all countries a growing workplace isolation of top earners and dramatically declining exposure of top earners to bottom earners. We do a first exploration of the main factors accounting for this trend: deindustrialization, workplace downsizing restructuring (including layoffs, outsourcing, offshoring, and subcontracting) and digitalization contribute substantially to the increase in top earner segregation. These findings open up a future research agenda on the causes and consequences of top earner segregation.

Keywords: work, earnings, segregation, inequality, elite

Introduction

Workplaces are places where people work together. This trivial statement underscores the inherently social dimension of work organization. While early social scientists insisted on the contribution of the division of labor to "organic solidarity" (Durkheim [1893] 1933) and to class solidarity and consciousness (Marx [1852] 1907), later scholarship has mostly approached social cohesion through the study of neighborhoods and schools (Massey and Denton 1993; Rugh and Massey 2014; Reardon and Yun 2001; Reardon and Bischoff 2011; Fiel 2013; Tammaru et al. 2015). But, of course, most adults spend more time at work interacting with coworkers than with neighbors in their neighborhoods (Héran 1988). Moreover, when it comes to social mixing, workplaces routinely bring together people across the income hierarchy.

Many studies show that social mixing has a redistributive effect, allowing social or human capital to flow from the top to the bottom of social hierarchies through network ties (N. Lin, Ensel, and Vaughn 1981; Sacerdote 2011; Chetty et al. 2022). In addition, demographic mixing of different social groups in neighborhoods, schools, and workplaces can promote integration (Allport 1954; Pettigrew et al. 2011) and social contact can reduce prejudice and promote empathy, at least when interactions are repeated, identities are shared, dependence is bilateral, and mixing norms are positive (Amir 1994; Moody 2001; Dinesen and Sønderskov 2015).

Workplaces combine these two dimensions of redistribution and integration but also add a third element of relationality. They are not only sites of co-presence, but also of hierarchical coordination and competitive claims over the distribution of valued organizational resources, such as wages, jobs, promotions, good working conditions, and the like (Tomaskovic-Devey and Avent-Holt 2019). Organizational membership legitimizes claims to a share of collectively produced resources. The separation of high and low earners in different workplaces affects the extent to which top earners, who often set the distribution of others' wages and working conditions, face embodied labor claims. Thus, earnings segregation has potential distributional consequences through relational processes unique to the workplace.

While workplace gender and ethnic segregation are the subject of ongoing research (Tomaskovic-Devey et al. 2006; Baunach 2002; Hellerstein and Neumark 2008; Ferguson and Koning 2018), little is known about the evolution of earnings segregation at work. Our paper helps to fill this gap by first and foremost documenting the level and the dynamics of between workplace earnings segregation in several high-income countries, with a particular focus on top earners. In order to make sense of these trends in workplace earnings segregation, it then also offers a first exploration of the main socioeconomic factors accounting for top earner segregation.

Indeed, the study of earnings segregation at work is all the more urgent as workplaces have undergone profound reorganizations that could impact its magnitude and its evolution. The reorganization of work through geographic and sectoral reallocation, deindustrialization, financialization, digitalization, globalization, and workplace restructuring all point to an increase in workplace earnings segregation. For example, industrial manufacturing has long been the site of a deep and hierarchical division of labor, bringing together in the same workplace a variety of occupations from different levels of the wage scale such as blue-collar workers, supervisors, engineers, managers, and executives. Deindustrialization (Alderson 1999; Kollmeyer 2009; Kollmeyer and Pichler 2013), which combines both a reduction in the size of the manufacturing sector and a profound reorganization of its functioning through outsourcing and subcontracting, can only shrink the opportunities for top-down exposure at work (Whitford 2005). In contrast to traditional manufacturing, the growing sectors of the "knowledge economy" (especially high-tech and finance) do not require many low-skilled workers or a strong workplace coordination of design, supervision, and execution tasks (Powell and Snellman 2004). Within sectors and workplaces, both technological change (Autor, Katz, and Kearney 2006) and offshoring to low-wage countries (Alderson 1999; Kollmeyer 2009) have favored the disappearance of low skill routine jobs. Firms concentrating on their core activities and outsourcing non-core activities to subcontractors and service-to-business firms lead to fissured workplaces (Zuckerman 1999; Weil 2014; Goldschmidt and Schmieder 2017).

Consistently, in many countries the between-workplace share of wage variance has substantially increased over time (Card, Heining, and Kline 2013; Song et al. 2019; Tomaskovic-Devey et al. 2020). Moreover, at least in the US, high-wage occupations cluster increasingly in high-wage workplaces (Wilmers and Aeppli 2021) and the network of mobility between occupations has fragmented substantially in recent decades (K.-H. Lin and Hung 2022).

We contribute to this literature with a classical segregation measure (Bell 1954). Instead of using metrics based on wage variance, we approach the evolution of earnings segregation at work with standardized measures of co-worker exposure based on earnings fractiles. This method precisely adresses the heterogeneity of the process. Since the exposure measure is based on ranks, rather than nominal wages, it also isolates the evolution of segregation from that of wage inequality. Finally, this method allows us to compare earnings segregation with other forms of workplace segregation. Using this approach, we uncover a dramatic and robust increase in the isolation of top earners at work, one that is much more pronounced than the evolution of other forms of social segregation.

We conducted these analyses in twelve developed countries between 1990 and 2019 using population and large sample longitudinal linked employer-employee datasets, hereafter referred to as COIN database. The choice of countries is partly a matter of data availability and accessibility. Only advanced capitalist economies with a dominant formal economy and a structured and entrenched welfare state offer fine-grained linked employer-employee data on wages. We leverage our team's diversity to cover countries with high quality, accessible administrative data. Our sample is well-designed to study earnings segregation at work and its transformation in high income countries. In advanced capitalist economies, formal employment is the backbone of economic activity, with more than 85% of the labor force in wage employment (OECD 2023). Formal workplaces are thus appropriate sites for measuring income segregation at work. Moreover, the aforementioned processes of work transformation have strongly affected advanced capitalist economies and are suspected to have deeply altered segregation at work. Yet, advanced capitalist economies come in different "varieties" with different institutional state-economy arrangements that affect levels and trends in inequality, and potentially segregation (Hall and Soskice 2001). Therefore, a broad coverage of the variety of economies allows us to warrant the generality of our findings. Hence, we examine workplace earnings segregation in one "liberal" North American economy (Canada), three Scandinavian "social-democratic" economies (Denmark, Norway, Sweden), three "corporatist" Western European economies (France, Germany, and the Netherlands), one "Southern Europe" economy (Spain), two "transitioning" economies (Czechia, Hungary), and two Asian economies (Japan and South Korea) (Esping-Andersen 1990; Katrougalos 1996; Hall and Soskice 2001). The diversity of institutional contexts allows us to contrast the generalizability and specificity of the estimated trends. Beyond second-order variations in intensity, the generality of the trend in top earner segregation across the twelve countries suggests that we have uncovered a general phenomenon of contemporary capitalist high income economies during the last three decades. Of course, we would like to see analyses in additional high income countries as data become available, and this paper is silent on trends in low income countries.

This paper builds on our previous article showing that between-workplace wage variance has increased substantially in multiple countries (Tomaskovic-Devey et al. 2020). That article took a macro perspective, showing for multiple countries that increasing earnings inequality occurred more robustly between than within workplaces and was tied to shifts in national labor market institutions. The present contribution approaches a similar phenomenon, rising workplace inequality, but now with a focus on opportunities for interaction between employees in distinct positions within the income distribution. Thus, we have moved to a more relational perspective. The earlier article speculated as to the causes of rising between workplace inequality. In the present article we examine those potential causes directly. Additionally, this article offers a shift in inequality measures, from global to relational fractiles. By focusing on co-worker exposure to different fractiles of the income distribution this analytic shift has clear implications for the interactional consequences of workplace earnings differentiation, providing a set of original investigations of the socioeconomic causes of the increased segregation of high earners from the rest of the workforce. This shift to exposure measures of segregation also permits a focus on the compositional sources of income segregation trends and direct comparisons to other bases of segregation (e.g. sex, age, citizenship, occupation).

This paper makes a number of fundamental contributions. First, we identify a new stylized fact – top earners in many countries are increasingly isolated from lower earners, and this trend is quite distinct from other workplace segregation trends. Second, we begin to explain why and how this is happening. We isolate three key intertwined factors that account for this development: 1) deindustrialization and reorganization of the manufacturing sector, 2) decline in workplace size and restructuring of workplaces, through outsourcing, layoffs, offshoring and subcontracting, 3) and digitalization of the labor process. Our paper therefore shows that the restructuring of national economies and workplaces, highlighted by previous research on the current transformation of work and firms (Whitford 2005; Weil 2014; G. F. Davis 2016), is also leading to a significant change in the potential for social cohesion. Together, these contributions inform the social science literatures focused on segregation, inequality and cross-class cohesion and antipathy. Our core findings also have implications for understanding the interactional processes that undermine the quality of employment, isolate elites from the masses, and perhaps even fuel the rise of populist resentment against increasingly isolated elites.

The paper is organized as follows. In the first section, we draw on previous literature to conceptualize workplace earnings segregation and to outline the potential economic and organizational factors governing its evolution. Next, we detail data, measures and models. In the fourth section, we present our main finding, an increase in top earner segregation in twelve countries. Section five examines the impact of socioeconomic factors on workplace segregation. Finally, we discuss a research agenda for further exploring the sources and consequences of top earner segregation.

1. Conceptualizing workplace earnings segregation

Most of the existing literature on segregation focuses on ethnoracial or migrant residential segregation (Musterd 2005), especially in the context of the segregation of African Americans in the US as a legacy of slavery and apartheid (Massey and Denton 1993). The evolution of socioeconomic residential segregation (measured either by income, occupations, or education) has received increasing attention. Reardon and Bischoff (2011) found for the US a strong increase in income residential segregation among families. Although debated and possibly overestimated (Logan et al. 2018), this trend seems to hold in other countries. Préteceille (2006) and Godechot (2013), for France, also documented an increase over the previous twenty years, notably in the degree of residential segregation of top earners. More broadly, Tammaru et al. (2015) and Musterd et al. (2017) find that residential segregation between the rich (defined variously as top income quintile, top occupations, or high level of education) and the poor has been rising in twelve major European cities between 2001 and 2011.

The study of workplace segregation has been mostly devoted to gender and ethnicity (Baunach 2002; Tomaskovic-Devey et al. 2006; Hellerstein and Neumark 2008; Bygren 2013; Ferguson and Koning 2018). Ferguson and Koning (2018) find rising between workplace racial segregation in the US after 1980, a pattern also observed in Sweden (Åslund and Skans 2010). Some studies provide evidence of growing segregation at work by levels of skill (Kremer and Maskin 1996). Recent research showed a fragmentation of the mobility network between occupations, a result consistent with increased occupational segregation at work (Wilmers and Aeppli 2021; K.-H. Lin and Hung 2022; Bergeaud et al. 2021).

While earnings segregation at work *per se* is an underdeveloped topic, it can be linked to a stream of recent research on rising between workplace wage variance. Research conducted by Card, Heining, and Kline (2013) using West Germany data and by Song et al. (2019) with US data show that the growth in inequality in both countries occurred mainly between rather than within establishments. Tomaskovic-Devey et al. (2020) generalized this finding to a set of thirteen of fourteen high-income countries examined. Both Card et al. (2013) and Song et al. (2019) find that growing between establishment inequality is mostly due to the increased sorting of high earners into high-paying firms and low earners into low-paying firms.

Previous research has adopted a macro-perspective and mostly characterized whether the locus of the increase in wage inequality happened between or within establishments. For this aim, it decomposed wage variance into various components: variance and covariance of worker and workplace fixed effects (Abowd, Kramarz, and Margolis 1999). We approach the same phenomenon but through a radically different conceptual and methodological lens. Instead of decomposing wage variance, we use the more intuitive measures of *exposure* of higher and lower wage groups to one another in workplaces. This approach produces several advantages. First, our measures of the evolution of wage segregation based on wage ranks, rather than on absolute wages, are independent of the evolution of global inequality. Contrary to research on wage variance components, an increase in wage segregation based on exposure measures can occur not only when overall variance increases, but also when it stagnates, or even decreases. Second, in contrast to Song et al. (2019) who proposed an indicator of segregation based on the variance of firms' means of workers fixed effect, we do not limit earnings segregation measures to the assortative matching of workers by supposedly fixed productivity profiles. Instead, we believe that these measures must also account for possible firm or occupational premiums. Thus, we simply consider the concentration of high- and low-wage workers in particular establishments as a segregation process. Third, our measures tracing various wage groups' exposure to one another enable us to go beyond a single variance-based measure of segregation at work. Indeed, our measurement strategy shows whether growing workplace earnings segregation happens mainly at the top, in the middle, or at the bottom of the earnings hierarchy. This shift is similar to the move from Gini-type measures of inequality to top income shares, revealing the social locations involved in increases in inequality (Piketty [2013] 2014; Godechot 2017). Moreover, in contrast to variance related measures, our exposure measures of segregation are less likely to be biased by small unit measurement errors.[1] Fourth, we provide measures that are readily comparable to other forms of segregation, such as gender or nativity segregation, giving us a sense of which group distinctions are more extreme and dynamic. Finally,

1 If a given parameter p_i* is measured within the unit i with an unbiased error e_i–which is likely when the unit i is small–, then the empirical expectation $E(p_i)$ is not biased: $E(p_i)=E(p_i^*+e_i)= E(p_i^*)+E(e_i)= E(p_i^*)$. In contrast, the empirical variance $V(p_i)$ will be biased: $V(p_i)=V(p_i^*+e_i)=V(p_i^*)+V(e_i)\neq V(p_i^*)$.

and perhaps most substantively important, our exposure measures directly express workers' chances of interaction at work.

Potential drivers of workplace earnings segregation

Drawing on recent research on the evolution of work, we review a number of potential mechanisms driving the evolution of segregation at the workplace level. All focus on the restructuring of national economies and firm organization, and include shifts in geographic and industry composition, the role of technological change and globalization, and the restructuring of firm boundaries.

Geographic polarization. While within country geographic earnings inequality declined in the mid-twentieth century, geographic polarization appears to have increased more recently (Manduca 2019). Hence, Moretti (2012) shows that in the US, traditional industrial regions are declining and people, notably skilled workers, are leaving these low-wages areas for high-skill and high-wage urban areas. Financial centers appear to be a major contributor to geographic polarization. Sassen ([1990] 2001) developed the concept of Global City, further refined as "global financial centers" (Sassen 1999), to pinpoint that these financialized centers concentrate idiosyncratic, non-standardized and high value-added functions in charge of coordinating a dispersed worldwide economic activity.

Shift in industry composition. Since the 1980s, deindustrialization is a continuous trend in all high-income countries. In 1991, 31% of employment in high-income countries worked in manufacturing, down to 22% in 2020. The share of employment in the service sector moved from 62% to 74%.[2] The traditional manufacturing of goods came with a complex division of labor within the same plant linking executive managers, engineers, and clerks with skilled and unskilled blue-collar workers. This mutual exposure creates bilateral dependence, limits inequality, and can offer routes for upward mobility (Seltzer 2020). In contrast, the service sector is polarized, with some subsectors mainly hiring high skilled workers (e.g. finance) and others concentrating low-skilled workers (e.g. retail or cleaning services). Therefore, even if the organization of

2 Cf. https://data.worldbank.org/indicator/SL.SRV.EMPL.ZS?locations=XD and https://data.worldbank.org/indicator/SL.IND.EMPL.ZS?locations=XD

work remains stable within sectors, the shift from manufacturing to service firms can contribute to the decline in average exposure of top earners to bottom earners.

There are also compositional shifts of note within the service sector itself, particularly a surge in top 1% pay in the finance sector in multiple countries (Godechot et al. 2023). If we see rising top earner segregation with the service sector it could plausibly be merely a result of earnings surges in finance, at least in some countries.

Technological change. Digitalization has become a major source of work reorganization. It has led to some jobs disappearing (like personal secretaries) and with them possibly daily interactions between various levels of the pay scale (for instance managers-secretary interactions). Previous research focused mostly on the impact of information technology on wage inequality (Autor, Katz, and Kearney 2006). On the one hand, low skill routine jobs are the most at risk of being replaced by computers and robots. On the other, both low skill non-routine jobs (like care work) and high skill non-routine jobs (like engineering) are resistant to technological displacement. This asymmetric technological advance decreased the number of jobs at the middle of the wage hierarchy and increased the number of jobs at both ends in at least some countries (Fernandez-Macias, Hurley, and Stone 2012).

Digitalization may also favor increasing workplace homogeneity, permitting some firms to concentrate on design tasks, which require mainly skilled non-routine jobs, without a strong need for the support of low-skilled workers, while others concentrate on less skilled non-routine tasks. Moreover, information technology enhances monitoring activity at distance through real time information transfer (Shams 2020). It requires less workplace co-presence and opens the door to workplace and firm specialization (Weil 2014). For instance, Bergeaud et al. (2021) show that broadband internet installation in French cities in the early 2000s is tied to a local increase in between workplace occupational polarization.

Globalization. Globalization has consequences similar to technological shifts, although via a different mechanism (Alderson 1999; Kollmeyer 2009). Rather than disappearing, low skill routine jobs are relocated to low-wage countries. However, the consequences of this shift are similar. It contributes to a greater homogeneity of workplaces in core economies, with managers and engineers remaining in the headquarters and the designing units of international firms and routine production relocating to low-wage countries.

Workplace restructuring. Firms are also under pressure to reorganize their activity (Jung and Lee 2022). In contrast to the growth and diversification objectives of the post-war decades, small size became the new corporate goal (G. F. Davis 2016). Corporation downsized and replaced the hiring of workers with the buying of intermediary goods and services (Goldstein 2012; Jung 2015), thus concentrating on core activities, outsourcing or subcontracting non-core activities (Zuckerman 1999; Weil 2014). Outsourcing, which implies the transfer of the workforce to a third party, is one of most visible form of workplace fissuring and led to a recent stream of research. For instance, in most large US firms, food, cleaning, security, and logistics workers, formerly regular firm employees, are now outsourced and provided by large low-wage service firms (Dube and Kaplan 2010). In Germany, Goldschmidt and Schmieder (2017) establish that the share among cleaning workers of those employed in cleaning firms moved from 10% in 1975 to 40% in 2008. During the same period, as a result of outsourcing, the share of retail establishments hiring at least one cleaning worker declined from 82% to 20%. Concomitant to the outsourcing of low-wage services and contributing to wage segregation, firms also dispatched highly skilled and specialized non-core tasks (such as accounting and legal counseling) to high-end service firms (Sassen [1990] 2001; Bergeaud et al. 2021).

Subcontracting, resorting to a third party for goods or services that are not yet produced in-house, is closely related to outsourcing but may be less visible as it does not entail workforce transfers. It nevertheless grew rapidly. In France, according to the REPONSE survey, the share of workplaces subcontracting some activity moved from 54% in 2005 to 76% in 2011 and 81% in 2017. Subcontracting creates complex value chains where firms' pricing power depend on the diversification of their transaction network, privileging dominant firms in value chains and producing downward earnings pressure on subordinate supplier firms (Wilmers 2018).

More generally, process at the heart of workplace restructuring, such as downsizing, outsourcing, subcontracting, franchising, subsidiarizing, offshoring and layoffs contribute to increase inequality between workplaces and diminish chances of upward wage mobility within them (Weil 2014; G. F. Davis 2016; Goldschmidt and Schmieder 2017; Bergeaud et al. 2021; Bilal and Lhuillier 2022). Workplace restructuring along these lines potentially increase income segregation, separating the top earners who remain in powerful organizations from externalized low earners in low exchange power firm.

The factors driving workplace composition point towards an increase in earnings segregation at work, and notably a growing isolation of top earners. We verify whether this increase in segregation did occur in section four and do an initial investigation of the relative importance of these factors in section five.

2. Leveraging administrative data

We track the evolution of segregation at work by using administrative data for twelve countries, covering a variety of advanced capitalist "economies" (Hall and Soskice 2001; Esping-Andersen 1990): Canada, Denmark, Sweden, Norway, France, the Netherlands, Germany, Spain, Czechia, Hungary, Japan, and South Korea (Table 1). This yields a little more than one billion worker-year observations (up to fifty million workers per year). Some countries (Canada, Denmark, Norway, Sweden, France, and the Netherlands) provide exhaustive information on the working population, allowing very reliable estimates even for small groups in small units. In Czechia, the data covers 80% of the workforce in establishment of 10 and more employees. It covers the public sector, all large workplaces (more 250 employees) and a very large sample of 10-250 employee workplaces, where all employees are included. In Hungary, the data consists of a 50% random sample of the Hungarian population. In Germany, Japan, and South Korea, we have samples of between 4 and 8% of the working population based on a sample of workplaces, from which a sample of workers is drawn. Importantly, in the small workplaces of these latter countries (below 1000 in Germany, 30 in Japan, 99 in South Korea), all workers are included in the final sample. This avoids sampling bias when we further restrict to workplaces with two employees or more. Finally, in Spain, a representative 4 percent of the population registered in the social security system is sampled. We refer to these data sources as the COIN database, after the Comparative Organizational Inequality Network that has produced this and other papers using multiple-country linked employer-employee administrative data.

With respect to usual socioeconomic research, even our smallest samples are very large and enable reliable estimates of most of our segregation measures. However, estimates of segregation indicators for small groups, notably exposure of or to the national top 1%, are more fragile in Germany, Spain, Japan, and South Korea. This is especially the case for Germany, where, in addition to a smaller sample, we imputed top earnings as they are top coded around the top decile threshold.[3]

In every country, we exclude workers with very low earnings. For each country, we set a wage threshold based on the specificity of its administrative data and wage regulations (cf. Table 1 and Appendix A1). We use this cutoff to exclude cases with potential misreporting or job spells that are so short as to constitute failed hires, rather than low-paid jobs. We also limit our analyses to workplaces with two or more employees so that exposure and isolation measures are computable. As we do not have workplaces identifiers for Canada and Hungary, we use the intersection of region and firm identifiers to proxy workplaces. In supplementary file S4, we show that switching from workplace to firm units does not substantially modify the pattern of earnings segregation as work.

3 Our imputation strategy uses contemporaneous and lagged information from both individuals and workplaces to predict high earnings, using a Tobit model estimated separately for cross-classification of gender, education, and East and West German residence (Stüber, Grabka, and Schnitzlein 2023). Code and further discussion available upon request.

Table 1. Characteristics of country linked employer-employee data

Country	Start	End	Field	Definition of marginal job threshold	Threshold earning (end year)	Number of workers in establishments size>1 (end year)	Number of establishments (end year)	Number of firms (end year)	Source
Canada	1990	2019	Exhaustive	1/2 full time full year minimum wage	8,921 Can $	15,571,107	697,953*	686,598	Statistics Canada
Denmark	1994	2018	Exhaustive	1/4 average yearly wage#	109,412 Da. Kr	2,039,139	117,700	83,382	RAS, IDAN and BEF
Norway	1996	2018	Exhaustive	1/4 average yearly wage#	139,875 No. Kr	1,410,206	111,453	72,670	Statistics Norway
Sweden	1990	2018	Exhaustive	1/3 prime age P50	100,663 Sw. Kr	4,049,300	242,806	172,758	Statistics Sweden
France	1993	2019	Exhaustive private and partial public sectors	1/2 full time full year minimum wage	8,024 €	14,328,590	939,634	718,333	BTS
Netherlands	2006	2018	Exhaustive	1/2 Age-specific minimum hourly wage	4 € per hour	10,493,473	295,697	291,270	CBS
Germany	1999	2015	Sample of workers (6%) in 20,000 establishments	1/2 full time P10	12,871 €	1,119,590	9,713	*Missing*	IEBS
Spain	2006	2018	Random sample of workers (4%)	1/2 full time full year minimum wage	5,837 €	239,159	48,769	40,869	Continuous Sample of Working Histories (CSWH) and tax records
Czechia	2002	2016	Sample of workers (80%)	1/2 full time full year minimum wage	52,830 Cz. Kr	1,917,812	27,667	16,602	Average Earnings Information System (ISPV) survey
Hungary	2003	2017	Sample of workers (50%)	1/2 full time yearly minimum wage	765,000 HUF	1,017,665	90,131*	79,254	Admin2 and Admin3
South Korea	1990	2012	Sample of workers (8%) out of a sample of private sector establishments size>5	1/2 full time full year minimum wage	4,764,000 KRW	613,369	17,327	*Missing*	Wage Structure Survey
Japan	1990	2013	Sample of workers (4%) out of a sample of private sector establishments size >5	1/2 full time P10	1,056,700 Yen	994,687	56,277	*Missing*	Basic Survey of Wage Structure

* In Canada and Hungary, establishments are proxied through an intersection between regions and firms. # Source: OECD.

In section five, we analyze the impact of deindustrialization, decrease in workplace size, globalization, global cities, digitalization and financialization on the evolution of segregation in cross-country regressions. Our COIN database allows us to directly proxy some of these socioeconomic processes. We use the size of the manufacturing sector as an indicator of deindustrialization (Kollmeyer and Pichler 2013), size of workplaces as an indicator of workplace shrinking (G. F. Davis 2016), and the wage share of each country's global financial center (defined as the urban area concentrating stock exchange activities) as an indicator of the global city phenomenon (Sassen [1990] 2001; 1999).

We complement our COIN data with variables from international datasets. We proxy financialization with the stock market value traded to GDP variable from World Bank's GFDD database (GFDD.DM.02 series) (Godechot et al. 2023); globalization with outward foreign direct investment stock to GDP from the UNCTAD dabatase of United Nations (Kaya 2010); digitalization with the share information and communication technology assets in country's total assets from the OECD database (variables N1113INA, N11NA from SNA Table 9A) and, for missing observations, from EU-Klems (variables K_ICT and K_TOT from all_capital_17i, all_capital_input_08I and can_capital_input_08I) (Zwysen 2022). Furthermore, we also construct two control variables based on series provided by the OECD: log of working age population (HISTPOP series) and log of average wages (AV_AN_WAGE series).[4]

For one country, France, we could find additional datasets documenting workplace restructuring events and measure their impact on the evolution of workplace segregation. For this aim, we use the MMO (*Mouvements de main d'oeuvre*) survey to measure layoffs at the workplace level between 2002 and 2014, the 2011 CAM (*Chaînes d'activités mondiales* / International Sourcing and Global Value Chains) survey to document firms' offshoring practices between 2009 and 2011, and the 2005, 2011 and 2017 REPONSE surveys to document

4 Databases can be downloaded at the following addresses: GFDD, https://databank.worldbank.org/source/global-financial-development ; UNCTAD, https://unctadstat.unctad.org/wds/ ; OECD, https://stats.oecd.org/ ; EU-KLEMS, https://www.rug.nl/ggdc/productivity/eu-klems/.

changes in subcontracting practices. Following the literature on outsourcing (Goldschmidt and Schmieder 2017; Bergeaud et al. 2021; Bilal and Lhuillier 2022), we also construct an indicator of outsourcing based on flows of six and more workers moving from a workplace in a non-outsourced sector to a workplace in an outsourced sector (e.g. transports, logistics, restoration, security, cleaning). We provide more details on the French data in Appendix A2.

3. Measuring and modeling workplace segregation

Measuring exposure and isolation

We utilize traditional measures of group exposure and isolation for various fractiles of the income distribution (Bell 1954; Massey and Denton 1988). [5] We focus primarily on earnings (i.e. yearly wages) from the observed job. We limit our sample to people who have been employed in the focal job either for a full year or – when information on starting and end dates are not available – have at least one year of tenure in the workplace. We do so in order to ensure that we measure exposure for employees present at the same time in the same workplace. It also enables us to have full-year, rather than part-year, earnings.

We choose to use yearly earnings in our analysis for two reasons. First, it approximates well the income on which people live thanks to their job. Second, it is the wage measure most commonly available in the register data used for this paper. Some consider hourly wage to provide a better measure of wage because it is more closely tied to the concept of productivity. However, the number of hours is not an exogenous dimension. It depends on the preferences and the productivities of the worker and the firm, as well as on norms and eventual discriminations surrounding the allocation of working hours. Moreover, we are not interested in productivity, but rather in propinquity. Among our robustness checks, we compare yearly earnings results to the hourly concept where possible and find similar trends.

The exposure ${}_{g}P^{*}_{h}$ of group g to group h is simply the average of the proportion of group h in the local unit i of each member of group g. It is generally defined as:

5 The exposure of a group to itself is called isolation.

$$_{g}P_{h}^{*} = \sum_{i} \left(\frac{n_{gi}}{n_{g}}\right) \cdot \left(\frac{n_{hi}}{n_{i}}\right) \tag{1}$$

where n_{gi} is the number of workers of group g in unit i.

To produce more robust estimates of exposure for small groups in small units (for instance the top 1% in small establishments), we adapt this measure according to the "drop one" rule (Hellerstein and Neumark 2008). We consider that an individual is not exposed to herself. For instance, in an establishment of two workers, one belonging to the national top 1% and one to the national bottom 25%, we consider that the worker from the top 1% is exposed to 0% of the top 1% workers, and 100% of the bottom 25% of workers (and not 50% and 50% respectively as computed with the traditional measure). This corresponds in fact to the initial P – "the probability that the next person a random individual from group 1 will meet is from group 2" – from which Bell (1954) derived the approximation P^*.

$$_{g}P_{h} = \sum_{i} \left(\frac{n_{gi}}{n_{g}}\right) \cdot \left(\frac{n_{hi} - 1_{h=g}}{n_{i} - 1}\right) \tag{2}$$

where $\mathbf{1}_{h=g}$ is equal to 1 when h=g and 0 otherwise.

This measure comes with several interesting properties. When we use it for measuring the exposure of national earnings fractiles to one another, such as the top 1% exposure to the bottom 25% (q_1), it allows for robust and simple comparisons through time and space, as the given earnings groups are each a constant proportion. We can also easily make comparisons to a benchmark corresponding to a perfectly non-segregated society. In such cases, $_{top1\%}P_{q1}$ would be equal to 25%. Exposure also has quasi-symmetry properties: cross-exposures are linked by a multiplicative parameter ($n_{h.}/n_{g}$): $_{g}P_{h}$= ($n_{h.}/n_{g}$)×$_{h}P_{g}$. For instance, $_{top1\%}P_{q1}=25{\cdot}_{q1}P_{top1\%}$. This means that the patterns described for $_{g}P_{h}$ will hold true for $_{h}P_{g}$. Hence, when based on groups of equal size, such as deciles, cross-exposures are equal (Massey and Denton 1988).

Finally, it is important to assess the quality of our exposure measures in the light of current controversies on the biases of segregation measurement relying on entropy-based (Logan et al. 2018) or variance-based measurements (Bonhomme et al. 2022). Indeed, Logan et al. (2018) showed that Reardon and

Bischoff's (2011) measurement of the evolution of income segregation in the US was upwardly biased as the authors were using a sample of declining size and did not correct for the sampling bias. Thus, after correction, Reardon et al. (2018) did find that the increase was substantially diminished, at least divided by three. Recent literature related to the "AKM" (Abowd, Kramarz, and Margolis 1999) decomposition also uncovered that earnings segregation based on fixed effects variance are also biased, even when measured on the full population (Bonhomme et al. 2022). This bias, which increases sharply when using a sample, is due to the "incidental parameter" problem (Andrews et al. 2008): the variance of fixed effects measured with errors adds the variance of errors to the true variance of fixed effects.[6]

Our exposure measure of segregation also has the advantage of its simplicity. It is a mean. In contrast to variance, the mean of a variable measured with errors enables estimates of the true mean (as long as the expectation of error measurement is zero). Moreover, following central limit theorem, the mean of a representative sample is an unbiased estimator of the population mean. In our procedure, sampling can still produce a small bias as we select within the sample workplaces with at least two workers. Hence, the chance of small workplaces to have at least two of its workers present in the sample will be smaller than for large workplaces, leading *de facto* to an under-representation of very small workplaces.

In Supplementary file S2, we use French data to estimate the magnitude of the bias of our measures based on a random 10% sample in relation to the full population. The bias remains modest ranging from 2 to 8% of the true measures and disappears if we properly reweight the estimates to account for the under-representation of small establishments. In contrast, bias for classical measures such as dissimilarity index is substantial on a 10% sample and increases when we reweight our sample.

We used this reweighting procedure for Spain, which is a 4% representative worker panel. We could not use the reweighing procedure for the Hungarian data, because we do not know the true size of workplaces. However, the

6 If we measure a variable X with some measurement error ε (i.e. $X' = X + \varepsilon$), and even if the error ε is independent of X (i.e. $cov(X,\varepsilon)=0$), than $V(X') = V(X) + V(\varepsilon) \neq V(X)$.

Hungarian sample is very large (50%) and time invariant and is unlikely to substantially affect our results. In German, South Korean, Japanese and Czech samples, there are always at least two workers per workplaces. Sampled workplaces do not drop out of the analysis due to an insufficient number of workers sampled. We can thus use the original weights without supplementary reweighting.

As for any segregation measure, the most critical component is the number of units. Our exposure measure is no exception: The more units used, the more fine-grained the measure of segregation will be. Thus, we must keep this in mind when we compare Canada and Hungary where units are firms interacted with region and all the other countries where units are proper establishments. However, as we will see, this mostly affects levels of segregation and not trends.

Evolution of exposure

In order to compute comparable evolutions, we estimate the yearly trends in exposure ratios evolution with equation 3 for country evolution and with equation 4 for estimating an overall evolution.

$$f(exposure) = \beta_k.country_k \times year + country_k + u \quad (3)$$

$$f(exposure) = \beta_{all}.year + country_k + u \quad (4)$$

To compare evolutions in segregation when baseline proportion are very heterogeneous (top 1% isolation versus bottom 25% isolation), we use the log-odds of absolute exposure measure as the dependent variable, which takes into account that exposure measures are percentage bounded by 0% and 100%.

$$f({}_gP_h) = log(\frac{{}_gP_h}{1 -_g P_h}) \quad (5)$$

This specification measures the average rate of increase of our exposure measure and regression estimates provide a rule of thumb for deciding whether the evolution is significant or not.

Models for explaining the evolution of top earner isolation

In the fifth section of this article, we explore the main factors driving the evolution of top earners segregation thanks to three types of models. A first class of models breaks down country trends within each country by region, sector, workplace and workplace size (Equations 6 to 8). A second set of analyses focuses on one country, France, examining the role of workplace restructuring events in an event study regression framework (Equations 9 and 10). Finally, a cross-country panel regression examines multiple potential explanations for rising top earner segregation (Equation 11). In all regressions, we use top 10% isolation measure as our main dependent variable. Here, in contrast to the prior models for establishing trends (Equations 3 and 4), we use top 10% isolation absolute level rather than its log odds. Indeed, while the absolute exposure measure is less comparable for groups of different size than log odds of absolute exposure, it yields consistent estimates when we change the level of aggregation in the regression (individuals, workplaces, sectors, nations) and offers interesting decomposition properties.

Breaking down country trends by region, sector, workplace and workplace size

In Table 3, we adapt Tomaskovic-Devey et al.'s (2006) methodology and measure the decline of the top 10% isolation parameter, when introducing coarsened or detailed region, sector, or workplace fixed effects. We estimate equation 6 with OLS regressions:

$$Isolation_{kjt}^{top10\%} = \beta_{all}.year_t + cat_j \times country_k + u_{kjt} \tag{6}$$

This enables us to compare the linear yearly trend β_{all} with or without coarsened cat_j region, industry fixed effects. Due to privacy protection, we could not export measures of workplace segregation within detailed regions, industries or workplaces to estimate a stacked regression. Therefore, we estimate equation 6 separately in each country and compute the average (weighted by years) of separate regression parameters (displayed in Table S8.1) to obtain global segregation trends with detailed region, sector or workplace fixed effects.[7]

In Table 4, we break down the β_{all} yearly trend into β_j yearly trends for coarsened regional and industrial categories (Equation 7). This OLS regression enables to characterize the regions or sectors in which segregation trends are more or less pronounced.

7 Stacked regressions and average of separate regressions usually yield very similar results.

$$Isolation_{kjt}^{top10\%} = \beta_j.(cat_j \times year_t) + cat_j \times country_k + u_{kjt} \quad (7)$$

We also further decompose these categorical trends into a "between category component" and a "within category component" by decomposing the dependent variable top earner workplace isolation $Isolation_{workplace}$ in two dimensions: top earner categorical between isolation $Isolation_{category}$ (this is simply the concentration of top earners within a regional or sectoral macro category) and top earner workplace isolation within a category that we calculate as follows: $Isolation_{within} = Isolation_{workplace} - Isolation_{category}$. This additive decomposition checks whether the increase in workplace isolation in a given category is mostly due to the growing concentration of top earners in this category as a whole or if it corresponds to growing segregation within this category.

In Table 5, in separate country regressions, we introduce the effect of the log of workplace size as our independent variable, controlling for a yearly linear trend, and workplace *w* fixed effects.

$$Isolation_{wt}^{top10\%} = \beta_{sz}.log(size_w) + \beta_y.year_t + w + u_{wt} \quad (8)$$

The parameter β_{sz} combines the effect of size increase and decrease. As we suspect that workplace shrinking has a specific effect (G. F. Davis 2016), we further introduce in a modified version of equation 8 the cumulative decrease in workplace size $C_{w,t}$, which is calculated as follows:

$$C_{w,t} = \sum_{i=2}^{i=t} ([(log(n_{w,i}) - log(n_{w,i-1})) < 0].[(log(n_{w,i}) - log(n_{w,i-1})])$$

for $i>1$ and $C_t=0$ for $i=1$ where i is the rank order of apparition of the workplace *w* in the database.

This variable indicates whether, in addition to the main effect of log size, there is a specific effect of decrease in log size.

Event study models in order to measure the impact of workplace restructuring events

To study the impact of restructuring events in France, we adopt an event study design based on two-way fixed effects difference in differences models, for which we measure the impact effect of a restructuring event both before and after it occurred. These models reinforce a causal interpretation of the link between organizational events and workplace segregation. Indeed, if there is no divergence between "treated" and "counterfactual" workplaces before the restructuring event, and if the divergence only begins on the year of the restructuring event, one can reasonably assume that divergence is due to the restructuring event and not to a confounding factor.

We thus estimate the following model:

$$y_{jt} = \sum_{h=-l,h\neq-1}^{h=m} \beta_h [M_e.(t = t_e + h)] + j + t + X\delta + u_{jt} \tag{9}$$

In this equation, t_e represents the year of the event e (or the start of the event period), M_e its magnitude, h the number of years before or after the start of the event, j workplace fixed effects, t year fixed effects. We estimate models with or without taking into account the event's magnitude (hence, in the latter case, $M_e = 1$ if an event occurred and 0 otherwise), with or without control variables X (*i.e.*, workplace log size and cumulative decrease in log size).

As the design of the outsourcing and layoff event studies is staggered, we need to take note that the absence of time treatment homogeneity can lead to biases in the estimation of the average treatment effect (de Chaisemartin and D'Haultfoeuille 2023). In order to address this problem, we estimate a stacked version of the two-way fixed effects model (Cengiz et al. 2019; Bergeaud et al. 2021). We create one database for each year of event k, containing the treated and counterfactual workplaces for a window of years around the year k. In each database, we use the treated workplace in year k as the "treated group" and the "never treated" and the "not yet treated" (and in the case of the layoffs the "the not treated workplaces") as the counterfactual group. We stack these databases together. In the model, each workplace has database specific workplace ($j \times k$) and year ($t \times k$) fixed effects. Hence, we avoid the problem of the "forbidden comparison" of newly treated to already treated observations. The clustering of the standard errors at the firm level handles for the artificial multiplication of observations.

The model is thus as follows:

$$y_{jtk} = \sum_{h=-l,h\neq -1}^{h=m} \beta_h[M_e.(t = t_e + h)] + j \times k + t \times k + X\delta + u_{jtk} \quad (10)$$

In the case of the outsourcing event study, the stacked version generates a big dataset which exceeded computer processing capacity. To avoid this limitation, we randomly draw 10% of the counterfactual workplaces in each dataset.

The main estimates are presented in Figure 5, and detailed estimations can be found in Supplementary file S9.

Summarizing the main factors with cross-country regressions

Finally, in Table 6, we run OLS regressions with country and year fixed effects, as defined by equation 11. They enable us to summarize and compare the contribution of the main variables isolated in previous estimates and to introduce variables, such as digitalization, for which we only found country-level statistics.

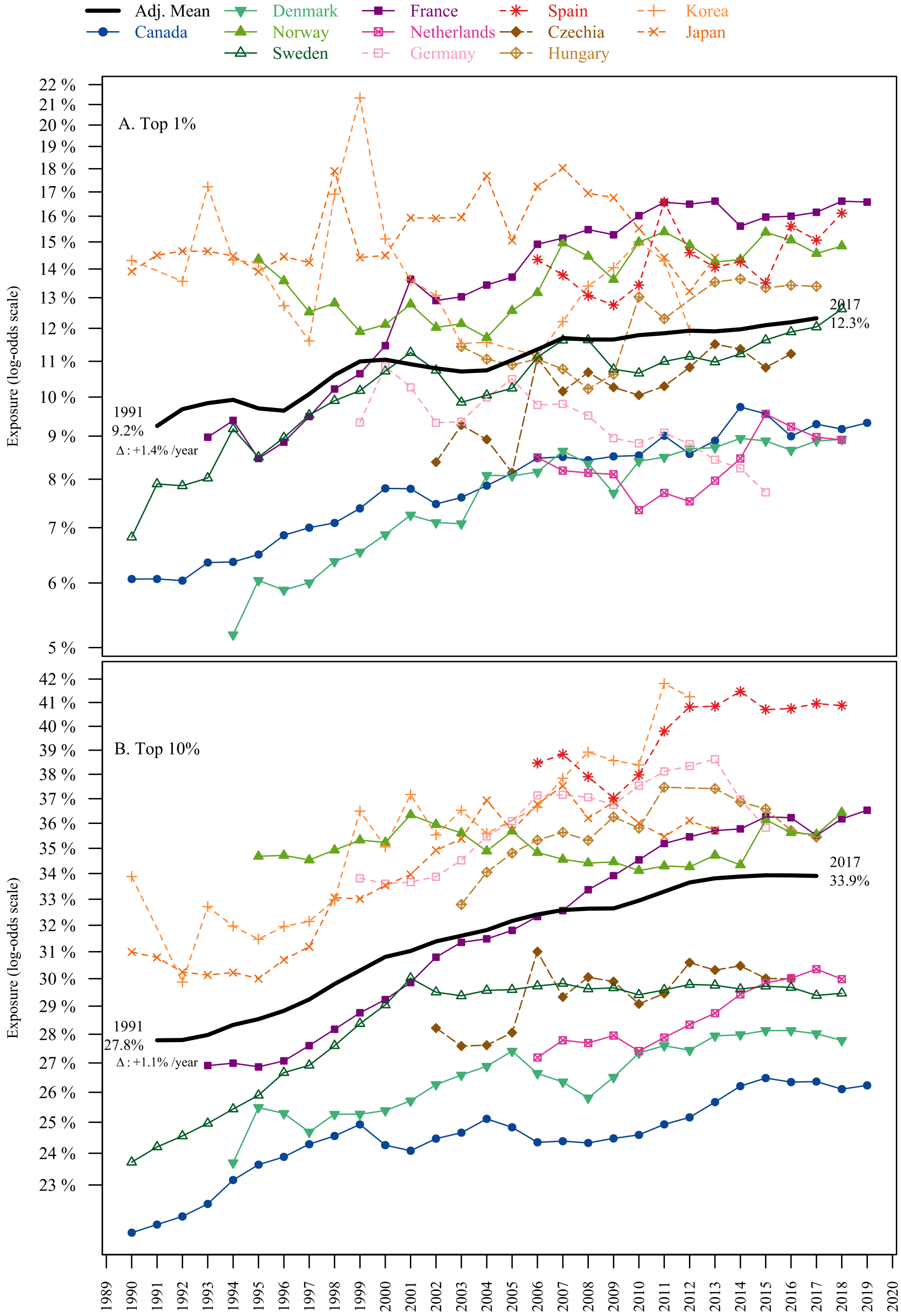
$$Isolation_{kt}^{top10\%} = X.\beta + t + country_k + u_{kt} \quad (11)$$

4. A strong increase in workplace earnings segregation

Two decades of research on distributional inequality (Piketty [2013] 2014) and more recent research on residential segregation (Tammaru et al. 2015; Musterd et al. 2017) have shown that a dramatic and specific trend is occurring for top earners. Therefore, when moving to the analysis of segregation at work, this invites us to focus first on the segregation of top earners, a group that we approach with two measures: employees belonging to the national top 1% and top 10% of earners respectively.

Figure 1 displays the evolution of top earner isolation. This measure documents both the evolution of top earners' exposure to their own earnings group and summarizes the complementary inverted evolution of their exposure to all other earnings groups. During the period, top 1% isolation increased in nine of twelve countries.

Figure 1. Top earner workplace isolation



Note: We use a log-odds scale in order to give a correct visual representation of evolution of absolute exposures in terms of odds ratios. We construct an adjusted mean as the arithmetic mean when the set of countries is complete, that we further prolong with the mean of evolutions when the set of countries is incomplete (cf. Supplementary file S1). We also indicate the log-odds linear trend (*i.e.* Δ: +1.4% / year), which is the yearly trend parameter in a country fixed effect regression where log-odds of exposure is the dependent variable (equation 4). Sources are detailed in Table 1 and Appendix A1.

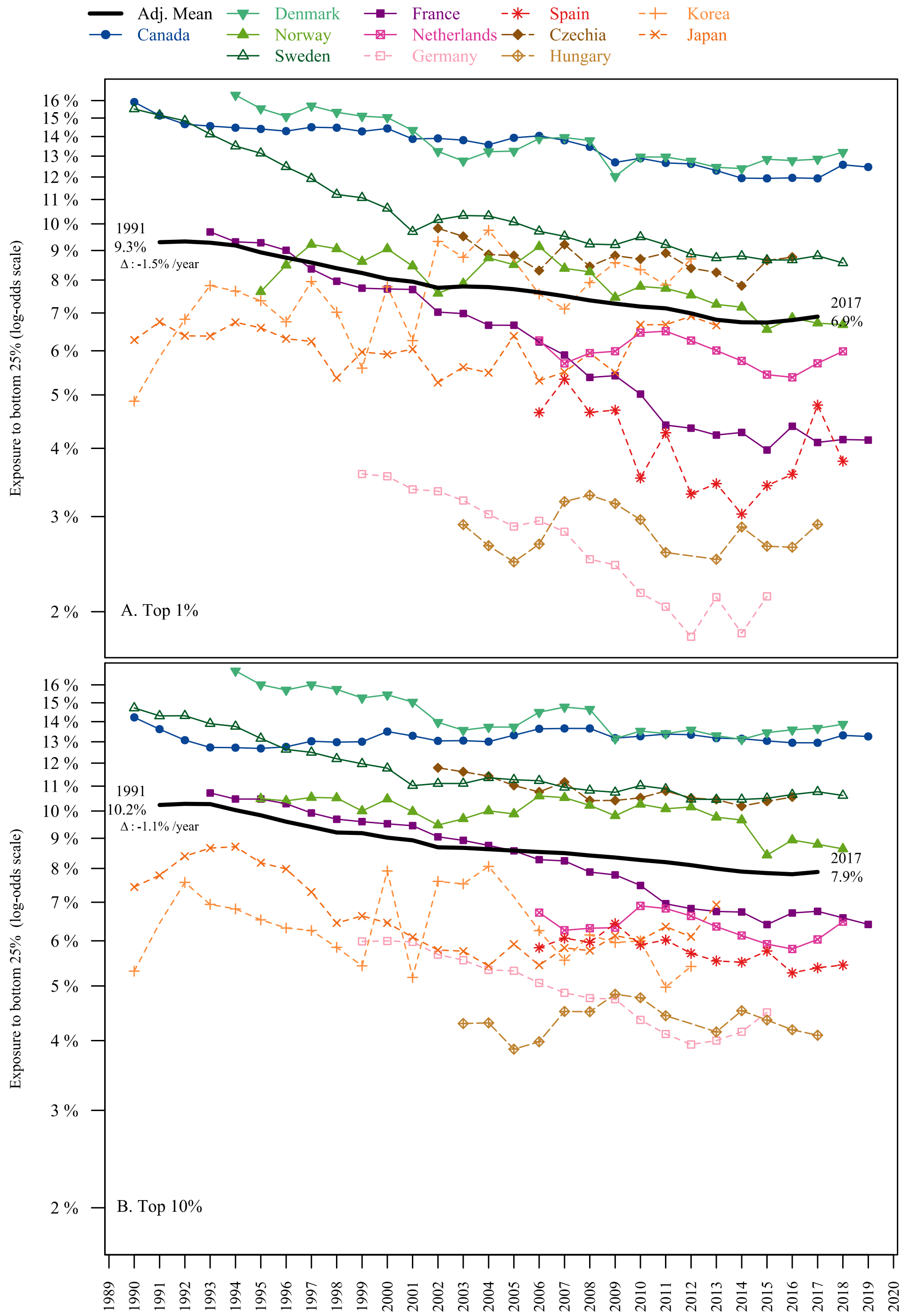
In 1994, France's national top 1% worked in establishments where 9% of their coworkers belonged to the same earnings group. In 2019, 16% of their coworkers belonged to the national top 1%. Thus, the isolation index nearly doubled in twenty years, with a substantial +3.0% yearly rate of increase. These trends towards separation of the most affluent workers from the rest of the earnings hierarchy are less dramatic in other countries, but remain pronounced. We find an increase in top earner isolation in Czechia (+2.2%), Hungary (+2.2%), Denmark (+2.0%), Canada (+1.7%), Sweden (+1.7%), Spain (+1.3%), the Netherlands (+1.2%), and Norway (+1.1%) (Table 2).

We do not see any increase in top earner isolation in Japan and it even declines in South Korea and in Germany. In the two Asian countries, this may be due to sampling issues (as shown by the volatility of the curves and the larger confidence intervals, cf. Supplementary Figure S3.1) and to the fact that executives are not included in the Japanese data. The singularity of the German decrease in top 1% isolation (–1.6%) may also be owing to the top coding of earnings at a relatively low level (around P90), which our imputation strategy only imperfectly overcomes.

These plausible limitations in our data led us to also consider top 10% isolation, a more robust proxy for top earnings (Figure 1B). In comparison to top 1% evolutions, the magnitude of the increase is attenuated for "population data" countries. However, we do find for the "sample data" countries a more consistent trend towards isolation of top earners. Growing isolation of the top 10% appears to be a general and homogeneous trend that we find in almost all countries. Its yearly rate of increase ranges in most countries between +0.7% and +2.0% per year. Norway is the sole exception with almost no evolution in top 10% isolation (+0.04%). This exception should be qualified: in Norway both the top 1 percent and the top 20% strongly isolate from the rest of the population. Importantly, in no country is top 10% integration with lower earning employees growing.

These annual rates of increase in top earner segregation may seem modest. However, they are comparable to the growth rate of world population (+1.3% between 1990 and 2012) or to the growth rate of European GDP per capita (+1.5% between 1990 and 2012) (Piketty [2013] 2014). While evolution from one year to the next may seem barely noticeable, over a 25-year period it results in substantial societal changes.

Figure 2. Top earner workplace exposure to bottom earners



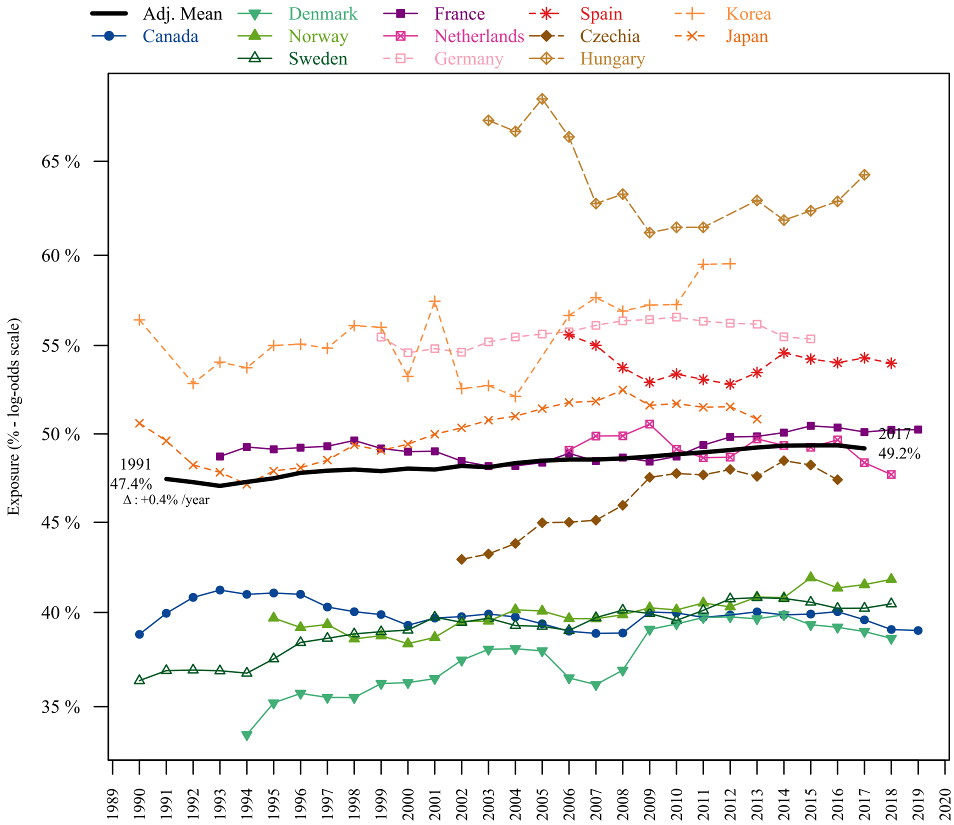
Note: Cf. Figure 1.

Growing top earner isolation and consequently declining exposure to the rest of the earnings hierarchy is not homogeneous. Figure 2 makes clearly visible that top earners in almost all countries are separating mostly from employees at the bottom of the earnings hierarchy. This evolution is particularly striking for France, where top 1% exposure to the bottom quartile decreased at a –4.0% annual rate. We also find that top earner exposure to the bottom quartile declined substantially in nine out of twelve countries, with rates of decrease ranging from –0.7% to –4.5%. We do not find similar trends for Hungary, Japan or South Korea, possibly due for the latter two to the sampling and measurement concerns raised earlier.

The annual rate of decline in top 10% exposure to the bottom quartile is both a little less pronounced than that of the top 1% (especially in France (–2.4% versus –4.0%), Sweden (–1.3% versus –2.4%)) and also more general: Japan and South Korea follow this trend of growing elite isolation, although at a slower pace. Canada and Hungary (for which we have a shorter timeframe) do not display any significant trend.

Supplementary Figure S3.2 shows that the growing separation of top earners from bottom earners also holds true for mid quartile earners. Thus, top 1% exposure to the mid quartile earnings group dropped in France from 34% to 20% and in Sweden from 40% to 29%. If we add top earners' exposure to the bottom and mid quartiles, we find dramatic drops for some countries, which can be viewed as a fundamental change in elite's segregation from the rest of society. In France, top 1% exposure to the bottom 75% dropped from 44% at the beginning of the period to 24%. Sweden moves from 55% to 37% and Canada from 57 to 49%.

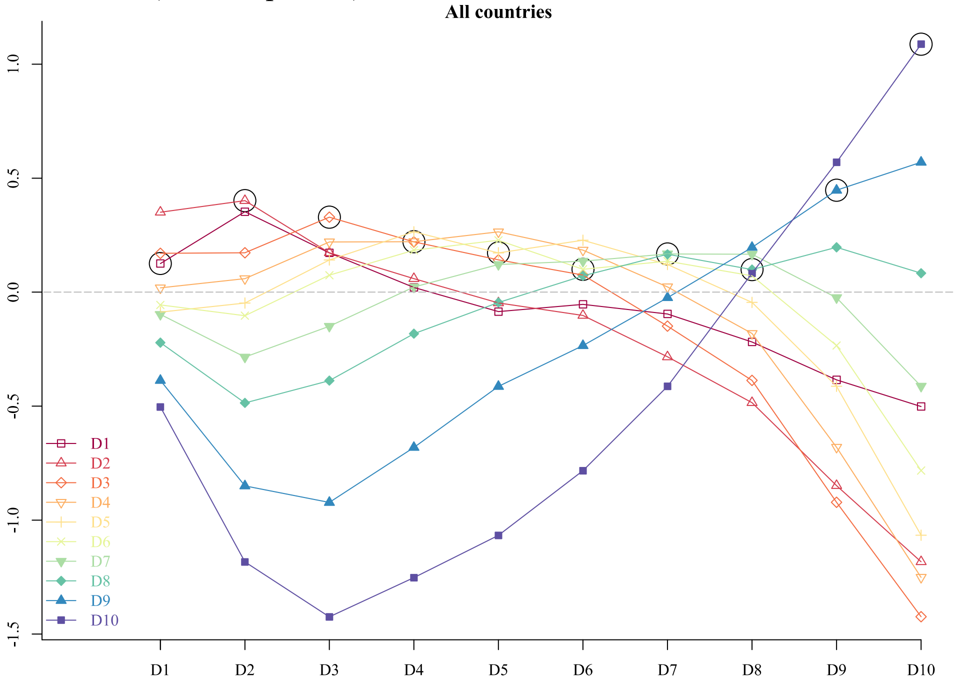
Figure 3. Bottom 25% workplace isolation



Note: Cf. Figure 1.

One might suspect that these separation trends reflect a single and uniform mechanism of assortative matching of workers all along the wage hierarchy (Kremer 1993). However, we find that isolation trends are much less pronounced at the bottom of the earnings hierarchy than at its top (Figure 3 and Table 2) and that trends are less general. While some countries (Denmark and Czechia, and to a lesser extent South Korea, Norway, and Sweden) face increasing segregation at the bottom, others, such as Hungary, the Netherlands, Spain, and Canada do not and France and Germany show only modest positive trends. In many countries there is increased mixing at the bottom of the wage hierarchy, with increased exposure between the bottom and mid quartiles.

Figure 4. Linear trend (yearly rate) of evolution of each decile's exposure to one another (General pattern)



Note: Top decile's (D10) exposure to bottom decile (D1) decreased at a linear yearly rate of -0.5%. We circle in black the points that measure the evolution of isolation (exposure to one's own group), such as D1 to D1, D2 to D2, etc.

Table 2, Figure 4 and S3.3 where we plot the yearly rate of evolution of each decile's exposure to one another summarize the common patterns in the evolution of segregation at work and the main contrasts between countries. First, we find in all countries a consistent and significant increase in top earner workplace isolation when proxied either with the top 10% exposure measure (South Korea, Japan, Germany), with the top 1% (Norway), or with both (all other countries). Second, in all countries (except Hungary) the exposure of top earners to bottom earners decreased. Third, in the majority of countries top earner exposure to bottom earners decreased more than to all other groups. Fourth, in the majority of countries, the most dramatic shift in the evolution of segregation concerns top earners.

Table 2. Levels and linear trends of wage group segregation in establishments

Levels (end year)	Top 1% isolation	Top 10% isolation	Top 1% exp. to mid-quartiles	Top 10% exp. to mid-quartiles	Top 1% exp. to bottom 25%	Top 10% exp. to bottom 25%	Bottom 25% isolation	Bottom 10% isolation	Between workplace share of earnings variance	Top 1% earnings share	Top 10% earnings share
Canada (2018)	9%	26%	38%	39%	12%	13%	39%	19%	34%	8%	30%
Denmark (2017)	9%	28%	31%	36%	13%	14%	39%	20%	32%	5%	22%
Norway (2017)	15%	36%	23%	30%	7%	9%	42%	20%	42%	4%	21%
Sweden (2017)	12%	30%	29%	36%	9%	11%	40%	19%	37%	4%	21%
France (2018)	16%	36%	20%	30%	4%	7%	50%	33%	52%	6%	26%
Netherlands (2017)	9%	30%	35%	37%	6%	6%	49%	29%	46%	7%	33%
Germany (2014)	(8%)	37%	(18%)	29%	(2%)	4%	56%	35%	59%	(4%)	23%
Spain (2017)	16%	41%	22%	28%	4%	5%	54%	30%	70%	7%	28%
Czechia (2015)	11%	30%	28%	36%	8%	10%	48%	30%	40%	6%	26%
Hungary (2016)	13%	36%	26%	34%	3%	4%	63%	43%	58%	7%	29%
South Korea (2011)	14%	40%	34%	27%	8%	5%	59%	50%	61%	4%	24%
Japan (2012)	14%	36%	30%	32%	7%	6%	51%	35%	51%	4%	23%
Adj. Mean (2017)	12%	34%	28%	33%	7%	8%	49%	30%	48%	5%	25%
Linear trend											
Canada	1.8***	0.7***	-1.3***	-0.3***	-1.0***	0	-0.1**	-0.4***	0	1.1***	0.7***
Denmark	2.0***	0.7***	-1.0***	-0.3***	-1.1***	-0.9***	0.8***	1.1***	1.3***	1.4***	0.5***
Norway	1.0***	0	-0.8***	-0.4***	-1.3***	-0.7***	0.5***	0.3***	0.9***	0.9***	0.4***
Sweden	1.7***	1.0***	-1.8***	-0.8***	-2.4***	-1.3***	0.6***	0.6***	1.3***	0.8***	0.3***
France	3.0***	2.0***	-3.5***	-1.8***	-4.0***	-2.4***	0.2***	0.2**	1.8***	0.9***	0.3***
Netherlands	1.2***	1.3***	-1.8***	-1.5***	-0.7*	-0.7**	-0.4**	-0.5**	-0.3	0.2	0.3***
Germany	(-1.6***)	1.2***	(-2.3***)	-1.8***	(-4.5***)	-2.9***	0.3**	-0.3*	1.8***	(0.2)	0.6***
Spain	1.3***	1.3***	-1.8***	-1.1***	-2.4**	-1.2***	-0.1	-0.6	0.5*	0	0.2***
Czechia	2.2***	0.8***	-1.5***	-0.8***	-0.9**	-0.9***	1.6***	2.4***	1.9***	0.9***	0.7***
Hungary	2.2***	0.8***	-0.1	-0.8	-0.2	0.1	-1.4***	-4.0***	0.3	-1.5***	-1.1***
South Korea	-0.8*	1.9***	1.1***	-2.4***	1.4***	-0.7	0.8***	1.0***	1.9***	1.2***	1.0***
Japan	0.4	1.5***	-1.6***	-2.0***	-0.2	-1.7***	0.7***	-0.9***	1.3***	0.7***	0.4***
All	1.4***	1.1***	-1.5***	-1.0***	-1.6***	-1.1***	0.4***	0.2***	1.1***	0.9***	0.4***

Note: End levels are calculated on the three last available years, to avoid capturing a sudden change due to specificities of data collection for some years. For instance, exposure for Canada calculated in 2018 is the average for 2017, 2018 and 2019. We calculate linear rates of evolution of log-odds of exposure following equations 4 and 5. Parameters are multiplied by 100 to express percentage of changes. German estimates for the top 1% (in parentheses) should be considered with caution due to the top coding of wages in German data.

***p<0.01, ** p<0.5, *p<0.1 (robust standard errors clustered at the year level). Sources are detailed in Table 1 and Appendix A1.

These trends are robust to alternative specifications using firms instead of establishments, and hourly wage instead of yearly earnings (cf. Supplementary File S4). They are also specific to earnings segregation. The increase in segregation is more pronounced and more general for earnings segregation than for other dimension such as gender, nativity or age, leading at the end of the period to a level of separation between top earners and bottom earners much larger than between polar groups on other dimensions. The only other dimension that shows a similar trend across countries is growing occupational class segregation (Supplementary file S5).

Beyond the general pattern of increased top earner isolation common to all countries, we can also establish second-order contrasts between three groups of countries. France, Germany, Sweden, and (to a lesser extent) Canada and Spain are countries following the general pattern where segregation increases mainly at the top, decreasing elite exposure to all other groups and most notably to bottom ones. Japan, South Korea, Hungary, and the Netherlands are countries where separation of top earners from middle earners increases more than from bottom earners. Finally, Norway, Denmark, and Czechia are countries presenting a combination of growing isolation at both the top and the bottom and where bottom isolation is slightly more dynamic.[8] These patterns do not fit easily in the usual contrasts put forward by the comparative capitalism literature (Esping-Andersen 1990; Hall and Soskice 2001). On the contrary, a wide variety of market economies ("liberal," "social-democratic," "corporatist", and "Southern Europe") constitute the first majority group and illustrate the generality of the trend toward top earner workplace segregation.

Finally, in order to put in perspective growing top earner segregation – our main finding common to all countries – we compare it with two related phenomena (Table 2): The increase of the between-workplace share of earnings variance, on the one hand, and the evolution of distributional inequality, on the other.

8 As Figure S3.3 shows, Czechia's evolution is particularly notable, with a visible segregation process at work all along the earnings hierarchy, and even more pronounced at its bottom than its top. In this country, indeed, for all deciles, isolation increases and exposure to one another decreases. This produces a mountain range type of graph where the local summits correspond to each decile's isolation evolution.

As discussed in Supplementary file S6, top earner isolation and between-workplace share of earnings variance are linked. However, the between-workplace share of earnings variance is an all-encompassing measure, which misses the heterogeneity of the segregation process. Even in countries where between share of earnings variance did not increase substantially (Canada, the Netherlands, Spain, and Hungary), top 10% isolation did. It is worth noting that similar to between-workplace share of earnings variance (and any income segregation measure), our exposure measure captures workplace heterogeneity in wage evolution in addition to change in coworker composition. Following Manduca (2019), we show in Supplementary file S7, that change in coworkers' wages accounts for two third and change in the composition of coworkers for one third of French top 10% isolation evolution between 2002 and 2011.

Following Piketty and Saez' seminal work (2003), many consider that top earnings share increased at a rapid pace and this development constitutes a major transformation of contemporary societies. As shown in Table 2, the rate of increase in isolation of top earners is faster (except in Norway) than the rate of increase in their earnings share. The comparison of Figure 1 and Figure S3.4 also shows top 1% earners have a more unequal share of top 1% coworkers (12% on average at the end of the period) than of earnings (6%). Moreover, we see that the two phenomena follow different patterns, notably after the 2008 financial crisis. For instance, in Canada, the top 1% earnings share dropped sharply while, in France, it stabilized. By contrast, after 2008 top 1% isolation was stable in Canada and continued increasing in France.

5. Factors impacting workplace segregation evolution

What are the factors behind this dramatic increase in top earner isolation? In Section one, we identified multiple trends restructuring the workplace and the economy that could increase workplace earnings segregation, including geographical and sectoral employment shifts, deindustrialization and financialization, various mechanisms of workplace downsizing, globalization, and digitalization. The aim of this section is to document the relationship between these social processes and trends in workplace segregation.

There are two challenges with this analysis. First, the measure of workplace segregation is a distributional parameter that is established at the country-year level. Although it is possible to find variables that correlate with measures of top earner segregation in within-country units (such as regions, sectors, workplaces), we must keep in mind the strong interdependence between units: an increase in top earner concentration in some units may be offset by its decrease in other units. Thus, within-country analyses using regions, sectors, or workplaces as observation units miss potential spillover effect.[9] Cross-country regressions using countries as observation units avoid this limitation, but they are also much less precise statistically. Therefore, we have chosen to combine within-country decompositions and regressions, which allow us to precisely identify the locus of top earner concentration, and cross-country regressions, which estimate the overall effect. Second, the social processes studied (deindustrialization, financialization, workplace restructuring, globalization, digitalization) are highly intertwined and it is difficult to characterize whether these factors are independent or whether one mediates the other. Therefore, we examine these factors both separately and simultaneously.

We therefore examine the determinants of top earner isolation using three types of approach. First, we decompose segregation between and within regional and sectoral categories to measure the impact of geographic and sectoral shifts. Second, we analyze the role of workplace restructuring on workplace segregation, using workplace size as a crude proxy of these processes in ten countries and precise restructuring events in one country, France. Third, we combine and compare different factors in cross-country panel regressions.

Geographic and sectoral composition

To measure the role of the workforce restructuring by region, and sector, we measure in Table 3 the decrease of the segregation trend, when we introduce coarsened and detailed region or sector fixed effects.

9 However, we did this exercise for factors implying traceable worker flows, such as outsourcing and subsidiarization, cf. Supplementary file S9.

Table 3. Variation in top 10% isolation trends when introducing region, industry, and workplace fixed effects

	Region	Industry	Workplace
1. Benchmark trend	0.230	0.231	0.229
2. Trend with aggregated category fixed effects	0.219	0.198	.
3. Trend with detailed category fixed effects[#]	0.205	0.137	0.113
Aggregated categories	Nuts[##]1 or equivalent	1-digit	.
Detailed categories	Nuts 3 or equivalent	2-digits	Workplace IDs
Number of countries	8	10	10

Note: Each cell corresponds to the year trend parameter in different regressions. For consistency reasons, in small units, we opt for linear yearly trends. Hence, overall, top 10 % isolation ratio increases by 0.23 percentage point per year.
Country estimates are displayed in Table S8.1.
[#] In row 3, we compute the average (weighted by years) of separate regression parameters displayed in Table S8.1.
[##] *The NUTS (Nomenclature of Territorial Units for Statistics)* classification is a standardized hierarchical system for dividing up the economic territory.

Regional composition is not a strong driver of top earner workplace isolation. The segregation measures decrease by only 5% when we introduce coarsened regional fixed effects (based on NUTS-1 classification), and by 11% when introducing detailed regional fixed effects (based on NUTS-3 classification). In contrast, sector composition seems to contribute more to top earner segregation. Introducing coarsened sector fixed effects (grouped in 10 categories) diminished the top earner segregation trend by 10% and more detailed, NACE 2-digits, sector fixed effects accounts for 40% of the initial trend.

Table 4 complements previous analysis with a study of the heterogeneity of segregation trends across regions and sectors. In order to produce such estimates, we interact regional, and sectoral categories with a yearly trend.

The first panel of Table 4 shows that process of segregation is 1.5 times more pronounced in global financial centers than in other regions (0.26 vs 0.17), consistent with Sassen's ([1990] 2001) hypothesis that the development of global cities favors increased income segregation (Van Ham et al. 2020). Most of the increased isolation of top 10% earners is, however, a within and not a between region phenomena.

Table 4. Variation in top 10% isolation trends by region and industry

Dependent variable	Workplace Isolation Trend	Average categorical isolation (in 2012)	Category isolation Trend	Within cat. Isolation Trend
Panel A. Category: 2 regions (11 countries)				
Global financial center × year	0.258***	19.1%	0.009	0.249***
	(0.078)		(0.017)	(0.066)
Rest of the country × year	0.170***	8.6%	-0.004	0.174***
	(0.035)		(0.007)	(0.034)
FE (country × aggregate region)	Yes		Yes	Yes
Panel B. Category: Industry (10 countries)				
Manufacturing × year	0.473***	13.6%	0.137***	0.336***
	(0.080)		(0.014)	(0.081)
Wholesale and retail trade × year	0.180**	8.4%	-0.039	0.219**
	(0.068)		(0.024)	(0.073)
Transportation and storage × year	0.234**	8.5%	-0.036	0.270***
	(0.103)		(0.033)	(0.072)
Finance × year	0.462***	29.1%	0.204***	0.258***
	(0.053)		(0.047)	(0.073)
Support service activities × year	0.021	9.2%	-0.186***	0.207***
	(0.058)		(0.050)	(0.022)
Other activities × year	-0.016	12.5%	-0.070	0.054
	(0.051)		(0.039)	(0.041)
FE (country × aggregate sector)	Yes		Yes	Yes

Note: In the first column, the dependent variable is top earner workplace isolation, and in the second and third columns top earner *category* isolation. Category isolation refers to the exposure of top earners to themselves within coarsened geographic or industry categories. For example, in 2012 (the last year in which all countries are present), the share of top earners in global financial centers is 19.1%, implying that top earners' isolation within this coarsened category is 19.1%. In the last column, the dependent variable is the within-category workplace isolation, defined as the difference between workplace isolation and category isolation.
***p<0.01, ** p<0.5, *p<0.1. Robust standard errors clustered both at the country and year level in parentheses.

In the second panel, we look at differences in top earner isolation trends between broad sectoral categories, and decompose between category and within category evolutions as explained in Section 3. This exercise shows that the segregation trends are much more pronounced in two sectors, manufacturing and finance, with a yearly rate of increase of 0.47 percentage points per year while the rhythm is only weak on average in other sectors (0.04) (column 1). This is due to both the growing concentration of the working rich in finance and manufacturing (+0.20, +.14) and to within-sector segregation between workplaces (+0.26, +.34). Finance stands out as having by far the highest concentration of top earners. In manufacturing, the within-category segregation trend (+0.34) is 2.5 times more pronounced than in other categories, consistent with the observation that subcontracting and outsourcing are increasingly widespread in manufacturing (Whitford 2005). Both transportation and trade sectors also contribute to rising top earner isolation, and for both this happens primarily within the sectors.

Overall, these two analyses point to the sectoral dimension of workplace segregation evolution and the specific role of manufacturing and to a lesser extent finance. We find an even stronger impact of finance when we move to top 1% isolation trends (Table S8.2). This result is in line with previous literature on financialization showing that the increase in financial activity, and notably in financial markets' activity, led to the development of a small and segregated niche with very high wages (Godechot et al. 2023). At the top 10 percent level, manufacturing seems one of the key loci of growing segregation. This sectoral contribution could also be seen as a manifestation of high earning countries de-industrialization. Indeed, deindustrialization, is not just a decline of manufacturing employment, but a profound reorganization of industrial activity through offshoring and outsourcing and the organization of industrial activity along complex and highly segregated value chains.

Workplace restructuring

The last column of Table 3 shows that an important share (45%) of the segregation process is still happening within workplaces. This invites us to analyze the role of workplaces' internal restructuring. Unfortunately, it is difficult to find indicators of these processes. Therefore, we opt for a two-level strategy. First, we proxy workplace restructuring processes with a workplace size variable, and more precisely measure the specific effect of reduction in workplace size in a set of ten countries. Second, in one country, France, where increase in top earner segregation was particularly pronounced, we were able to use complementary surveys that allowed us to identify more precisely the processes of workplace restructuring contributions to top earner segregation.

Table 5 shows the impact of workplace size on top earner isolation, controlling for linear time and workplace fixed effects. We find that workplace size has a negative impact in nine countries out of ten (model 1) and is significant in eight. On average (last line), when workplace size decreases by 10 percentage points, top earner isolation increases by 0.3 percentage points. While the effect could seem small, it is worth noting it is 3 times the 0.1 yearly linear trend workplace fixed effects estimates reported in Table 3. Since this estimate averages the negative effect of a workplace increase and the positive effect of a workplace size decrease, we also directly introduce a cumulative workforce decrease variable to estimate asymmetric effect of workplace size (model 2). We find an asymmetric effect in eight countries out of ten, significant in four. Overall, on average, when workplace size increases by ten percentage points, top 10% isolation decreases by 0.28 percentage points. Conversely, when size decreases by ten percentage points, top 10% isolation increases by 0.34 percentage points. This shows the specificity of workplace downsizing on top earner segregation. As suggested by Goldstein (2012) for the United States, downsizing has varying consequences across the wage hierarchy. It has asymmetric effects on the workforce. It targets workers from its bottom, excluding them from the workplace and contributing to the workplace isolation of top earners.

As Table 5 indicates, workplace downsizing reduces the number of low-wage workers and increase top earner isolation. We now move to one country, France, to examine potential organizational processes involved in this trend thanks to supplementary data on outsourcing, layoffs, offshoring and subcontracting (cf. Section 3 and Appendix A2). As explained in the method section, we take advantage of the longitudinal dimension of our data to implement difference-in-differences event study designs to measure the impact of a given reorganization. Indeed, current econometric research consider that these models are good candidates for a causal interpretation of the parameters: they enable to measure precisely whether the divergence between "treated" and "counterfactual" units started with the considered event.

Table 5. The effect of workplace size on top 10% workplace isolation evolution

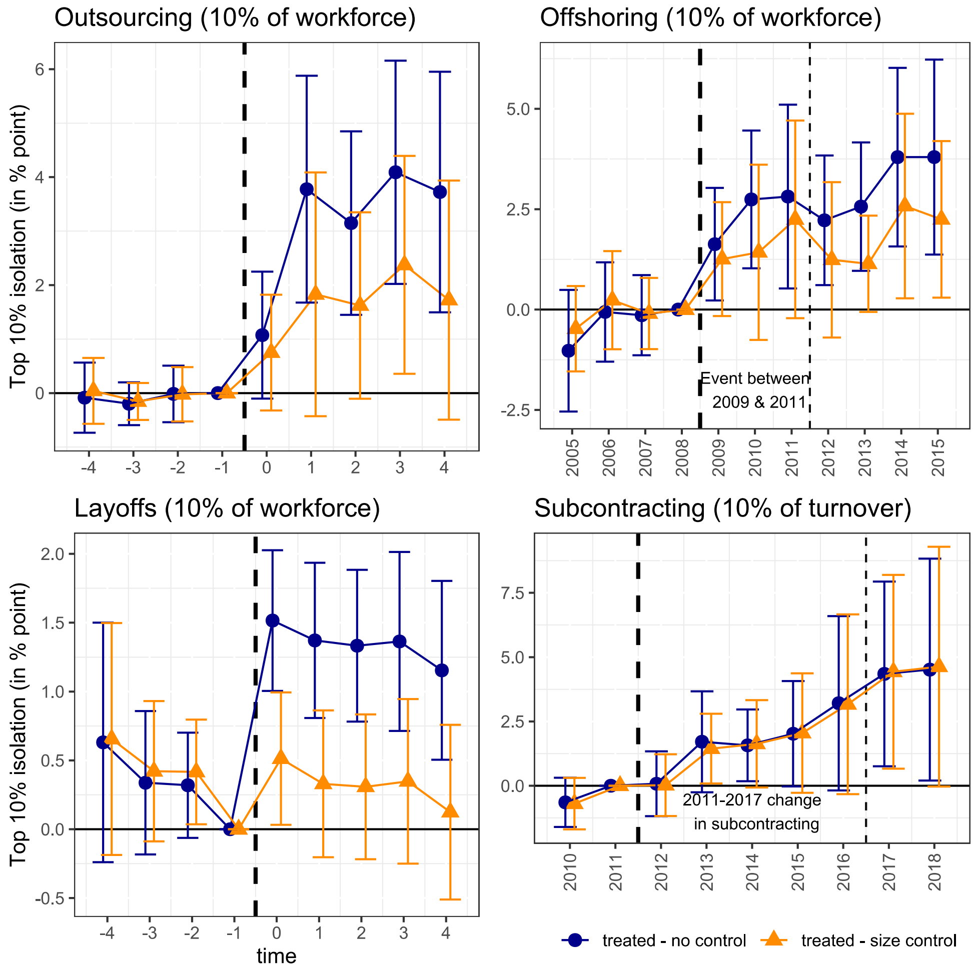
	Model 1	Model 2	
Variables	Workplace log size	Workplace log size	Cumulative decrease in workplace log size
Canada	-2.534*** (0.013)	-1.274*** (0.015)	-2.531*** (0.013)
Denmark	-3.320*** (0.244)	-3.210*** (0.328)	-0.224 (0.377)
Norway	-4.420*** (0.291)	-4.410*** (0.318)	-0.002 (0.358)
Sweden	-3.710*** (0.222)	-3.680*** (0.251)	-0.066 (0.309)
France	-5.570*** (0.143)	-5.410*** (0.16)	-0.306** (0.141)
Netherlands	-6.440*** (0.352)	-5.910*** (0.371)	-1.190** (0.474)
Spain	-0.178 (0.191)	-0.362 (0.245)	0.338 (0.253)
Hungary	-7.310*** (0.105)	-7.310*** (0.116)	0.016 (0.103)
South Korea	2.510*** (0.134)	2.740*** (0.143)	-0.538*** (0.137)
Japan	-0.749*** (0.285)	-0.494 (0.470)	-0.490 (0.791)
All#	-3.102*** (0.068)	-2.820*** (0.087)	-0.568*** (0.118)

Note: On each line, we display the parameters of two different regressions with top 10% isolation as the dependent variable, and workplace and linear time fixed effects. Models 1 uses the log of workplace size as independent variable. Model 2 also adds the cumulative decrease in log size to capture an eventual asymmetry of size on top earners' concentration.
In the last row, we compute the average (weighted by years) of separate regression parameters. To proxy the standard errors, we draw 1,000,000 values for each country in normal law distributions scaled by the country's regression parameters. We then compute the standard deviation of the weighted average of these values.
Robust standard errors clustered at the workplace level in parentheses (except for Canada). ***p<0.01, ** p<0.5, *p<0.1

Figure 5 presents the result of this approach. To better compare the outcomes, we multiply the restructuring events by their intensity in terms of workforce decline (or sales involved for subcontracting models).[10]

10 Figure S9.1 shows similar qualitative effects when we replace variables based on the intensity of the restructuring events with dichotomous variables for the existence of such events.

Figure 5. Impact of weighted workplace restructuring events on top 10% isolation in France



Note: We measure the impact in France of four types of restructuring events (outsourcing, layoffs, offshoring, subcontracting) on top 10% isolation. In this figure, subcontracting is not based on a discrete event study but captures the 2011-2017 change in subcontracting magnitude (in terms of sales). Restructuring events are weighted by their magnitude in terms of workforce (outsourcing, layoffs and offshoring events). Here, point estimates correspond to a 10% intensity event. Hence, outsourcing 10% of the workforce increases top earner isolation on year *t+1* by 3.8 percentage point more than in "control" workplaces. As workplace size decrease could be the mediator, we also estimate in separate models (triangle points) the impact of those events controlling for size. All models are OLS with workplace and year fixed effects, clustered at the firm level. We plot the 95% confidence interval. To avoid the issue of time-heterogeneity of treatment for the staggered outsourcing and layoff models, we use a stacked version of two-way fixed effects models, where database are constructed separately for each year of events and further aggregated (Cf. Appendix A2).

Source: We approach outsourcing events (top-left panel) in the BTS social security files (2001-2017) with 6+ worker-flows in a given year towards outsourced sectors (logistics, transport, restoration, cleaning, and security). In the bottom left-panel, we use *MMO* survey (*Mouvements de main d'oeuvre* – Labor force movements) for the years 2002-2014 which documents "economic layoff plans" (*plan de licenciement économique*). The top-right panel is based the *CAM* survey of 2012 (*Chaînes d'activités mondiales* / International Sourcing and Global Value Chains) which asks to managers whether they off-shored between 2009 and 2011 and how many jobs were suppressed as a consequence of offshoring. Finally, in the bottom right panel, we use the variation of the share of subcontracted activity between the 2011 REPONSE (*Relations professionnelles et négociations d'entreprise)* survey and that of 2017. Outsourcing, layoff, offshoring and subcontracting events (treated and counterfactuals) are then merged at the workplace or firm level (Offshoring) with our workplace segregation measures based on the social security BTS wage files (Cf. Appendix A2).

Outsourcing 10% of the workforce in a given workplace increases top 10 percent isolation in year *t+1* by 3.8 percentage points relative to counterfactual workplaces which did not outsource (Figure 5, upper left panel). As outsourcing and counterfactual workplaces do not evolve differently before the outsourcing event, this reinforces our interpretation of outsourcing as a causal factor. In Table S9.1, we provide several alternative estimations showing the robustness of the outsourcing effect. It holds true when we combine outsourcing both to low and high skill sectors (model 2) and when we combine the variation of top earner isolation both in departure and arrival workplaces (models 5 and 10).

Offshoring and subcontracting also contribute to top earner isolation at a similar magnitude. Offshoring 10% of the workforce increases top earner isolation by 2.5 percentage point one year after the end of the offshoring period (Figure 5, upper right panel). Increasing subcontracting by a magnitude of 10% of the workplace's sales between 2011 and 2017 increases top earner isolation by 4.3 percentage points (Figure 5, bottom right panel). Finally, layoffs have a slightly lower effect. Firing 10% of the workforce in an "economic layoff" (*plan de licenciement économique)* increases top earner isolation by 1.5 percentage points (Figure 5, bottom left panel). We also investigated the impact of "subsidiarization" events: sending 10% of the workforce to a new subsidiary firm increases top earner isolation by 0.8 percentage points (table S9.1, models 6 and 11).

As these workplace restructuring events generally decrease workplace size, we tested whether these organizational events continue to hold when we control for the (asymmetric) evolution of workforce size, viewed here as a mediator. In Figure 5, this is represented by the blue triangle line. It shows that half of the outsourcing and offshoring and two-thirds of the layoff effects operate through a reduction in workforce size. By contrast, the effect of subcontracting is independent of the reduction in headcount.

While the marginal effects of these restructuring events are strong, we should keep in mind that some of these events are rare, notably outsourcing events. Only 0.04% of top earners are on average exposed in their workplace to outsourcing events as we define them. In contrast, 18% are exposed in their workplace to layoff events and 8% to offshoring. Thus, even if we capture only the tip of the iceberg with our restrictive definition of outsourcing, the contribution of outsourcing to top earner isolation is probably limited. With our definition, it amounts to 1% of the trend (cf. Table S9.6). In contrast, offshoring and layoffs contribute more and could account for respectively 11 and 17% of the trend (cf. Table S9.6).

Therefore, these combined estimates on ten countries and on France show that workplace size reduction, through outsourcing, layoffs, offshoring and subcontracting contributed substantially to the increase in top earner segregation.

Global cross-country evidence

The above estimates provide evidence that manufacturing, finance, and shrinking workplaces are the locus of increased top earner concentration. However, these estimates do not give a full picture of the country level evolution of segregation, as they do not account for the potential spillover segregation effect of the excluded workforce once these workers are re-hired in other workplaces. Once rehired, these workers could reduce top earner segregation and therefore cancel out the increase associated with workplace size reduction. Thus, in order to have estimates that overcome this limitation, we need to use an observation unit where our index accounts for the full segregation distribution. We do this with cross-country panel regressions (Table 6), where we use top 10 percent isolation as our dependent variable, country and year fixed effects, and log mean wage and log working age population as control variables. To facilitate comparison of parameters, our variables have been country-demeaned and standardized. Thus, we measure the impact of a within-country standard deviation change of the independent variables on a within-country standard deviation change in top 10% isolation.

Table 6. Top 10% isolation. Cross-country panel regressions

Panel A.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Log mean wage (OECD)	-0.305***	-0.412***	-0.470***	-0.359***	-0.337***	-0.491***	-0.245*
	(0.084)	(0.108)	(0.091)	(0.082)	(0.115)	(0.085)	(0.120)
Log 20-64 population (OECD)	-0.149***	-0.130*	-0.155**	-0.187***	-0.113*	-0.235***	-0.178***
	(0.053)	(0.067)	(0.064)	(0.062)	(0.064)	(0.073)	(0.061)
Deindustrialization: Manufacturing share of workforce	-0.428***						
	(0.099)						
Average log-size of workplaces		-0.170**	-0.067				
		(0.071)	(0.067)				
Cumulative decrease in average log-size of workplaces			-0.135***				
			(0.030)				
Globalization: Outward FDI stock (UNCTAD)				-0.029			
				(0.048)			
Global financial center wage share#					0.022		
					(0.040)		
ICT share of assets (OECD and EU Klems)						0.306***	
						(0.050)	
Financialization: stock-exchange volume (GFDD)							0.173**
							(0.079)
Num. obs.	251	249	249	251	243	235	217
R^2 (full model)	0.773	0.744	0.780	0.720	0.746	0.806	0.733
Country FE (Num. groups)	12	12	12	12	12	12	12
Year FE (Num. groups)	30	30	30	30	30	30	30

Panel B.	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Log mean wage (OECD)	-0.415***	-0.307***	-0.351***	-0.505***	-0.461***	-0.224**	-0.244**
	(0.088)	(0.070)	(0.069)	(0.081)	(0.086)	(0.108)	(0.112)
Log 20-64 population (OECD)	-0.171***	-0.188***	-0.155***	-0.200***	-0.241***	-0.355***	-0.341***
	(0.055)	(0.049)	(0.053)	(0.056)	(0.063)	(0.085)	(0.091)
Deindustrialization: Manufacturing	-0.333***	-0.481***	-0.463***	-0.299***	-0.293***	-0.377***	-0.367***
share of workforce	(0.111)	(0.076)	(0.084)	(0.053)	(0.058)	(0.063)	(0.065)
Average log-size of workplaces	-0.107*	-0.132**	-0.136**	-0.230***	-0.224***	-0.259***	-0.265***
	(0.058)	(0.061)	(0.056)	(0.051)	(0.047)	(0.050)	(0.047)
Cumulative decrease in average	-0.064*	-0.067	-0.100	-0.108*	-0.014	0.072	0.073
log-size of workplaces	(0.032)	(0.064)	(0.069)	(0.054)	(0.064)	(0.064)	(0.061)
Globalization: Outward FDI stock	0.088**	0.103***	0.098**	0.038	0.017	-0.028	-0.035
(UNCTAD)	(0.035)	(0.035)	(0.036)	(0.031)	(0.032)	(0.054)	(0.052)
Global financial center wage share#			0.075*	0.091**	0.067**	0.118***	0.125***
			(0.037)	(0.034)	(0.032)	(0.041)	(0.043)
ICT share of assets (OECD and					0.186**	0.147*	0.148*
EU Klems)					(0.070)	(0.082)	(0.083)
Financialization: stock-exchange							-0.087
volume (GFDD)							(0.067)
Num. obs.	249	241	241	225	225	191	191
R^2 (full model)	0.800	0.803	0.807	0.825	0.833	0.842	0.844
Country FE (Num. groups)	12	12	12	12	12	12	12
Year FE (Num. groups)	30	30	30	30	30	30	30

Note: Dependent and independent variables are country-demeaned and standardized. Therefore, in model 1, one within-country standard deviation in manufacturing share leads to −0.43 within-country top 10% isolation standard deviation. Unless we specify the source of the variable in parentheses, the variables are estimated thanks to the linked employer-employee data to which our team had access, listed in Table 1.
Robust standard errors clustered by years in parentheses. ***p<0.01, ** p<0.5, *p<0.1
As we don't have geographical variables in our database for South Korea, we complete the global financial wage share with statistics provided by the Korean Ministry of Employment and Labor.

In the first panel, we measure the impact of the variables separately to estimate their first order impact. This exercise shows the critical importance of deindustrialization: one standard deviation drop in manufacturing size increases 0.43 of a standard deviation in top earner segregation. This effect is followed by digitalization (+0.30), financialization (+0.17), and workplace size (-0.17), which is mainly a size shrinking effect (cf. -0.067-0.135=-0.2 in model 3). Globalization and global cities do not have a first order impact.

In the second panel, we combine all of the above variables. To make sure that changes in estimates are due to the introduction of a variable and not to the reduction in sample size due to missing values, we estimate the regression on a consistent sample before and after introduction of the variables for which we have missing values. This exercise shows that the deindustrialization effect remains consistent throughout the various specifications and related change in sample size with an effect ranging from -0.29 to -0.48. It is followed by the size variable (ranging from -0.10 to -0.26) and then digitalization (0.15 to 0.18). Financialization is not significant once we control for other variables. Globalization has unstable estimates. Global financial center does become significant once we take into account other variables, but its intensity remains smaller than the variables mentioned above.

Analyzing the determinants of the strong trend towards top earner isolation points therefore towards the critical role of three strongly intertwined processes: 1) deindustrialization, which is not just a reduction in size of the manufacturing sector, but the profound reorganization of manufacturing activity, 2) workplace restructuring (through, as shown for France, outsourcing, layoffs, offshoring and subcontracting) and 3) the digitalization of the economy, which is notably the key condition for the reorganization of activity in the manufacturing sector. Financialization becomes a critical factor, mainly when we approach top earner isolation for the top 1%.

6. Discussion

Using administrative linked employer-employee datasets covering twelve countries, we established a new stylized fact. Over the last twenty years, in addition to capturing a larger fraction of the wage bill (Piketty [2013] 2014), top earners work increasingly with one another and decrease their exposure to other workers.

We observe this phenomenon, with different levels of intensity, in a variety of political economies and institutional settings, which gives generality to our statement. Within countries, this pattern is robust: it holds true when we change how we operationalize wage and the working unit.

Top earnings segregation is more pronounced, increases more sharply and displays different patterns than other forms of segregation at work, notably age, gender, and nativity. In sum, we show that in the high-income countries that we study, there is a great separation occurring: The rich elite increasingly segregates from the majority of the population at work. This is confirmed by increased occupational class segregation, a pattern also observed for the United

States (Wilmers and Aeppli 2021), suggesting that had we had access to US data we might have found similar top income segregation trends there.

We isolate three major factors accounting for this trend: deindustrialization and the reorganization of the manufacturing sector, workplace restructuring (through, as shown for France, outsourcing, layoffs, offshoring and subcontracting) and digitalization of the economy. Financialization is a weaker factor, contributing mostly to the separation of the top 1%.

This research comes with several limitations that future work can explore. In order to give maximum external validity to our results, we relied on sources with different level of precision, ranging from full population data to 4% national samples. Thus, the fact that some countries followed only the top 10% isolation trend at work but not the top 1% trend (Germany, Japan, and South Korea) is likely due to sampling and top coding issues. However, it could plausibly also relate to a different role of their wage elites in the division of labor. More precise datasets for these countries and the inclusion of additional countries could help to gauge the generality of the trends uncovered here.

Although the initial motivation of this research is to analyze the evolution of social cohesion and interactions at work, this contribution only documents the levels and evolutions of propinquity. Like for most studies on segregation, heterogeneity within units of analysis (establishment, neighborhoods, schools) leads to a gap between propinquity estimates and patterns of actual social interactions. Within workplaces, interactions are structured by floors, occupations, departments, and hierarchies. Does this mean that patterns of propinquity are uninformative of the evolution of social cohesion? We do not think so. First, let us note that our units are often small, much smaller than neighborhood units and schools used in more common segregation studies: in 2012, 58% of workers are in workplaces with less than 200 workers and 38% in workplaces with less than 50 workers. In those small establishments, it is likely that workers have at least eyesight interactions with most of their colleagues.

Moreover, if we could further hold constant the structure of interactions within units, more propinquity among top earners can only diminish the expectation of concrete interactions between top earners and other workers. As part of this segregation process is due to the outsourcing of non-core activities (such as food, logistics, janitors, and cleaning services), one could still object that in such cases it is only contractual similarity between top and bottom earners which declines and that real propinquity at work remains unchanged. However, outsourcing also changes the nature of interaction, as outsourced workers are often made invisible to core workers (Brody 2006), and lack the agency to make direct claims on pay or working conditions (Tomaskovic-Devey and Avent-Holt 2019). Moreover, as we saw in the previous section, outsourcing accounted for only a small part of the increase in segregation in France. Layoffs, offshoring, subsidiarizing, and subcontracting, all organizational process entailing physical separation between top and bottom earners, contributed much more to the increase in workplace segregation. Hence, the trend uncovered here is not just a decline in contractual similarity. The increase in top earner segregation at work is quite likely to translate into a decline in social interactions between top and bottom earners.

However, we are fully aware that, based on our administrative data, it remains unclear to what extent the increase in workplace segregation has actually led to a decline in top-down social interactions at work. To overcome this limitation, we can only call for further research using relational data to examine the patterns and evolution of social interactions.

More work is also needed to measure and disentangle the precise mechanisms at play. Some mechanisms identified, such as digitalization, are only available at the country level and are therefore measured crudely here. They need to be confirmed with more precise measures at the workplace level. A first attempt (cf. S10 and Table S10.1) provide suggestive evidence that workplace digitalization increases top earner isolation in France. Nonetheless, results are only significant one year after the digitalization change and their effect on top earner segregation shrinks rapidly. It seems likely that the more important impact of digitalization is to foster outsourcing, subcontracting and similar forms of workplace restructuring.

Potential mechanisms, such as outsourcing and layoffs, are only measured precisely in one country (France). While these measures provide support for the role of these restructuring events on increased top earner segregation, their occurrence probably varies from country to country depending on work regulations and institutional settings. Although our measure was less restrictive than that of Goldschmidt and Schmieder (2017), we find fewer outsourcing events than for Germany. Measuring these events on more countries would thus help to size their impact on workplace integration.

In this paper, we mostly estimated first order relations between causal factors and segregation measures. More generally, we need to address the causal articulation of these factors in depth. At first sight, deindustrialization, workplace restructuring, and digitalization could be seen as independent causal factors, whose impact we could estimate through a classical multi-variable regression. For instance, we can probably find in the service sector workplaces that digitalize without restructuring and *vice versa*. However, in most cases, these three components are substantially intertwined. "Deindustrialization" is a process of manufacturing reorganization through digitalization and restructuring. This indicates that these factors are more causal mediators of one another rather than independent variables. Measuring more broadly their impact supposes to characterize their causal order. Social sciences often adopt the technological hypothesis: digitalization enables and governs workplace restructuring. For instance, Bergeaud et al. (2021) formulate the hypothesis that it is digitalization (here broadband internet diffusion) that leads to outsourcing and consequently to increased segregation. While the technological hypothesis is plausible, we should also consider the ideological dimension of restructuring which could reverse the causal order. Several articles show the critical role of a new generation of managers, trained in the shareholder value paradigm, who viewed downsizing as an organizational imperative (Goldstein 2012; Jung and Shin 2019; Jung and Lee 2022; Acemoglu, He, and le Maire 2022). These managers may then search for or invent new technologies in order to shed workers.

A research agenda on rising workplace segregation

Growing top earner segregation raises the specter of an increasingly isolated elite. Since in many countries they are also increasingly rich, high-income market economies are at risk of being led by a socially disconnected, but increasingly powerful elite influencing multiple aspects of economic, civic, and political life. While we have documented an important and disturbing trend across multiple countries, there is much we do not know. Future research should thus delve further into both the causes and consequences of growing top earner segregation.

In addition to the results established in this article, we need to scrutinize carefully the complex mediating effect of workers' declining organizational power on workplace segregation. Indeed, declining worker power could both decrease workers' resistance to outsourcing (Doellgast 2008) and modify firms' incentives to outsource (Kramarz 2017; Dekker and Koster 2018). Establishing the role and interplay of these, and other, potential causes of increased top earner segregation would contribute to the understanding of the trend uncovered here.

There are also possible consequences of increased workplace segregation, which could contribute to an increase in residential segregation, a decline in social mixing and social mobility, an increased elitism at the top fueling increased inequality, and growing frustration at the bottom possibly nourishing contemporary forms of populism, all of which warrant a closer inspection.

Decline in social mixing. Less propinquity at work between top and bottom earners could translate to less geographic propinquity. Indeed, when we investigate top earner spatial isolation, based on their municipality of residence, we also find an increase, at least for the top 1% (Figure S3.5). This evolution is globally less pronounced than that of workplace isolation, but remains notable in France, Sweden, and Canada. Top 1% workplace and spatial isolation country trends are correlated, and an earlier analysis suggests that workplace segregation determines spatial segregation more powerfully than the reverse (Godechot et al. 2020). A more fine-grained approach to the relation between the two dimensions might contribute to current debates on the evolution and the determinants of income residential segregation (Reardon and Bischoff 2011; Logan et al. 2018; Musterd et al. 2017).

The increased homogeneity of top earners' work environment could also contribute to explaining the recent decline in income mobility measured both in the US (Kopczuk, Saez, and Song 2010; J. Davis and Mazumder 2020) and in Denmark (Harding and Munk 2020), putting an end to the post-WWII era of stability in both intra-generational and intergenerational social mobility (Erikson and Goldthorpe 1992; Chetty et al. 2014). When low earners no longer work in the same firm as top earners, they will have little chance of being promoted internally to a top earner position. In addition, in a context of increased work segregation, low earners lack access to the richer set of information and influence that the upper class enjoys and face, as a result, lower prospects for upward mobility (N. Lin 2002; Chetty et al. 2022). Finally, growing workplace segregation influences social mixing and social mobility through its impact on employment, residential and educational segregation (Engzell and Wilmers 2022): fewer top-bottom interactions may lead to growing mating endogamy at the top of the social hierarchy (Schwartz and Mare 2005; Bouchet-Valat 2014).

Increasing isolation and increasing inequality. As top earners are increasingly isolated from others, they are also isolated from their norms, manners, and ways of thinking. Growing isolation could therefore impact their vision of what is a just society and of who deserves what (Dubet 2015). Kuusela (2022) has recently documented the discursive blindness of the wealthy to the structural sources and consequences of inequality. We fear that a similar blindness to the lived experience of their subordinates at work will follow from the increased isolation of top earners from their co-workers. At the same time, a homogeneous top earner work environment could increase status competition. A possible outcome of increased top earner isolation is an increase in inequality, with higher levels of pay for the top earners, a greater dispersion of pay among them and increasing neglect of the claims of lower-level workers.

Elitism and growing populism. Increased top earner isolation may also change how elites engage with the rest of society. Bartels (2008) for the US, Elsässer, Hense and Schäfer for Germany (2021) and Schakel for the Netherlands (2021) show that governments are more responsive to the preferences of the top 1% than to the rest of society. The response of politicians to this latter group may be further distorted by growing isolation of elites from the rest of society.

Increasing segregation at work could transform not only the upper classes' views of society but also those of bottom earners. The latter still know of the existence of top earners for instance via the media or references to "headquarters", but they rarely interact with them. This situation could increase feelings and experiences of being left behind, ignored and misunderstood. Consequently, it may fuel new social struggles, such as the Yellow Vest protest in France (Algan, Malgouyres, and Senik 2019), Trumpism (Patenaude III 2019) and other forms of populism. The growing spatial political polarization, between large metropolises and the rest shown by recent elections in the UK (Brexit 2016), the US (2016 and 2020 presidential elections), and France (2017 and 2022 presidential elections), could find some of its origin in the new organizational and spatial structure of jobs and the limited cross-class social interactions at work that it produces.

In short, the great separation of top earners from bottom earners at work that is documented in this article may also be implicated in some of the key social and political challenges of our time.

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Appendices

A1. Data sources and sample definition

For all countries, we exclude very low yearly earnings, which we interpret as corresponding to failed job matches and short-tenure temporary work and, more rarely, reporting errors. We set the earnings exclusion threshold at a low level in order to include most part-time workers in our main analysis. In countries where we have a minimum wage, we exclude person-job matches which reported earnings of less than half a yearly minimum. In countries without a minimum wage, we used various internal or external thresholds: half P10 of full-time workers (Germany and Japan), one third prime age P50 (Sweden), or one fourth of OECD country-year average (Denmark Norway) yearly wages.

Canada (1990–2019). Data were generated by Statistics Canada. The data are population-level and include all sectors and industries and employees. Statistics Canada provides firms' identification number but neither the establishment ID nor the precise geographical unit of the workplace (beyond the province). We therefore use the interaction of province and firm ID to proxy establishment. We lack information on hourly wages.

Czechia (2002–2016). Data were taken from the Average Earnings Information System (ISPV) survey conducted by the private agency TREXIMA. The data consist of the entire population of public sector workplaces, plus a sample of private sector workplaces. The private sector sample consists of workplaces with at least 10 employees. A stratified sampling of private sector workplaces with 10–250 employees was taken based on the size of the workplace. All private sector workplaces with over 250 employees are included in the data. All employees of sampled workplaces are included. The data also spans all industries and sectors. In the end, the dataset covers 80% of Czech workforce and 96% of the workforce in establishments with 10 and more employees. Estimates are weighted to correspond to the complete workforce in establishments with 10 and more employees. Data contains earnings, however hourly wage are not available.

Denmark (1994–2018). The data consist of population-level observations of both private and public sector workplaces extracted from the labor market statistic register (Den Registerbaserede Arbejdsmarkedsstatistik – RAS), and earnings from the job register IDAN. Demographics such as age, gender, and nativity come from the population register (Befolkningsregistret).

In order to drop marginal jobs, we exclude workers earning less than a 1/4th of the Danish yearly wage (source: OECD). In 1994, establishment ID is not available and we use firm ID instead. Occupation nomenclature changes in 2009, leading to a drop in the proportion of intermediate occupations from 22 to 14% and a subsequent increase of upper occupations from 20 to 30%.

France (1993–2019). Our analyses use data from the Insee's BTS (*Base Tous Salariés)* constructed from DADS (*Déclaration annuelle de données sociales*) social security register. Access to the BTS data was obtained through the CASD (*Centre d'accès sécurisé aux données*) dedicated to researchers authorized by the French *Comité du secret statistique*. The data consist of population-level observations of private sector workers, plus all hospital and local civil service workers. State civil servants are missing before 2009 and excluded in the following years for consistency.

We consider people born outside France as a good proxy for "immigrants." This variable is missing in 2011 and of poor quality between 2002 and 2004. We therefore completed it with information on other years through the construction of a pseudo panel.

This pseudo panel also served for decomposing the role of sorting and between workplace heterogeneity in wage increase (Supplementary file S7). The French BTS is not proper panel data as the individual IDs (starting in 2002) are different from one yearfile to another. However, each yearfile *y* contains information both on the current year *t* and the preceding year *t-1*. Following Babet, Godechot and Palladino (2023), we take advantage of this overlap to build a pseudo panel based on common information (establishment ID, gender, number of hours, duration of the job, start and end dates of the job, municipality of work and residence, earnings and age) between year *t* of yearfile *y-1* and year *t-1* of yearfile y. We can successfully perform a single match with 98% of the individuals.

Germany (1999–2015). Data come from a customized sample for the project "Dynamics of Organizational Earnings Inequality: Investigation within the Comparative Organizational Inequality International Network (COIN)" of the Integrated Employment Biographies Sample (IEBS) of the Federal Employment Agency. It covers roughly 5% of the German working population and about 20,000 establishments, spanning the years 1999–2015. Estimates are weighted to correspond to the complete workforce.

The basis for the data is the integrated notification procedure for health, pension and unemployment insurance, which came into effect in 1973 and was extended to cover Eastern Germany in 1991. Under this procedure employers are required to submit notifications to the responsible social security agencies concerning all their employees covered by social security at least once a year. Thus, our data covers the approximately 80 percent of the workforce that is liable for social security contributions, but excludes elite civil servants (*Beamte*) and the self-employed.

These data represent a sample of firms and their employees. We first randomly sample 20,000 establishments among all establishments that existed in Germany between 1993 and 2013 (without regard to the duration of their existence or their region). The establishments were drawn proportionally to their size across the whole panel period. For privacy reasons, we limit the maximum of the sampling probability to 0.3, as otherwise, due to the skewness of the workplace size distribution, nearly all large workplaces would be drawn into the sample.

We then select employees from the 20,000 establishments. For very large establishments, the number of employees was limited to 1,000 randomly selected employees. For all others, all employees are selected. This sampling strategy reproduces both workplace and individual population parameters.

Earnings not subject to social security because they are below the threshold for small-scale employment (e.g., newspaper delivery), which is currently 450 euros per month, are excluded from the sample. The earnings are also top coded at the social contribution limit, which differs by year and for East and West Germany. To impute the top-coded earnings, an imputation strategy based on the imputation from Card, Heining, and Kline (2013) was established, which accounts for individual and establishment wage prior to the censored period. However, rather than focusing on the mean individual and establishment wage prior to the censored observation as was done by Card, Heining, and Kline, we utilize information on lagged earnings. Given the limitation of our imputation, measures of exposure involving the top 1% should be therefore considered cautiously.

In the German data, we find a strong discontinuity in 2011 in occupation categories, leading us to drop the years after 2010 for studying segregation along those dimensions. While we have establishment IDs, firm IDs are lacking. Similarly, we have no hourly wages.

Hungary (2003–2017). Our analyses use Admin2 and Admin3 data processed by the Databank of the Centre for Economics and Regional Studies. These data are generated by linking data from five governmental institutions (the Pension Directorate, the Tax Office, the Health Insurance Fund, the Office of Education, and the Public Employment Service). Both Admin2 and Admin3 data are 50% random sample of the Hungarian population followed from 2003 to 2011 and 2003 to 2017 respectively. As wages are right-censored in Admin3 before 2013 and not in Admin2, we combine results from the two datasets. The earnings concept is monthly earnings from each person's primary job. Monthly data were aggregated to obtain yearly earnings. Low-wage workers, defined as workers earning less than half of the yearly minimum wage, are dropped from the sample.

In the Hungarian data, we lack establishment ID and firm's geographical unit. We proxied establishments with an interaction between firms ID and workers' region of residence (NUTS2 7-level regions).

Japan (1989–2013). Data are from the Basic Survey on Wage Structure conducted by the Ministry of Health, Labor, and Welfare of Japan. The survey is a two-stage design in which a sample of private sector establishments with at least five employees are selected, and then a uniform random sampling of workers among these establishments is taken. The sampling ratio is 1/1 in establishments with 5-29 workers, 1/2 in those with 30-99 workers, and a certain rate by industry in establishments with 100 or more workers. Firms' executives are not included in the data. Given this limitation and the small size of the sample, measures of exposure involving the top 1% should be therefore considered cautiously, but 10% thresholds are treated as more reliable. The sample covers 4% of the workforce working in establishment with more than five workers. Estimates are weighted to correspond to the complete workforce.

In the Japanese data, we lack information on nativity. We have the establishment IDs, but not the firm.

Netherlands (2006-2018). Yearly data on employee wages and companies' sector and industry are provided by the Statistics Netherlands (CBS) within the System of Social-Statistics Database (SSB). We linked data on employees and employing firms to construct a dataset with population-level coverage of wages across all sectors and industries. The analyses include the highest-paying jobs of each employee in a given year and jobs with wages lower than age-specific minimal hourly wage are excluded.

Norway (1996–2018). Data were generated by Statistics Norway and are population-level, including all sectors and industries. In order to drop marginal jobs, we exclude workers earning less than a 1/4th of the Norwegian yearly wage (source: OECD). Occupations are not available in this dataset.

South Korea (1982–2012). Data are from the Wage Structure Survey conducted by the Korean Ministry of Labor. The data consists of a sample of private sector establishments, first stratified by size and then by region and industry. To be included in the sample, an establishment must have had a minimum of five employees in 1990 and ten employees beginning in 1999. From each establishment, employees were randomly drawn depending on the size of the establishment—all employees for 5-99 employees, 80% for 100-299, 70% for 300-499, 50% for 500-999, 30% for 1,000-4,999, 20% for 5,000-9,999, and 10% for 10,000 or more. All industries except Agriculture are included. The dataset contains only full-time jobs. Estimates are weighted to produce national estimates.

The data does not provide information on nativity. Changes in occupational nomenclatures led us to limit estimation of occupational segregation to the 1993–2007 period.

Spain (2006–2018). Our analyses use data from the Continuous Sample of Working Histories (CSWH) *(Muestra Continua de Vidas Laborales con datos fiscales)* from Spain's Social Security Office. The CSWH contains matched anonymized social security, income tax and census records for a 4% non-stratified random sample of the population who in one specific year had any connection with Spain's social security system (whether via employment, self-employment, unemployment, or retirement). The CSWH provides information on individuals' complete labor market histories from 1980 (or the year the individual registers with Social Security) to the year of data collection.

Because earnings from the social security records are capped at the top and bottom, we use earnings from tax records containing uncensored gross labor earnings for each job (tax records are available from 2006 onward). Thus, the procedure is as follows: first, we identify personal information from social security records then match those records with the individuals in the tax dataset, thereby obtaining 2006–2017 earnings from tax records. When multiple jobs overlap, we only consider the main job, which is either that with the longest spell within the same firm or that with the highest earnings across firms. In this way, we build a yearly panel that covers job spells, with a start/end date and tied to a firm identifier.

Sweden (1990–2012). The data are from population-wide administrative registers from Statistics Sweden (the LISA database) and cover all sectors and industries. Occupations are only available after 2001 and hourly wages are not available.

A2. French data for studying the impact of workplace restructuring on top earner isolation

Outsourcing and subsidiarizing

In order to identify outsourcing events, we follow recent work on outsourcing (Goldschmidt and Schmieder 2017; Bergeaud et al. 2021; Bilal and Lhuillier 2022) where this phenomenon is approached through the identification of consistent worker flows from non outsourced to outsourced sectors. We take advantage from the fact that the BTS social security files are exhaustive, contain a year-file worker ID (starting in 2002), and that they always cover two years, *t* and *t-1*, enabling to track worker flows from one place to another during a 2-year period.

We define an outsourcing flow when the following conditions are met:

– 6 workers and more move from one workplace to another.

– the workers are present on January 1st of year *t-1* in departure workplace.

– they all leave departure workplace during year *t-1*;

– they arrive in arrival workplace either in year *t-1* or year *t*;

– they are present on December 31st of year *t* in arrival workplace;

– departure and arrival workplace do not belong neither to the same firm or nor to the same corporate group;[11]

– departure and arrival workplace do not have the same 2-digit industry code;

– arrival workplaces are in "outsourcing sectors".

Outsourcing sectors are defined the following way. In most estimates, we consider only the "low-skill" outsourcing sectors:

– transports, NAF1[12] in (602) or NAF2 in (493,494);

– logistics, NAF1 in (631,634) or NAF2 in (521,522);

11 We use LIFI survey which contains capitalistic ties between firms in order to identify corporate groups. Two firms under the control of the same head of corporate group are considered as part of the same corporate group.

12 NAF1 and NAF2 stand respectively for *Nomenclature d'Activités Françaises rév. 1* (up to 2007) and *Nomenclature d'Activités Françaises rév. 2* (starting in 2008). These nomenclatures correspond closely to the European industry classification NACE rev. 1 and NACE rev. 2.

– restoration, NAF1 in (55) or NAF2 in (56);

– security, NAF1 in (746) or NAF2 in (80);

– cleaning, NAF1 in (747) or NAF2 in (812).

In a robustness estimate (table S9.1 model 2), we also include "high-skill" sectors:

– IT services, NAF1 in (72) or NAF2 in (62);

– legal and accounting consulting, NAF1 in (741) or NAF2 in (69,70);

– technical consulting, NAF1 in (742) or NAF2 in (71);

– advertising, NAF1 in (744) or NAF2 in (73).

We also study subsidiarization events in a similar way (cf. Table S9.1, models 6 and 11). We consider there's a subsidiarization flow when the following conditions are met:

– 6 workers and more move from one workplace to another.

– the workers are present on January 1st of year *t-1* in departure workplace.

– they all leave departure workplace during year *t-1*;

– they arrive in arrival workplace either in year *t-1* or year *t*;

– they are present on December 31st of year *t* in arrival workplace;

– departure and arrival workplace do not belong to the same firm but they do belong to the same corporate group;

– the arrival firm was created recently : it has less than three years of existence;

We track these flows between 2001 and 2017. Outsourcing flows to low-skill sectors (as defined here) are rare: between 50 and 120 events per year, and between 0.001% and 0.006% of the workforce. But we should keep in mind that our definition is very restrictive and represents probably the tip of the iceberg.

Table A2.1. Outsourcing and subsidiarization events

Year	Workplaces	lsk	lsk_r	o49	o52	o56	o80	o81	hsk	sub
2001	819,374	124	0.0055%	33	59	23	<5	6	187	826
2002	863,523	107	0.0039%	31	38	22	<5	13	195	940
2003	872,012	106	0.0038%	26	38	23	5	15	173	896
2004	876,751	123	0.0060%	62	27	21	9	<5	181	1080
2005	899,326	86	0.0024%	29	22	24	<5	9	194	775
2006	916,718	63	0.0022%	22	24	15	<5	<5	166	914
2007	915,292	78	0.0028%	29	28	17	<5	<5	68	874
2008	930,029	59	0.0018%	17	20	14	<5	6	73	721
2009	955,445	58	0.0022%	19	22	15	<5	<5	84	879
2010	944,632	73	0.0035%	30	20	9	11	<5	85	869
2011	920,332	75	0.0029%	21	40	9	0	5	35	930
2012	928,399	51	0.0017%	14	20	9	<5	6	59	803
2013	925,415	50	0.0015%	15	21	6	<5	7	58	672
2014	939,588	57	0.0020%	18	27	7	<5	5	69	877
2015	927,977	55	0.0016%	11	27	10	<5	<5	33	868
2016	943,324	80	0.0023%	25	27	11	<5	15	80	889
2017	904,237	70	0.0021%	11	25	9	<5	24	67	818

Note: *lsk*: number of outsourcing events towards low skill sector; *lsk_r:* average ratio of workforce outsourced; *o49, o52, o56, o80, o81* are outsourcing events towards respectively transports, logistics, restoration, security and cleaning; *hsk:* outsourcing events towards high-skill sectors, *sub* represents subsidiarization events.

We merge these events with our segregation data based on the BTS between 2001 and 2019. We keep workplaces with top earners and we weight by the number of top earners to have representative measures top earner isolation.

Layoffs

We use the annual French survey MMO (*Mouvements de main d'oeuvre*) on workforce mobility where workplaces report entry and exit of workforce between 2002 and 2014 (years during which the sample is defined the same way). 58,000 to 70,000 workplaces are investigated every year. We drop further years as the sample changes dramatically in 2015. During the selected period, this survey is conducted among all workplaces of 50 workers and more, and a sample of workplaces below this threshold. We used the variables on the number of workers laid off in an "economic layoff plan" (*plan de licenciement économique*).

Economic layoffs are not as rare as outsourcing flows, but they are not very frequent. Each year, 4.6% of the workplaces resort to economic layoffs plans and 0.54% of the yearly workforce is fired.

Table A2.2. Layoff events in MMO

Year	Number of workplaces in MMO (non-weighted)	% workplaces with layoffs (weighted)	% laid-off workers (weighed)
2002	65,690	7.36%	0.63%
2003	67,503	8.47%	0.69%
2004	67,261	7.71%	0.58%
2005	68,445	7.37%	0.56%
2006	67,998	6.46%	0.52%
2007	58,662	2.90%	0.51%
2008	59,737	3.25%	0.51%
2009	65,191	4.64%	0.89%
2010	62,651	2.86%	0.51%
2011	68,136	2.19%	0.36%
2012	67,533	2.36%	0.36%
2013	71,349	2.71%	0.44%
2014	71,157	2.32%	0.39%

We merge this survey with workplace segregation data based on the BTS between 2002 and 2014. We keep workplaces with top earners and we use the MMO weights that we multiply by the number of top earners to have representative measures top earner isolation.

Offshoring

We use the French survey CAM (*Chaînes d'activités mondiales* / International Sourcing and Global Value Chains) where managers of 8,000 firms in the private sector with 50 and more workers (finance and agriculture excluded) were asked whether they off-shored part of their activity between 2009 and 2011. 4% of the firms offshored during this period and 0.26% of jobs were suppressed as a consequence of offshoring.

We merge this survey with workplace segregation data based on the BTS for the years 2005 to 2015. We keep workplaces with top earners, and we use the CAM weight that we multiply by the number of top earners to have representative measures of top earner isolation.

Subcontracting

We use the French survey REPONSE (*Relations professionnelles et négociations d'entreprise*, 2005, 2011, 2017) on social climate in respectively 2,930 workplaces in 2005, 4,023 in 2011 and 4,364 in 2017. 872 workplaces between 2005 and 2011 and 408 between 2011 and 2017 are panelized.

We use two independent variables on subcontracting based on questions asked to the workplace management. The first one is a dummy variable indicating whether part of the activity is subcontracted. In 2005, 54% of the workplaces resort to some subcontracting, 76% in 2011, and 81% in 2017. The second variable present only in 2011 and 2017 characterizes the share of subcontracted activity as a percentage of sales. For both years, the share amounts on average to 5% of the sales.

The first variable enables us to compare among the 272 panelized workplaces (where top earners work) that were not yet subcontracting activity in 2005 the difference in outcome between those (70%) who subcontracted their activity in 2011 (treated) and those (30%) who did not (control). As changes in subcontracting between 2011 and 2017 was very rare, we did not use this period.

However, we can use the 2011-2017 to measure the effect of the intensity of subcontracting. We use the difference for each workplace of the level of subcontracting in 2017 and 2011. The average difference is close to 0.

We merge this survey with workplace segregation data based on the BTS for the years 2000 to 2010. We keep workplaces with top earners, and we use the REPONSE weight that we multiply by the number of top earners to have representative measures top earner isolation.

Godechot, Olivier, et al. 2024. "The Great Separation: Top Earner Segregation at Work in Advanced Capitalist Economies." *American Journal of Sociology* 130(2): https://www.journals.uchicago.edu/doi/10.1086/731603.

Supplementary file

Table of contents

List of tables and figures

S1. Figure construction

Adjusted mean

Our adjusted mean is an average of the countries' evolution on a constant perimeter. In order to calculate this adjusted mean, we proceed as follows.

1) We interpolate linearly country series for missing years between the starting date and the end date.

2) We calculate the three-year moving average for all country series in order to avoid capturing short-term bumps due to inconsistencies in data collection.

3) We finally average this modified data:

– 3.1. When the number of countries is complete:

$$\overline{X}_t = \sum_i \frac{X_{it}}{n},$$

where X_{it} represents series X for country i and year t.

– 3.2. When the number of countries is no longer complete:

$$\overline{X}_t = \overline{X}_{t-1} + \sum_i \frac{\Delta X_{it}}{n}$$

Where $\Delta X_{it} = X_{it} - X_{i,t-1}$

– 3.3. When the number of countries is not yet complete:

$$\overline{X}_t = \overline{X}_{t+1} - \sum_i \frac{\Delta X_{i,t+1}}{n}$$

This adjusted mean is calculated only when series are available for at least three country series for the year t.

Scale

We adapt the scale to display evolution that are visually in line with the metrics used to measure them.

Log-odds scale for proportions

The "log-odds scale" is a scale for representing proportions *p* where vertical visual distances on the graphs are proportional to the log odds of the given proportions *log(p/1-p)*. For instance, with such scale, visual distance on the graph between 4.74% (whose log-odds is -3) and 7.59% (log-odds: -2.5) will be similar to the visual distance between 37.75% (log-odds: -0.5) and 50% (log-odds: 0), or to the distance between 92.41% (log-odds: 2.5) and 95.26% (log-odds: 3).

Log scale for odds ratios

When we represent evolution in relative exposure (expressed as an odds ratio), we adopt the classical log scale which gives the visual intuition of the multiplicative dimension of this measure.

S2. Bias due to sampling and reweighting correction

Following the debate on how sampling bias affects segregation indexes based on entropy measures (Reardon and Bischoff 2011; Logan et al. 2018; 2020; 2022; Reardon et al. 2018; Bischoff et al. 2022), we use French BTS 2016 to estimate the magnitude of this eventual bias with exposure measures (Table S2.1). In the first column, we estimate our exposure measures for the full population, which will serve as a benchmark. In the second column, we estimate our exposure measures on a 10% random sample, that we further restrict to workplaces with at least two workers sampled. In the last one, we use weights to correct the sampling bias.

Table S2.1. Sampling bias and its correction

Variables	Original population data	10% random sample further restricted to workplaces with at least two workers sampled	
Weighting	(No)	No	Yes
Number of observations	14,202,911	1,179,966	1,179,966
Mean wage	34,624 €	35,548 €	34,591 €
Top 1 % isolation	16.00%	14.69%	15.72%
Top 10 % isolation	36.23%	35.46%	36.17%
Migrants' exposure to migrants	32.50%	29.90%	32.69%
Natives' exposure to migrants	8.98%	9.13%	9.00%
Odds-ratio of migrants' and natives' exposures to migrants	4.88	4.25	4.91
Migrant Dissimilarity index	0.53	0.61	0.80

Note: This simulation is based on the French BTS 2016.

Compared to the benchmark, the sample exposure measures in column 2 are indeed slightly biased by a magnitude ranging from 2 to 8%. This is mostly due to the fact that we need at least two sampled workers per sampled workplace to estimate exposure measures. Hence, small workplaces are not well represented. For instance, a given worker from a two-worker workplace has only 1% chance (0.1*0.1) of being effectively used for estimation in the final sample. In contrast, a worker from a 100-worker workplace has a 9.9997% chance ($0.1*[1-(1-0.1)^{99}]$) of being used. The sample needs to include both her (0.1) and at least one of her 99 colleagues ($1-(1-0.1)^{99}$). As a consequence of this selection, the bias also affects average wages. Hence, a simple reweighting of small units suppresses the bias.

In column 3, we reweight observations with weights based on the original number of workers in the workplace. It reweights proportionally to the inverted probability that at least one coworker is sampled. When the probability for coworkers to be weighted is low, the weight is higher.

$$weight = \frac{1}{1 - (1 - sampling\_rate)^{(nbwkrs-1)}}$$

(1-sampling_rate)$^{(nbwkrs-1)}$ corresponds to the probability that all the coworkers are not sampled.

1-(1-sampling_rate)$^{(nbwkrs-1)}$ corresponds to the probability that at least one coworker is sampled.

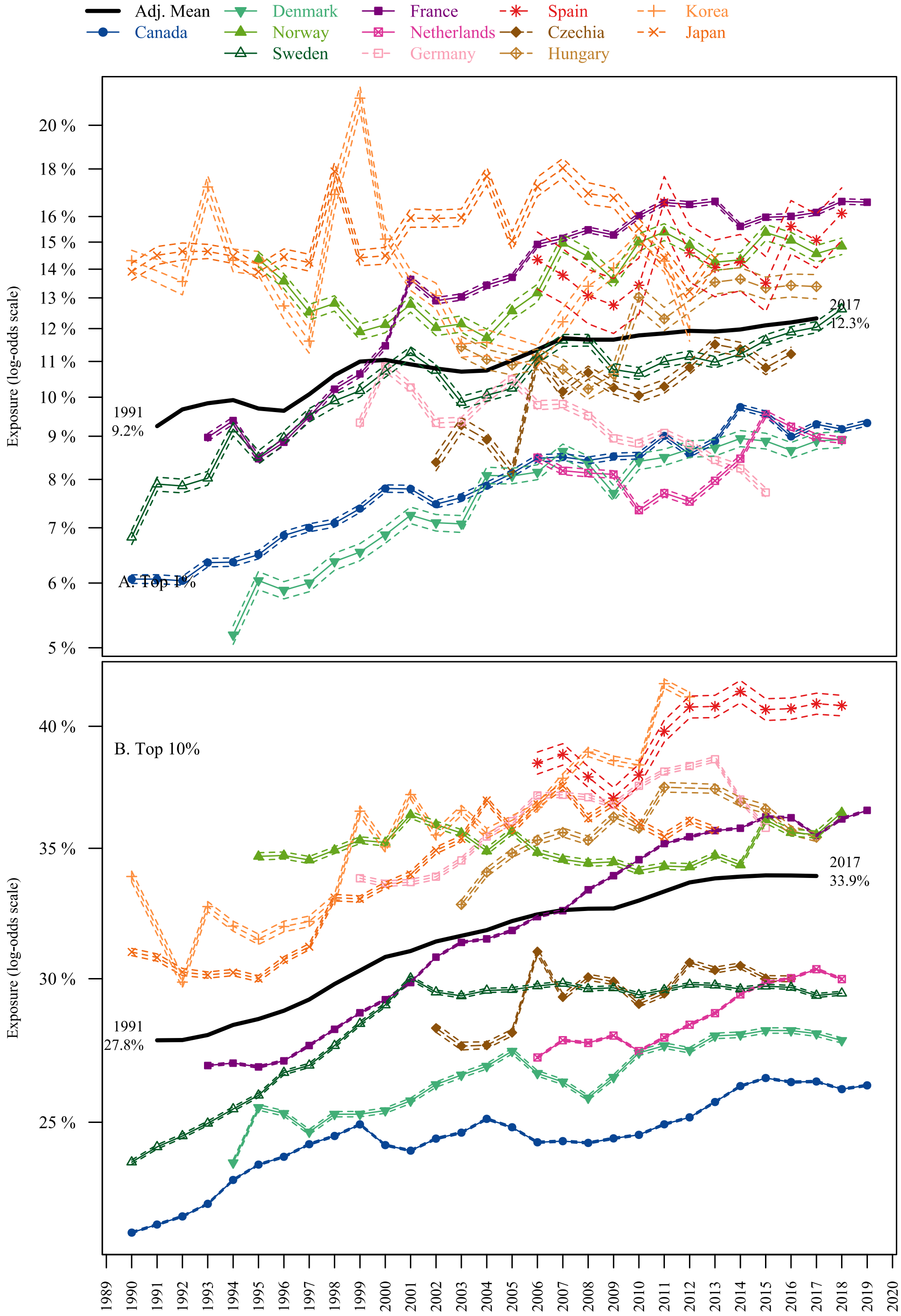
nbwrks is the original number of workers in the workplace

This formula does a very good job for correcting the sampling bias for all exposure measures as well as the mean wage and the odds ratio of exposure to migrants. In contrast, the bias for Duncans' dissimilarity index is substantial on a 10% sample and increases when we reweight our sample. The dissimilarity index measures a distance to an even distribution. However, it uses a benchmark where evenness is achieved in each unit, which is unlikely when units and groups in those units are small. In a sample of individuals, units will be smaller. This can only increase distance to evenness. Reweighting increases the weights of small units for which the distance to evenness is the largest.

Hence, in contrast to exposure measures, entropy measures and dissimilarity index are highly affected by sampling bias and more generally lack robustness when groups and units are small and heterogeneous in size.

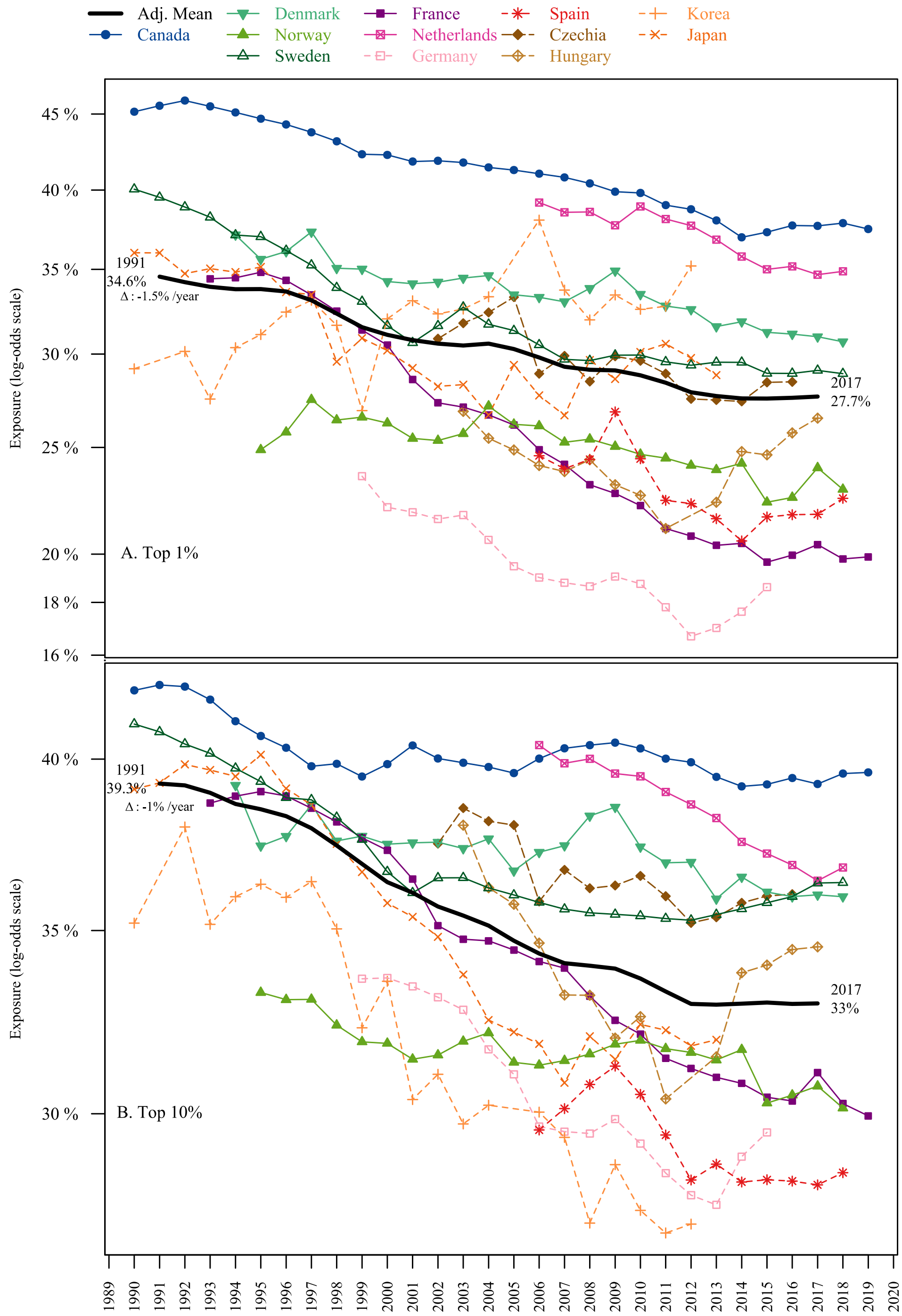
S3. Supplementary figures

Figure S3.1. Confidence intervals for Figure 1



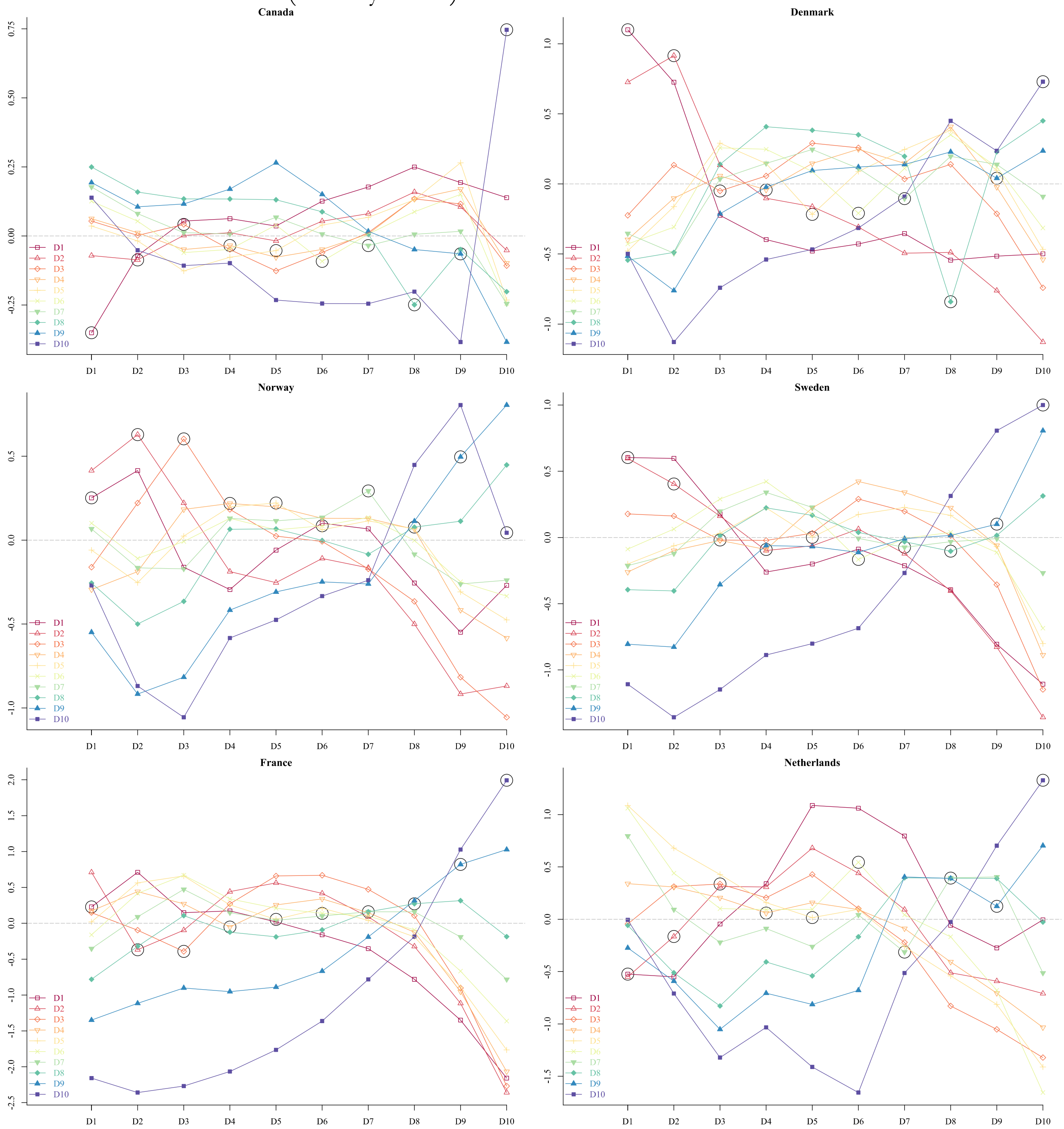
Note: cf. Figure 1.

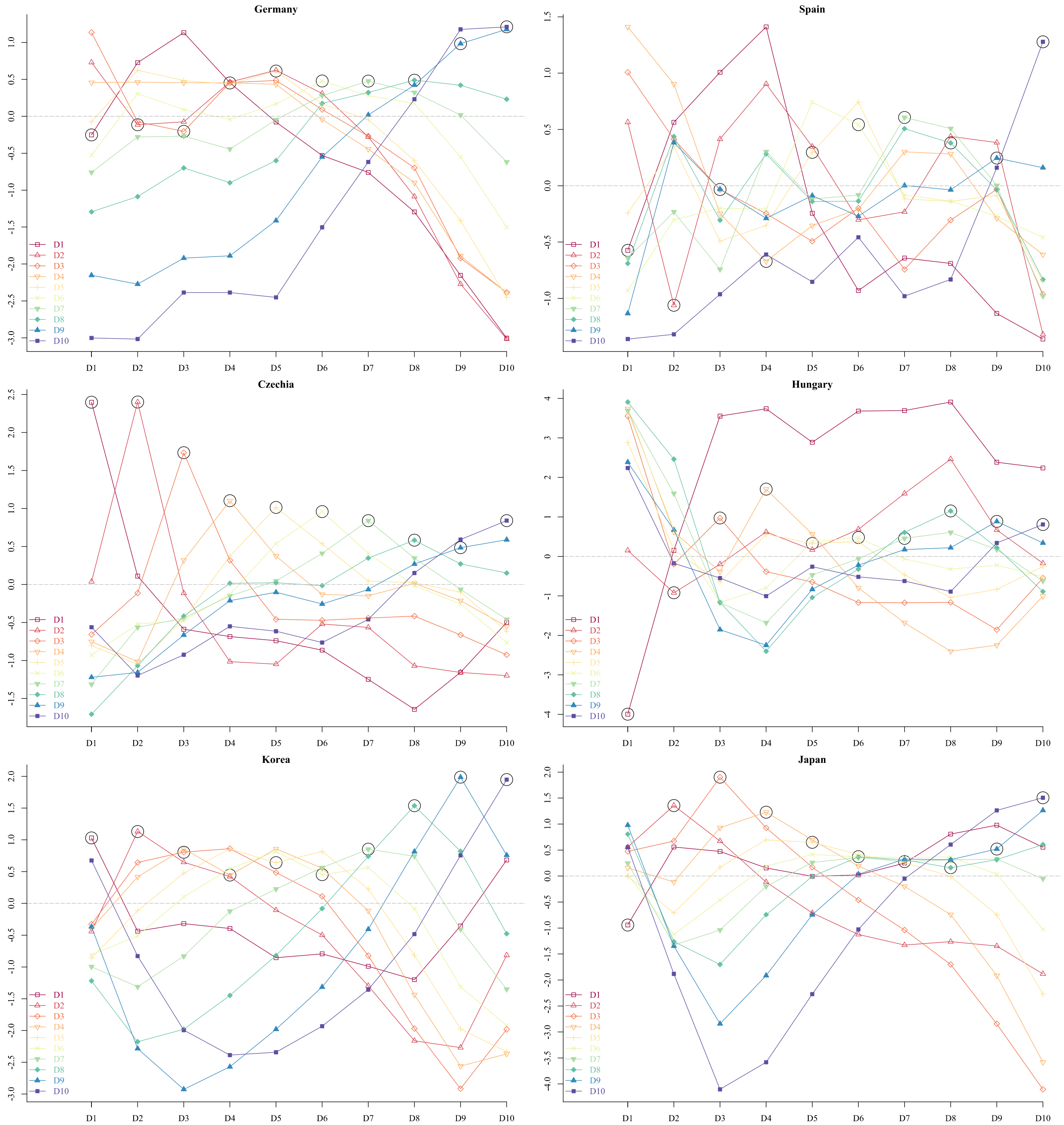
Figure S3.2. Top earner exposure to midquartiles



Note: cf. Figure 1.

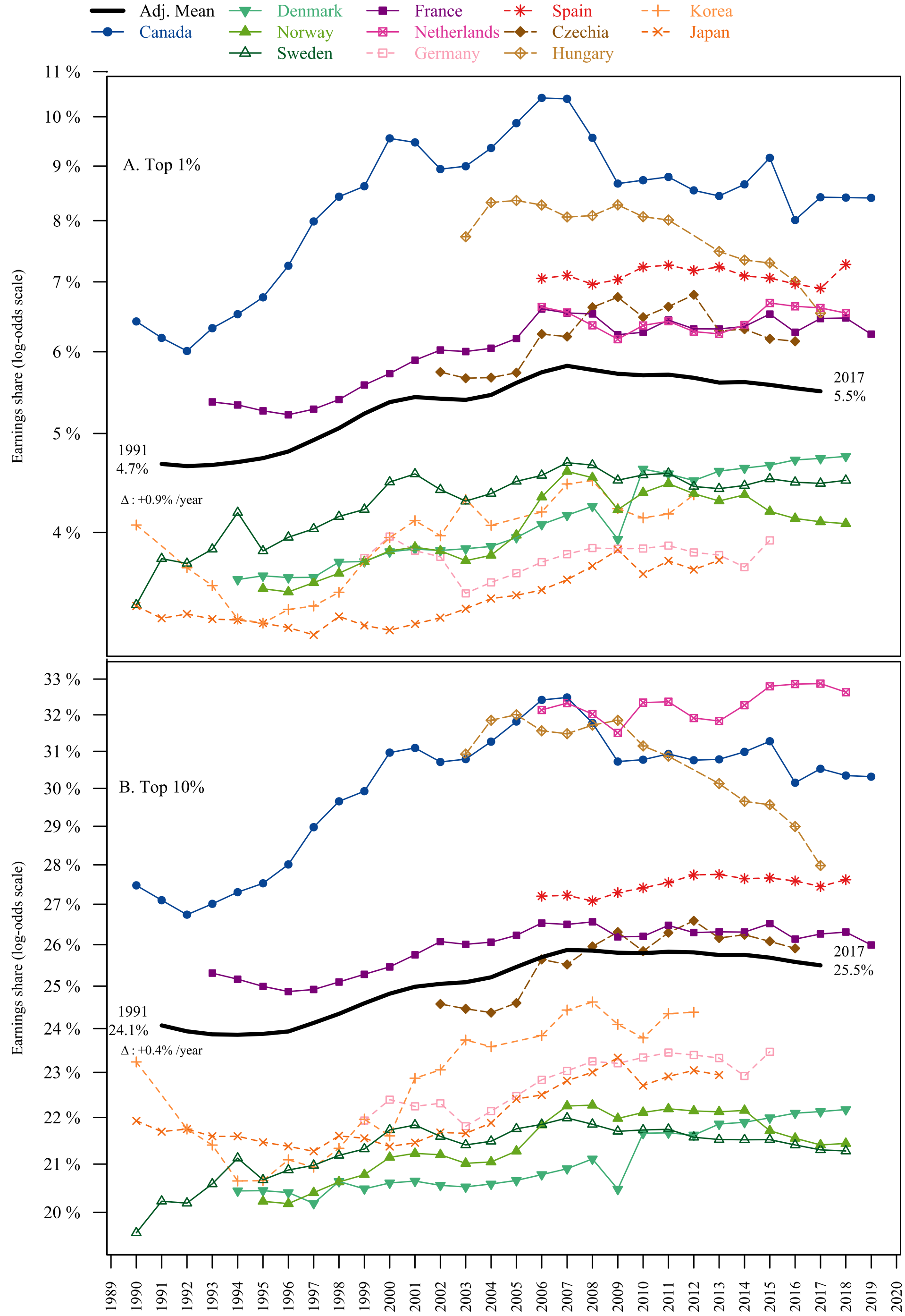
Figure S3.3. Linear trend (yearly rate) of evolution of each decile's exposure to one another (Country details)





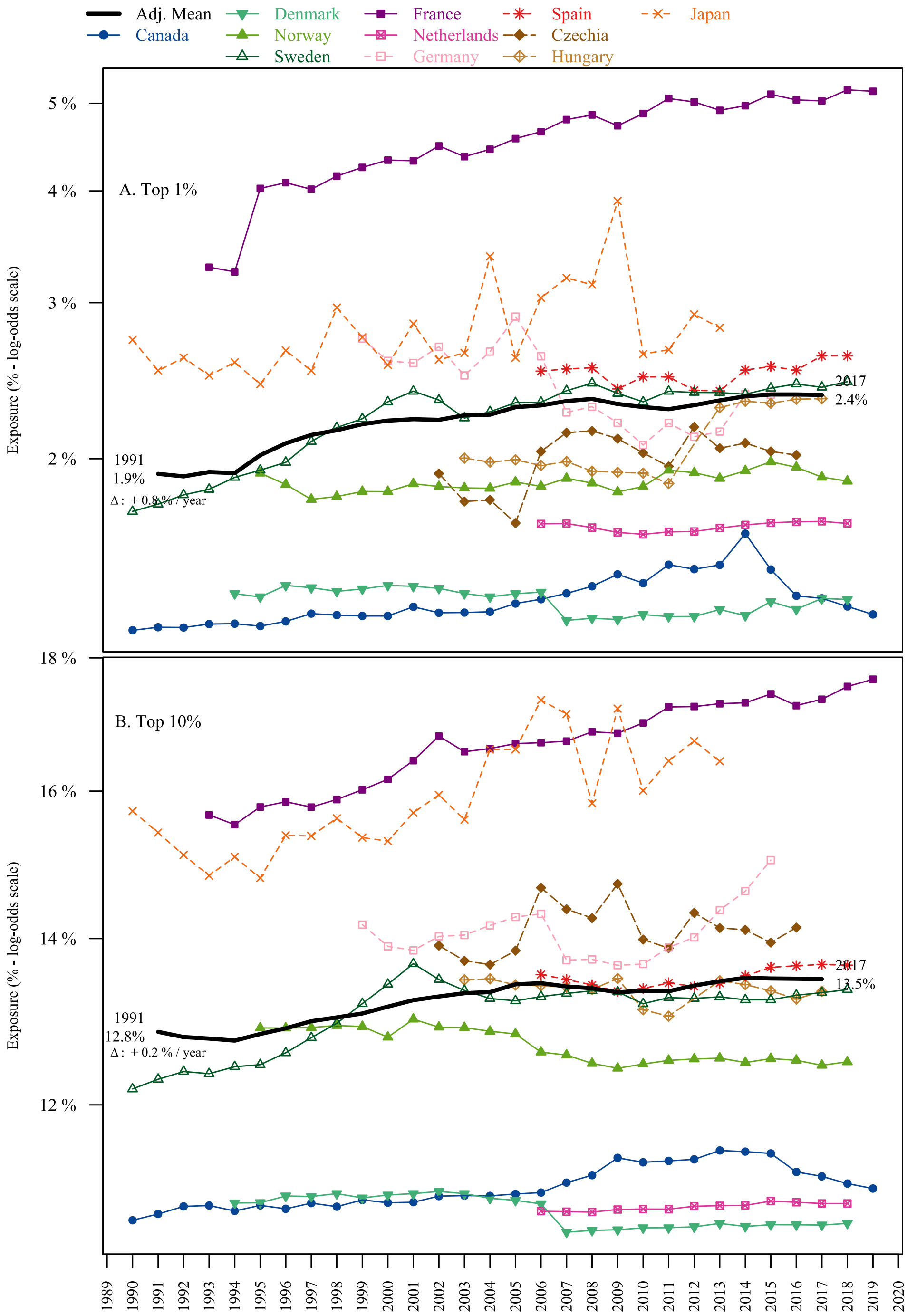
Note: Figure S3.3 displays for each country separately the yearly rate of evolution of the exposure of wage deciles to each other. To avoid capturing bumps due to inconsistencies in data collection, these rates of evolution were calculated on three-year moving averages. Hence, for France, D10's exposure to D1 declined by –2.44% per year (bottom left corner). We circle in black the points that measure the evolution of isolation (exposure to one's own group), such as D1 to D1, D2 to D2, etc.

Figure S3.4. Top earners' share of earnings



Note: cf. Figure 1.

Figure S3.5. Top 1% and 10% earner geographical isolation



Note: We estimate workers earnings exposure within the smallest geographical unit available generally municipalities – or parishes in Denmark. Although less fine-grained than usual residential segregation measures and limited to wage earners only, it is a reasonable proxy of spatial income segregation. The size and number of municipalities are very different from one country to another. In 2012, the number of units were the following: 147 in Canada, 997 in Denmark, 429 in Norway, 290 in Sweden, 36,034 in France, 415 in the Netherlands, 402 in Germany, 228 in Spain, 78 in Czechia, 198 in Hungary and 1772 in Japan. The greater granularity of French municipal units enables superior measurement of spatial segregation. Not surprisingly, the level of top 1% isolation is much larger in France than in Canada (for instance, in 2013, 5% in France versus 1.6% in Canada). We found, however, that a greater granularity did not impact its evolution. Following a municipality reform in Denmark, the perish definition changes in 2007. Reading, cf. Figure 1.

S4. Robustness

In this section, we will address the robustness of the phenomenon uncovered here. Indeed, one could wonder whether the increase in top earner segregation is conditional to our measurement conventions or to the earnings concept.

We conduct robustness checks in Table S4.1 where we use firms instead of establishments, and hourly wage instead of yearly earnings. This exercise leads to very similar conclusions.

Firms versus establishments. For countries where we have information on both establishments and firms (the Scandinavian countries, France, Netherlands, Spain, and Czechia), we can compare levels and evolution of segregation based on both work units. Our main results hold globally for firms and show that segregation occurs mainly between firms, rather than between establishments of the same firm.

Yearly earnings versus hourly wages. In the set of countries for which we have a reliable measure of hours worked (Denmark, France, Netherlands, Spain, Hungary, Japan, and South Korea), we compare segregation measures based on hourly wages with those based on yearly earnings. Generally, trends towards growing isolation of top earners and towards growing separation of this group from bottom earners are similar, regardless of the wage concept. The main difference consists in a slightly stronger process of segregation when we use yearly earnings. Most top earner segregation is due to the sorting of the workers between workplaces, and only a small fraction is due to sorting in the number of hours.

Table S4.1. The robustness of top earner segregation. Trends in segregation with alternative units and wages

	Δ Top 10% isolation (/year)			Δ Top 10% exposure to bottom quartile (/year)		
	Baseline: Establishments and earnings	Alt. unit: firms	Alt. wage notion: hourly wage	Baseline: Establishments and earnings	Alt. unit: firms	Alt. wage notion: hourly wage
Canada	(0.7***)	0.8***		(0.0)	0.0	
Denmark	0.7***	0.8***	0.3***	-0.9***	-0.8***	-0.6***
Norway	0.0	0.1		-0.7***	-0.8***	
Sweden	1.0***	1.1***		-1.3***	-1.3***	
France	2.0***	1.9***	2.0***	-2.4***	-2.2***	-2.7***
Netherlands	1.3***	1.7***	1.1***	-0.7**	-1.0***	-2.8***
Germany	1.2***			-2.9***		
Spain	1.3***	0.9***	1.2**	-1.2***	-1.9***	-0.6
Czechia	0.8***	0.4**		-0.9***	-0.6***	
Hungary	(0.8***)	0.6**	0.3	(0.1)	0.1	1.8***
South Korea	1.9***		1.0***	-0.7		-1.5***
Japan	1.5***		1.3***	-1.7***		-1.4***
All	1.1***	0.9***	1.0***	-1.1***	-0.9***	-1.2***

Note: For Canada and Hungary, we proxy establishments by combining firms and regions. We calculate linear rates of evolution of log-odds of exposure following equations 3 and 4. Parameters are multiplied by 100 to express percentage of changes.
Sources are detailed in Table 1 and Appendix A1.
***p<0.01, ** p<0.5, *p<0.1 (robust standard errors clustered at the year level).

S5. Specificity

Is growing top earnings segregation at work a specific phenomenon? Or is it just the manifestation of growing segregation along all social dimensions? In this supplementary section, we compare the evolution of top earner segregation with workplace segregation along other dimensions including gender, nativity, age and occupation.

Relative exposure

In order to conduct such comparison, we need to adapt our notion of exposure. For earnings fractiles – defined at the national level – absolute exposure measures enable robust and meaningful comparisons of propinquity through time and space. However, for groups whose size varies across time and space – such as gender or occupation – empirical measures of exposure are sensitive to the size of the group. In order to provide more meaningful comparisons across types of segregation, we calculate relative exposure (Åslund and Skans 2010; Fiel 2013). Our measure of relative exposure is defined as the odds ratio between the exposures of *g* to *h* and that of all other groups excluding *g* (i.e., -*g*) to *h*.

$$_gR_h = \frac{\frac{_gP_h}{1-_gP_h}}{\frac{_{\text{-}g}P_h}{1-_{\text{-}g}P_h}} \tag{S1}$$

This measure is also symmetrical. The relative exposure of *g* to *h* equals the relative exposure of *h* to *g*: $_gR_h = {}_hR_g$ (cf. Proof supra).

We estimate evolution in relative exposure, with the log of relative exposure measure as the dependent variable in equations 3 and 4 in the main text:

$$f(_gR_h) = log(_gR_h) \tag{S2}$$

This approach leads to estimated rates of evolution of relative exposure measures that are directly comparable to the yearly rate of growth of absolute exposure described above. When we calculate rate of growth for earnings fractile exposure with (5) and (S2), we get similar estimates.

General overview

In Table S5.1, we compare segregation along the nativity, gender, age, and occupation dimensions. Contrary to earnings fractiles, other social dimensions, especially those less related to earnings, such as nativity, gender, and age, do not show homogeneous and uniform trends towards more segregation. Only occupation, which is strongly correlated with earnings, shows a pattern of increasing segregation at work similar to that found for earnings segregation. Thus, this analysis confirms the specificity of the increase in earnings segregation.

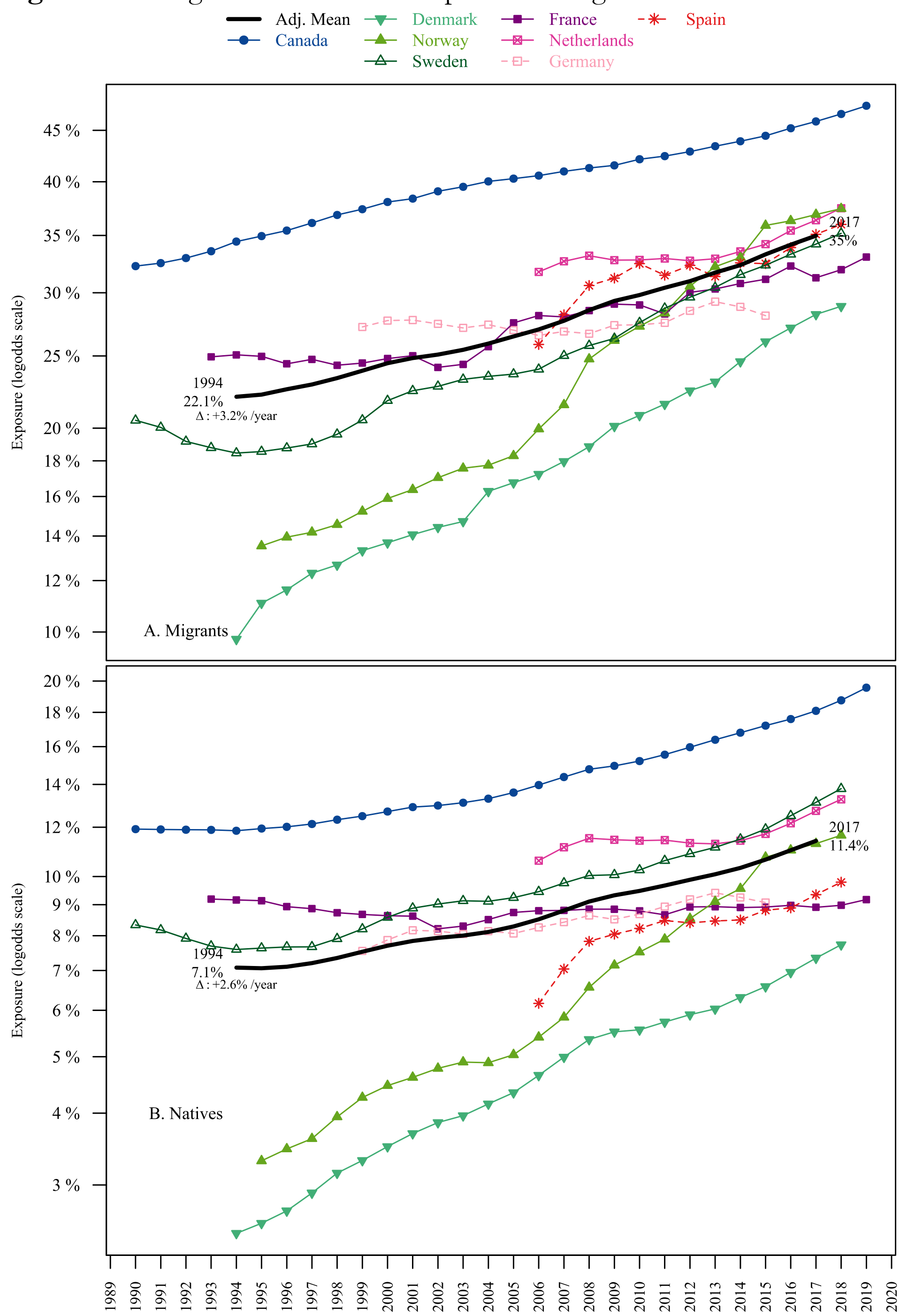
Table S5.1. The specificity of top earner segregation.

	Earnings		Nativity	Gender	Age		Occupation	
End year Level (relative isolation)	Top 1% earners	Top 10% earners	Migrant	Female	<31	>55	Managers & pro.	Working-class employees
Canada	11.0	4.0	3.8	2.7	1.7	1.8		
Denmark	10.4	4.5	4.9	3.9	1.5	2.2	6.3	8.6
Norway	20.1	7.3	4.6	5.3	1.6	2.2	4.9	7.6
Sweden	15.5	4.9	3.4	3.9	1.6	2.0	6.6	7.9
France	23.1	7.4	4.8	3.3	1.5	2.1	5.9	4.8
Netherlands	10.7	5.1	3.9	3.1	2.0	3.2		
Germany	9.4	7.9	4.0	4.3	1.5	1.7	10.2	8.8
Spain	21.5	9.8	5.2	3.7	2.0	2.8	10.1	8.5
Czechia	13.8	5.1		3.6	1.6	1.8	5.9	5.6
Hungary	17.5	7.3		3.5	1.6	2.0	4.8	5.6
South Korea	18.1	9.6		3.8	5.2	2.4	6.8	7.7
Japan	18.6	7.2		3.5	2.4	1.9	5.4	7.0
Adj. Mean	15.3	6.4	4.3	3.7	1.9	2.1	6.9	7.3
Yearly linear trend (Δ relative isolation)								
Canada	1.9***	0.9***	0.0	-0.2***	0.2**	-0.9***		
Denmark	2.2***	0.9***	0.4**	0.1**	0.8***	-0.4***	1.5**	2.8***
Norway	1.2***	0.1	0.5***	0.3	0.5***	0.2**	2.8***	1.2***
Sweden	1.9***	1.3***	1.0***	-0.3***	0.9***	0.0	1.7***	2.0***
France	3.4***	2.7***	1.7***	-0.1***	0.3***	-2.8***	2.6***	2.4***
Netherlands	1.3***	1.7***	0.2*	-0.7***	1.5***	-1.0***		
Germany	-1.7***	1.7***	-0.9***	-0.3***	0.1	-1.0***	-1.1***	1.2***
Spain	1.5***	1.8***	-0.1	-1.8***	3.8***	-0.6***	0.4	2.0***
Czechia	2.4***	1.1***		1.1***	0.9***	0.1	2.0***	2.4***
Hungary	2.4***	1.1***		0.3***	0.6***	0.3	4.2***	2.7***
South Korea	-0.9*	2.7***		0.4	0.9***	0.3	0.7	1.6*
Japan	0.5	2.0***		0.6***	-0.2	-1.5***	1.3***	1.0***
All	1.6***	1.5***	0.6***	0	0.6***	-0.7***	1.9***	1.9***

Note: End levels are calculated on the three last available years, to avoid capturing a sudden change due to specificities of data collection for some years. We calculate linear rates of evolution of log of relative exposure following equations 3 and 4. Parameters are multiplied by 100 to express percentage of changes.

***p<0.01, ** p<0.5, *p<0.1 (robust standard errors clustered at the year level). Sources are detailed in Table 1 and Appendix A1.

Figure S5.1. Migrants' and natives' exposure to migrants at work



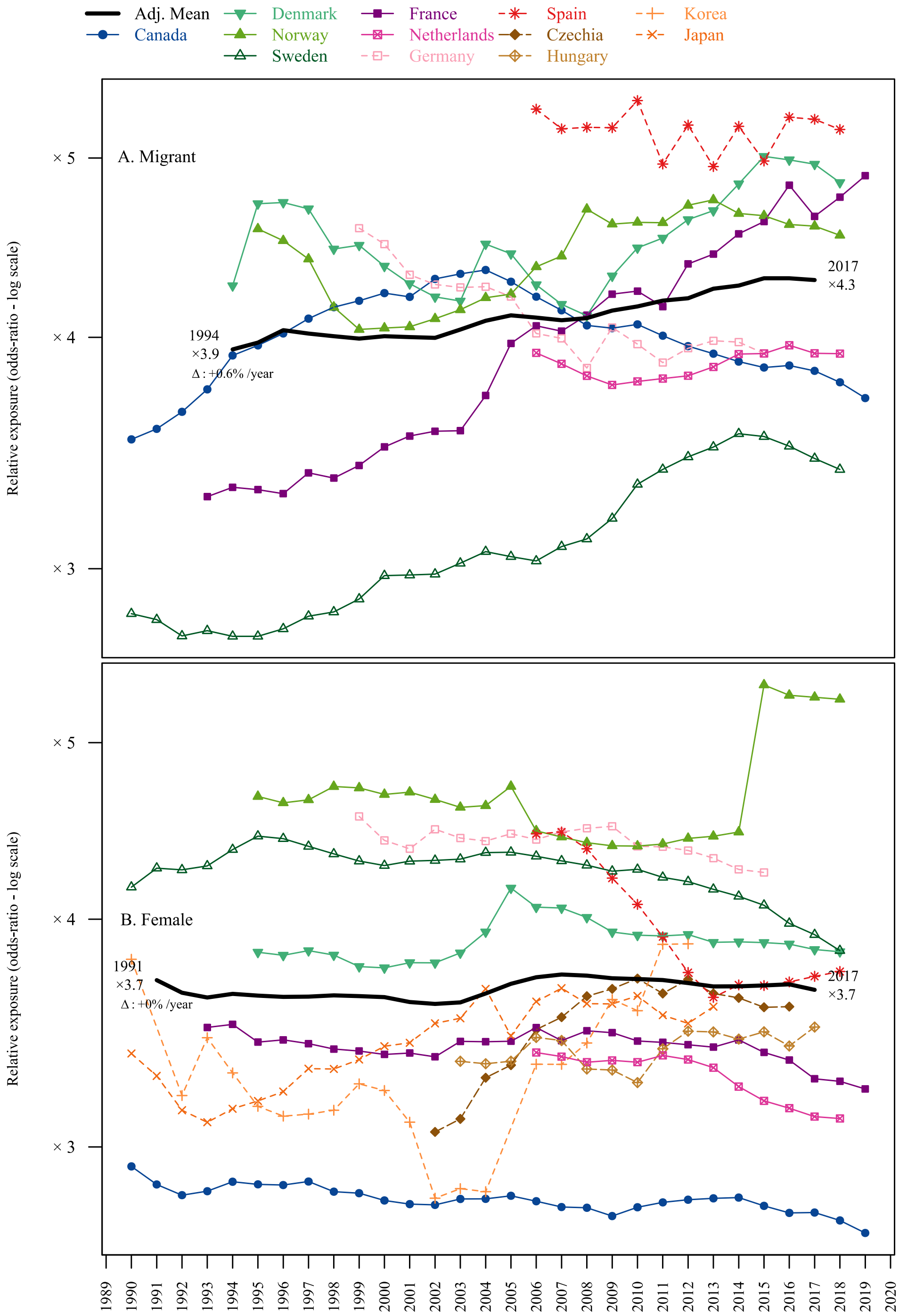
Note: cf. Figure 4.

Detailed trends

Nativity. The increase in the share of migrants among the working population leads to increased exposure to migrants for both migrants and the native-born (Figure S5.1). As explained previously, in order to control for this growth of exposure due to the simple growth of migrant share, we adopt here a measure of relative exposure (Figure S5.2A). Migrants are 4.3 times (in terms of odds ratio) more exposed to migrants than non-migrants are (Table S5.1). Although high, this level of segregation remains less pronounced than that estimated for top 10% earners (for which the relative isolation odds ratio is 6.4). Figure S5.2A shows an overall mild increase in the evolution of segregation along the nativity dimension, with sharp contrasts between countries. While the relative isolation of migrants at work increased at a yearly rate of +1.7% in France and +1.0% in Sweden, it shows an inverted u-shape in Canada and decreased by an annual factor of 0.9% in Germany. Nativity segregation remained stable or slightly increased in Spain, Denmark, and Norway.

Gender. The degree of separation of male and female workers remains quite high (Figure S5.2B). On average, women are 3.7 times more exposed to female workers than male workers are. We find some contrasts between countries with higher gender workplace specialization (Sweden, Norway, Germany) and lower (Canada). However, in most countries the level of gender segregation remains stable. Czechia and Japan show trends towards growing workplace gender segregation. In Spain and the Netherlands, the trend is towards desegregation.

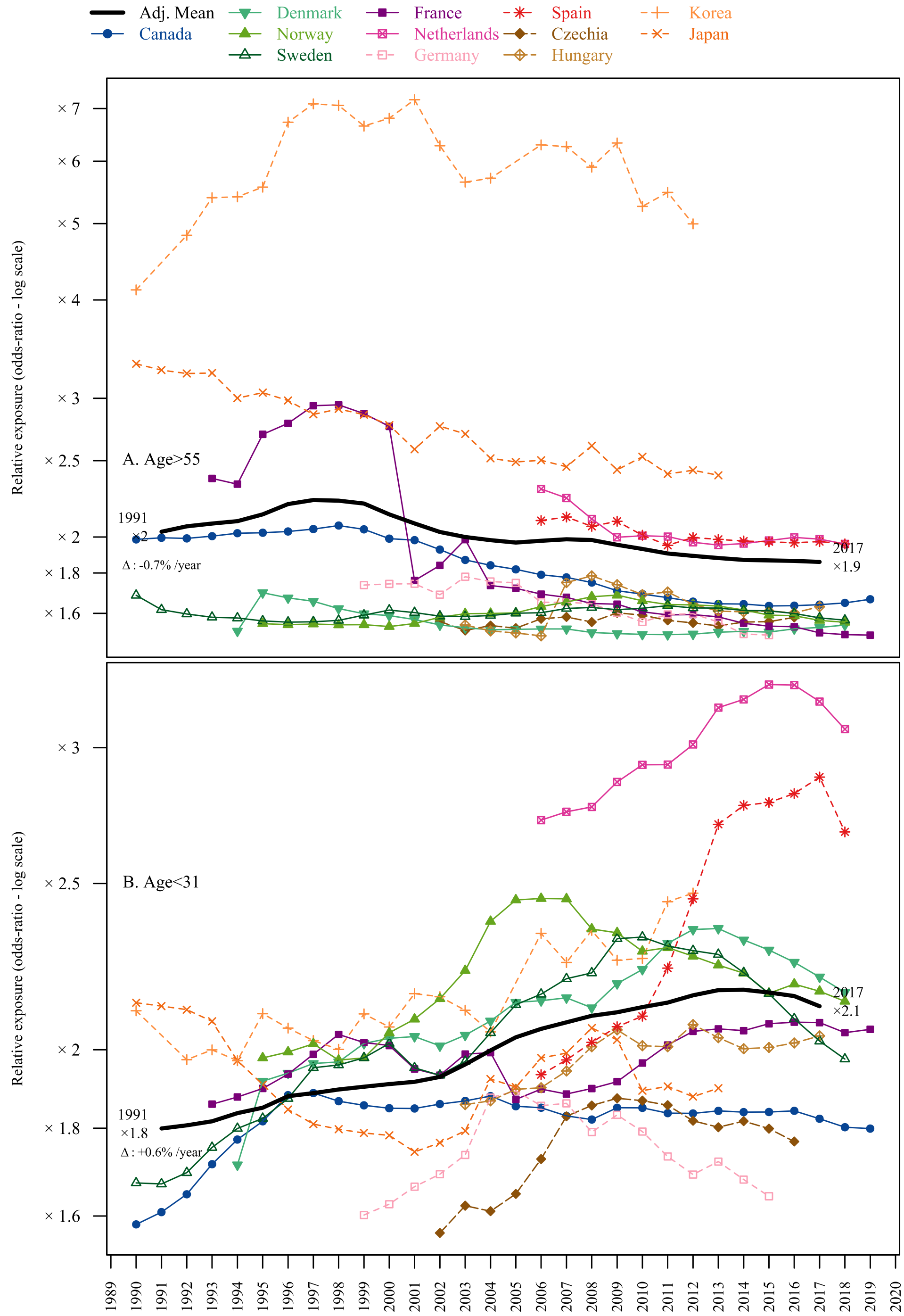
Figure S5.2. Migrant and Female relative workplace isolation



Note: We use a log scale in order to give a correct visual representation of evolution of relative exposures already expressed in terms of odds ratios. Adjusted mean is constructed as in Figure 1 (Supplementary file S1). We obtain the average yearly trend (i.e. "Δ: +0.6% / year"), with a country fixed effect regression where the log of relative exposure is the dependent variable and year is the independent variable. Sources are detailed in Table 1 and Appendix A1.

Age. We also explored age segregation in case our results reflected older workers' access to the top 1 and 10% and increased age segregation across workplaces. Trends are quite heterogeneous across countries (Table S5.1 and Figure S5.3). Contrary to earnings segregation, we estimate a decrease on average of older workers (age>55) isolation (–0.8% per year). We do find a substantial increase in isolation, for younger workers (+0.5% per year), both are much less pronounced than that found for top earners.

Figure S5.3. Older and younger employees' workplace relative isolation



Note: cf. Figure S5.2.

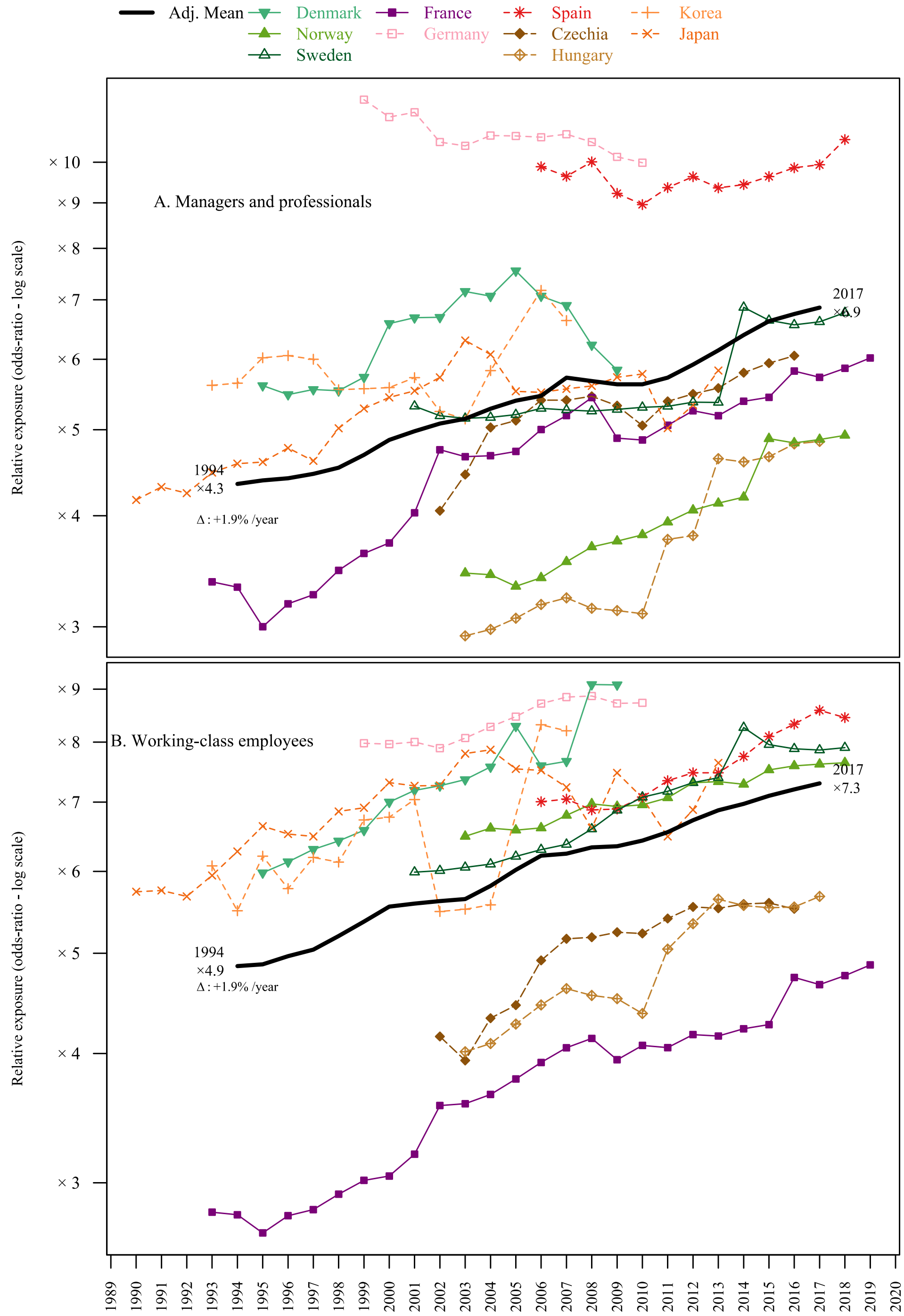
We finally examine one dimension more closely related to earnings: occupation.[1]

[1] In a previous version, we also estimated trends for education. Unfortunately, only Scandinavian countries, Germany, Hungary, Japan, and South Korea collect education data. Moreover, educational categories vary in time and are not fully comparable from one country to another. Therefore, this analysis, showing a stability of relative exposure of workers with tertiary education to workers with non-tertiary one, should be considered

Occupation. In order to study segregation along the occupation dimension, we use a three-category comparison: managers and professionals to represent upper class occupations, blue collar and low-skilled service workers as working-class employees, and intermediate workers as a semi-skilled intermediate class. The quality of occupation data is variable. The proportion of missing occupation is high in some countries, occupational schemes are heterogeneous from one country to another, and they sometimes change during the period. The use of a simple class comparison minimizes the impact of measurement quality at the more detailed occupational level and is more consistent with class theorization (Erikson and Goldthorpe 1992).

carefully. Results will be sent on request.

Figure S5.4. Relative isolation at work of managers and professionals, and working-class employees



Note: cf. Figure S5.2.

We find a growing isolation of managers and professionals, especially in France, Norway, Czechia, and Hungary (Table S5.1 and Figure S5.4). The trend towards isolation of the working class is even more pronounced and more general throughout the set of countries (notably in Denmark, Sweden, France, Spain, Czechia, and Hungary). On average, the isolation of this group increases by +2% per year. Thus, occupational segregation increases strongly and is consistent with trends in earnings segregation and with recent increases in occupational segregation in the US (Handwerker 2020; Lin and Hung 2022).

Proof of the symmetry of relative exposure

We want to show that $_gR_h = {}_hR_g$

$$_gR_h = \frac{\frac{_gP_h}{1 - {}_gP_h}}{\frac{_{\text{-}g}P_h}{1 - {}_{\text{-}g}P_h}}$$

with $_gP_h = \sum_i \left(\frac{n_{gi}}{n_g}\right) \cdot \left(\frac{n_{hi} - 1_{h=g}}{n_i - 1}\right)$

<u>Remarkable properties</u>

When $g \neq h$, $_gP_h$ can be expressed as a function of $w_{g,h}$ with $w_{g,h}$ symmetrical in h and g (*i.e.*, $w_{g,h} = w_{h,g}$).

$$_gP_h = \frac{w_{g,h}}{n_g}$$

with $w_{g,h} = \sum_i \left(\frac{n_{gi} n_{hi}}{n_i - 1}\right) = w_{h,g}$

Moreover, $_gP_h = \left(\frac{n_h}{n_g}\right) {}_hP_g$

and, as shown by Bell (1954), $\sum_j {}_gP_j = 1$

First, let us look at some properties of $_{\text{-}g}P_h$

$$_{\text{-}g}P_h = \left(\frac{n_h}{n_{\text{-}g}}\right) {}_hP_{\text{-}g}$$

$$_{\text{-}g}P_h = \left(\frac{n_h}{n - n_g}\right) \sum_{j \neq g} {}_hP_j$$

$$_{\text{-}g}P_h = \left(\frac{n_h}{n - n_g}\right) (1 - {}_hP_g)$$

$$_{\text{-}g}P_h = \left(\frac{n_h}{n - n_g}\right) - \left(\frac{w_{g,h}}{n - n_g}\right)$$

$$_{\text{-}g}P_h = \frac{n_h - w_{g,h}}{n - n_g}$$

Now, let us express the odds ratio as a function of $w_{g,h}$

$${}_{g}R_{h} = \frac{{}_{g}P_{h}}{1 - {}_{g}P_{h}} \times \frac{1 - {}_{\text{-}g}P_{h}}{{}_{\text{-}g}P_{h}}$$

$${}_{g}R_{h} = \frac{\frac{w_{g,h}}{n_g}}{1 - \frac{w_{g,h}}{n_g}} \times \frac{1 - \frac{n_h - w_{g,h}}{n - n_g}}{\frac{n_h - w_{g,h}}{n - n_g}}$$

$${}_{g}R_{h} = \frac{w_{g,h} \times (n - n_g - n_h + w_{g,h})}{(n_g - w_{g,h}) \times (n_h - w_{g,h})}$$ which is symmetrical in g and h.

Therefore, ${}_{g}R_{h} = {}_{h}R_{g}$.

S6. Relation between top earner isolation and wage inequality measures

How do top earner isolation measures relate with classical inequality measures? To understand further this relationship, we use both simulations and econometric exercises.

Simulation

To explore the relation between inequality and exposure measures, we simulate changes in the between, within and total variance of the French BTS 2016 log-wage distribution. For this purpose, we modify the β parameters in the following formula:

$$lwage_{ij}^{*} = E_{ij}(lwage_{ij}) + \sqrt{\beta_{tot}}\left[\sqrt{\beta_{wi}}\left[lwage_{ij} - E_i(lwage_{ij})\right] + \sqrt{\beta_{be}}\left[E_i(lwage_{ij}) - E_{ij}(lwage_{ij})\right]\right]$$

where E_k stands for the arithmetic mean along the k dimension.

For instance, in line 1, we set β_{tot} parameter to 1.1 and other β to 1.

Table S6.1. Variation in wage variance and impact on top 10% isolation measures

	Total variance	Within variance	Between variance	Between var. share	Top 10% isolation
0. Baseline	**0.272**	**0.132**	**0.140**	**0.514**	**36.2%**
1. +10% in total variance	0.299	0.145	0.154	0.514	36.2%
2. –10% in total variance	0.244	0.119	0.126	0.514	36.2%
3. +10% in within variance	0.285	0.145	0.140	0.490	34.6%
4. –10% in within variance	0.258	0.119	0.140	0.540	38.1%
5. +10% in between variance	0.286	0.132	0.154	0.538	37.9%
6. –10% in between variance	0.258	0.132	0.126	0.488	34.5%
7. –10 % in within variance and – 5% in between variance	0.251	0.119	0.133	0.528	37.2%
8. –1% for all wages in establishments with no top earners	0.291	0.131	0.159	0.548	36.2%
9. +1% for wages both in bottom 50% and top 10% workplaces	0.264	0.133	0.131	0.495	40.0%
10. –1% for wages both in bottom 50% and top 10% workplaces	0.283	0.130	0.153	0.541	32.7%

Note: This simulation is based on the French BTS 2016. n=14,202,911

This exercise shows that a simple change in total variance does not affect top earner isolation (Table S6.1, rows 1 and 2). For a change in wage variance to do so, we need a decoupling in the evolution of the between and within components. *Ceteris paribus,* an increase in within workplace wage variance decreases top earner isolation (rows 3 and 4) and an increase in between workplace wage variance increases it (rows 5 and 6). However, our segregation measure can also increase in a context of declining wage inequality, for example, if the decline in the within component is more pronounced than that in the between component (row 7). Thus, our exercise shows that our measure varies globally with the between variance share (column 4).

We can create even more complex cases where between variance share and top earner isolation evolve in opposite direction (rows 8 to 10). The reason for this discrepancy is that the between variance share is a measure based on the whole distribution, while the top earner isolation index only focuses on the top. The advantage of our exposure measures is precisely that they enable us to estimate an accordion phenomenon, with some extreme bellows spreading while others are regrouping.

Econometric approach

In Table S6.2, we use our country-level estimates of top earner segregation and various classical measures of inequality to measure the correlations between the two sets of variables. To do this, we use a classical two-way fixed effects regression with country and year fixed effects. This exercise shows that the top 10% income share is not correlated with top 10% isolation. We find a correlation of +0.1 between top earner isolation and log earnings variance. This is largely driven by the +0.25 correlation between our segregation index and the between-workplace log variance. Conversely, there is no correlation with the within-workplace log variance. As one would expect, the share of between workplace variance is the inequality variable most related to top earner isolation: one within-country standard deviation of the former is associated with 0.56 variation of the latter.

Table S6.2. Impact of various inequality measure on top 10% isolation at work

	(1)	(2)	(3)	(4)	(5)
Top 10% earnings share	0.034				
	(0.058)				
Total log earnings variance		0.097**			
		(0.042)			
Within-workplace log earnings variance			-0.028		
			(0.025)		
Between-workplace log earnings variance				0.250***	
				(0.064)	
Between-workplace variance share					0.557***
					(0.050)
Number of observations	251	251	251	251	251
R^2	0.674	0.681	0.674	0.718	0.808
Number of country fixed effects	12	12	12	12	12
Number of year fixed effects	30	30	30	30	30

Note: Robust standard errors clustered by years in parentheses. Dependent and independent variables are country-demeaned and standardized. Hence, one within-country standard deviation of top 10% earnings share increase by 0.03 within-country top 10% isolation standard deviation.
***p<0.01, ** p<0.5, *p<0.1

S7. The role of earnings increase and employee mobility in top earner segregation evolution

Evolution of top earner isolation combines change in workplace composition and between workplace heterogeneity in wage increase. Following Manduca (2019), which measures the respective role of sorting and wage evolution in the increase of US spatial earning segregation, we try to decompose for one country, France, the role of mobility and wage increase on our segregation measure.

For this purpose, we take advantage of our panelization of the BTS year-files (cf. Appendix A1) in order to estimate the counterfactual top earner isolation measure if no wage change had happened. We proceed as follows.

1) We use *t-3* wage ranks for wage-earners who are both present in year *t* and *t-3*.

2) We use *t* wage ranks for wage-earners who are only present in year *t*.

3) We append these two rank distributions and recompute a new one in order for the new rank distribution to be fully consistent.

This enables us in table S7.1 to compare the real isolation measures with the counterfactual one, had wages not changed from year *t-3* to year *t*.

Table S7.1. Comparison of true and counterfactual top earner isolation measures

Year	Isolation	Counterfactual isolation	3-year evolution	3-year counterfactual evolution	Share of evolution
		Panel A. Top 10%			
2002	30.77%				
2005	31.76%	31.14%	0.99%	0.37%	37%
2008	33.32%	32.10%	1.56%	0.34%	22%
2011	35.11%	34.05%	1.79%	0.73%	41%
		Panel B. Top 1%			
2002	12.94%				
2005	13.74%	13.01%	0.81%	0.07%	9%
2008	15.51%	13.90%	1.76%	0.16%	9%
2011	16.63%	15.67%	1.12%	0.16%	15%

Note: This simulation is based on the French BTS 2002, 2005, 2008, 2011, years for which we can rely on the panelization of the full BTS and during which the increase in top earner isolation is more pronounced (after 2012, top earner isolation stabilizes after 2012).

This exercise shows that change in coworkers' wages accounts for two thirds and between workplace sorting of coworkers for one third of French top 10% isolation evolution between 2002 and 2011. When we shift to the top 1% (Panel B), the role of wage change is even stronger (89%) and that of sorting lower (11%) (average of the last column).

This exercise gives a first decomposition of sorting over heterogeneity in wage increase. However, we must keep in mind that its rests on the fact that we conventionally use *t* wage rank as the counterfactual wage of wage-earners who were not present in year *t-3*. Other working hypotheses could be made yielding a different decomposition of sorting over wage increase.

S8. Supplementary tables

Table S8.1. Top 10% Isolation trend controlling for geography, industry, and workplaces

	(1)	(2)	(3)	(4)	(5)	(6)
Canada × year	0.137***	0.099***		0.151***	0.112***	0.122***
	(0.013)	(0.009)		(0.005)	(0.001)	(0.001)
Denmark × year	0.143***	0.173***	0.141***	0.066***	-0.036	0.007
	(0.008)	(0.015)	(0.025)	(0.012)	(0.027)	(0.018)
Norway × year	0.010	-0.007	-0.0467	0.015	-0.165***	-0.313***
	(0.017)	(0.023)	(0.046)	(0.017)	(0.038)	(0.033)
Sweden × year	0.198***	0.132***	0.129***	0.152***	0.142***	0.020
	(0.017)	(0.014)	(0.023)	(0.015)	(0.017)	(0.017)
France × year	0.431***	0.412***	0.389***	0.374***	0.271***	0.175***
	(0.014)	(0.013)	(0.018)	(0.015)	(0.018)	(0.017)
Netherlands × year	0.272***	0.261***	0.234***	0.265***	0.222***	0.264***
	(0.019)	(0.015)	(0.064)	(0.015)	(0.047)	(0.033)
Germany × year	0.278***					
	(0.023)					
Spain × year	0.327***	0.286***	0.287***	0.285***	0.247***	0.433***
	(0.029)	(0.025)	(0.058)	(0.022)	(0.053)	(0.046)
Czechia × year	0.140***					
	(0.028)					
Hungary × year	0.209***	0.220***	0.201***	-0.194***	-0.110*	-0.084*
	(0.027)	(0.023)	(0.053)	(0.016)	(0.058)	(0.046)
Korea × year	0.446***			0.451***	0.432***	0.459***
	(0.019)			(0.017)	(0.117)	(0.037)
Japan × year	0.335***	0.342***	0.353***	0.313***	0.271***	0.261***
	(0.017)	(0.013)	(0.019)	(0.017)	(0.063)	(0.050)
Fixed effects	Country	Country × Aggregate region	Detailed region	Country × Aggregate industry	Detailed industry	Workplace

Note: In models 1, 2, and 4, we opted for pooled regressions. In models 3, 5, and 6, each line is a separate regression with robust standard errors clustered in parentheses at the workplace level (except for Canada where clustering was not available). Robust standard errors clustered at the year level in model 1, at the country and year levels in models 2, and 4.
***p<0.01, ** p<0.5, *p<0.1.

Table S8.2. Top 1% workplace isolation trends controlling for aggregate sector

	Workpl. Isolation Trend	Average categorical isolation	Category isolation Trend	Within cat. Isolation Trend
Panel A. Category: 2 regions (11 countries)				
Global financial center × year	0.219***	2.6%	0.008	0.210***
	(0.042)		(0.005)	(0.038)
Rest of the country × year	0.064	0.8%	-0.002	0.066*
	(0.037)		(0.001)	(0.036)
Panel B. Category: Industry (10 countries)				
Manufacturing × year	0.125	1.3%	0.013**	0.112
	(0.071)		(0.006)	(0.067)
Wholesale and retail trade × year	0.080	1.0%	-0.009**	0.089*
	(0.049)		(0.003)	(0.047)
Transportation and storage × year	-0.069	1.0%	-0.016	-0.054
	(0.149)		(0.013)	(0.140)
Finance × year	0.273***	4.7%	0.053**	0.220**
	(0.074)		(0.018)	(0.074)
Support service activities × year	0.039	1.0%	-0.039***	0.078
	(0.076)		(0.010)	(0.069)
Other activities × year	0.033	1.6%	-0.014	0.047
	(0.081)		(0.012)	(0.070)
FE (country × Aggregate sector)	Yes		Yes	Yes

Note: In the first column, the dependent variable is top earner workplace isolation, in the third top earner category isolation and in the last top earner within category workplace isolation, calculated as the difference of the two previous. In the second column, average categorical isolation is calculated in 2011, the last year when all country are present.

***p<0.01, ** p<0.5, *p<0.1. Robust standard errors clustered both at the country and year in parantheses.

S9. Supplementary material on the impact of workplace restructuring on top earner isolation in France

Complementary information on estimation

In the case of outsourcing events, we use the first workplace outsourcing event as the treatment, we drop workplaces' years when a second treatment has occurred (very rare), and we use "never treated" and "not yet treated" as counterfactual groups. In the case of layoffs, we use a multi-event framework (Sandler and Sandler 2014).

Some heterogeneity in the treatment effect for different levels of treatment intensity can also lead to biases in the estimation of the average treatment effect (de Chaisemartin and D'Haultfoeuille 2023). We did not correct for this problem. However, we think this issue remains minor. It only affects estimations where we weight events by their magnitude and estimations with or without multiplying by treatment intensity give the same qualitative results (cf. Figures 6 and S9.1). As the events we study are rare, treatment effects are mostly driven by comparison between treated and non-treated (as shown by the similarity of result of stacked and non-stacked regressions).

Measuring the impact of an event on segregation both in departure and arrival workplaces

Generally, we can measure the impact of restructuring events on segregation only in workplaces where they occur. Hence, we don't have a full picture of the distributional impact of these reorganizations. We overlook the fact these events also impact other workplaces, via workers' moves.

The database on outsourcing and subsidiarization enable us to address this issue. We can combine departure and arrival events and measure their joint effect. We do such exercise on outsourcing and subsidiarization events (Table S9.1 models 5, 6, 10 and 11).

Estimates

Table S9.1. Impact of outsourcing and subsidiarizing events (2001-2017) on top 10% isolation in France

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
$S_{event} \times$ [year = (year$_{event}$ - 4)]	-0.39	-1.56	-0.42	-0.35	-0.85	-2.25^{**}	-0.48	-0.85	0.41	-3.03	-1.76^{**}
	(1.07)	(1.88)	(1.10)	(1.03)	(1.01)	(1.15)	(3.11)	(3.32)	(3.11)	(2.71)	(0.78)
$S_{event} \times$ [year = (year$_{event}$ -3)]	-0.82	-1.48	-0.76	-0.63	-1.46^{**}	0.09	-2.12	-1.97	-1.55	-2.29	1.86
	(0.73)	(1.69)	(0.75)	(0.66)	(0.72)	(0.53)	(1.92)	(2.02)	(1.75)	(1.88)	(1.21)
$S_{event} \times$ [year = (year$_{event}$ -2)]	0.07	-1.54	0.03	0.11	-0.83	-0.41	-0.22	-0.15	-0.22	-2.12	-0.83
	(0.95)	(1.76)	(0.96)	(0.92)	(0.86)	(0.27)	(2.56)	(2.67)	(2.57)	(1.85)	(0.52)
$S_{event} \times$ [year = (year$_{event}$ -1)]	0	0	0	0	0	0	0	0	0	0	0
$S_{event} \times$ [year = year$_{event}$]	2.39^{***}	0.11	2.37^{***}	1.79^{**}	2.00^{***}	0.56^{**}	10.96^{*}	10.73^{*}	7.5	8.31^{*}	2.31^{*}
	(0.81)	(0.39)	(0.82)	(0.84)	(0.66)	(0.26)	(5.92)	(6.00)	(5.47)	(4.85)	(1.21)
$S_{event} \times$ [year = (year$_{event}$ + 1)]	2.92^{***}	1.4	3.00^{***}	2.21^{**}	2.00^{**}	0.54^{*}	36.82^{***}	37.77^{***}	18.29	13.69^{***}	7.91^{***}
	(0.89)	(0.96)	(0.90)	(0.90)	(1.00)	(0.29)	(10.32)	(10.72)	(11.52)	(4.04)	(1.35)
$S_{event} \times$ [year = (year$_{event}$ + 2)]	2.88^{***}	3.03^{***}	2.90^{***}	2.44^{***}	1.49^{**}	0.82^{**}	30.06^{***}	31.49^{***}	16.23^{*}	13.10^{***}	8.81^{***}
	(0.72)	(0.95)	(0.73)	(0.81)	(0.76)	(0.33)	(8.03)	(8.67)	(8.81)	(4.06)	(1.83)
$S_{event} \times$ [year = (year$_{event}$ + 3)]	3.37^{***}	3.11^{***}	3.51^{***}	2.66^{***}	1.42	1.05^{***}	36.07^{***}	40.91^{***}	23.75^{**}	11.34^{**}	9.31^{***}
	(1.22)	(0.78)	(1.23)	(0.98)	(1.27)	(0.39)	(9.76)	(10.55)	(10.30)	(4.90)	(2.15)
$S_{event} \times$ [year = (year$_{event}$ + 4)]	3.11^{***}	4.76^{***}	3.25^{***}	1.92^{**}	1.98^{**}	1.30^{***}	32.73^{***}	37.24^{***}	17.23	11.48^{**}	9.00^{***}
	(1.07)	(1.27)	(1.10)	(0.90)	(0.80)	(0.42)	(10.63)	(11.37)	(11.30)	(5.43)	(1.60)
Size control	No	No	No	Yes	No	No	No	No	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,516,193	4,513,329	3,228,358	3,228,358	3,476,877	3,480,314	4,516,193	3,228,358	3,228,358	3,476,877	3,480,314
R^2	0.92	0.92	0.92	0.92	0.94	0.94	0.92	0.92	0.92	0.94	0.94
Establishment (fixed effects)	828,501	828,490	808,923	808,923	884,927	891,511	828,501	808,923	808,923	884,927	891,511
Event: Departure (D) or Depature and arrival (D&A)	D	D	D	D	D&A	D&A	D	D	D	D&A	D&A
Destination of the flow	Low-skill outsourced sector	Low & high skill outsourced	Low-skill outsourced sector	Low-skill outsourced sector	Low-skill outsourced sector	New subsidy	Low-skill outsourced sector	Low-skill outsourced sector	Low-skill outsourced sector	Low-skill outsourced sector	New subsidy
S_{event} =	1	1	1	1	1	1	Workforce share in flow	Workforce share in flow	Workforce share in flow	Workforce share in flow	Workforce share in flow
Stacked regression	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes

Note: Size control includes log size and cumulative decrease in log size. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, robust standard errors clustered at the firm level in parentheses.

Table S9.2. Impact of layoffs on top 10% isolation in France

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
S_{event} × [year = ($year_{event}$ - 4)]	0.23	0.164	0.321	0.248	6.31	6.554
	(0.24)	(0.23)	(0.40)	(0.39)	(4.44)	(4.30)
S_{event} × [year = ($year_{event}$ -3)]	0.273	0.398	-0.114	-0.015	3.378	4.211
	(0.28)	(0.27)	(0.71)	(0.63)	(2.66)	(2.60)
S_{event} × [year = ($year_{event}$ -2)]	0.351*	0.392**	0.172	0.195	3.194	4.162**
	(0.20)	(0.18)	(0.19)	(0.18)	(1.95)	(1.94)
S_{event} × [year = ($year_{event}$ -1)]	0	0	0	0	0	0
S_{event} × [year = $year_{event}$]	0.251	-0.107	0.127	-0.142	15.156***	5.129**
	(0.15)	(0.14)	(0.14)	(0.14)	(2.61)	(2.45)
S_{event} × [year = ($year_{event}$ + 1)]	0.224	-0.08	0.266	-0.009	13.713***	3.298
	(0.22)	(0.21)	(0.17)	(0.16)	(2.88)	(2.72)
S_{event} × [year = ($year_{event}$ + 2)]	0.162	-0.115	0.26	-0.052	13.326***	3.081
	(0.19)	(0.20)	(0.22)	(0.19)	(2.81)	(2.68)
S_{event} × [year = ($year_{event}$ + 3)]	0.524***	0.226	0.738**	0.442	13.640***	3.479
	(0.17)	(0.16)	(0.33)	(0.29)	(3.32)	(3.05)
S_{event} × [year = ($year_{event}$ + 4)]	0.885***	0.525***	0.547*	0.324	11.539***	1.24
	(0.20)	(0.19)	(0.31)	(0.30)	(3.31)	(3.24)
Size control	No	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Establishment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	309,177	309,177	1,693,291	1,693,291	1,693,291	1,693,291
R^2	0.95	0.95	0.96	0.96	0.96	0.96
Establishment (fixed effects)	67,855	67,855	307,637	307,637	307,637	307,637
S_{event} =	1	1	1	1	Share of workforce laid off	Share of workforce laid off
Stacked regression	No	No	Yes	Yes	Yes	Yes

Note: Size control includes log size and cumulative decrease in log size.
***p < 0.01; **p < 0.05; *p < 0.1, robust standard errors clustered at the firm level in parentheses.

Table S9.3. Impact of offshoring between 2009 and 2011 on top 10% isolation in France

	Model 1	Model 2	Model 3	Model 4
S_{event} × [year = 2005]	-1.62	-1.57*	-10.25	-4.77
	(1.23)	(0.87)	(7.73)	(5.42)
S_{event} × [year = 2006]	-0.33	-1.40	-0.59	2.34
	(1.17)	(1.21)	(6.31)	(6.24)
S_{event} × [year = 2007]	0.67	-2.16**	-1.41	-0.98
	(1.20)	(0.93)	(5.09)	(4.53)
S_{event} × [year = 2008]	0	0	0	0
S_{event} × [year = 2009]	1.44	-0.41	16.29**	12.57*
	(1.31)	(0.69)	(7.15)	(7.24)
S_{event} × [year = 2010]	3.41*	0.99	27.43***	14.26
	(1.80)	(1.14)	(8.76)	(11.13)
S_{event} × [year = 2011]	6.34**	-1.98	28.15**	22.46*
	(3.23)	(1.62)	(11.67)	(12.56)
S_{event} × [year = 2012]	2.99*	0.50	22.23***	12.40
	(1.53)	(1.57)	(8.23)	(9.87)
S_{event} × [year = 2013]	4.82**	1.47	25.64***	11.40*
	(2.17)	(2.02)	(8.16)	(6.12)
S_{event} × [year = 2014]	5.74***	1.35	37.96***	25.79**
	(2.17)	(1.90)	(11.35)	(11.73)
S_{event} × [year = 2015]	5.76***	1.34	37.97***	22.47**
	(2.20)	(2.10)	(12.39)	(9.95)
Size control	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Establishment fixed effects	Yes	Yes	Yes	Yes
Number of observations	290,192	290,192	290,192	290,192
R^2	0.89	0.89	0.89	0.90
Establishment (fixed effects)	55,410	55,410	55,410	55,410
S_{event} =	1	1	Share of the workforce offshored	Share of the workforce offshored

Note: Size control includes log size and cumulative decrease in log size.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, robust standard errors clustered at the firm level in parentheses.

Table S9.4. Impact of subcontracting between 2005 and 2011 on top 10% isolation in France

	Model 1	Model 2	Model 3	Model 4
[Year = 2001]	-0.34			
	(2.65)			
[Year = 2002]	0.28			
	(2.25)			
[Year = 2003]	-13.48			
	(9.65)			
[Year = 2004]	-1.46	-1.07		-1.00
	(1.62)	(2.21)		(2.24)
[Year = 2005]	0	0	0	0
[Year = 2006]	-0.39	-0.60		-0.43
	(2.07)	(2.00)		(2.06)
[Year = 2007]	1.77	3.05		3.12
	(2.00)	(2.21)		(2.28)
[Year = 2008]	-1.92	0.08		0.17
	(2.77)	(3.03)		(3.09)
[Year = 2009]	1.67	2.98		3.18
	(2.37)	(2.77)		(2.82)
[Year = 2010]	2.53	4.15*		4.32*
	(1.64)	(2.20)		(2.25)
[Year = 2011]	1.69	3.45	3.25*	3.59
	(1.64)	(2.21)	(1.87)	(2.25)
[Year = 2012]	0.65	2.48		2.67
	(3.18)	(3.43)		(3.46)
[Year = 2013]	0.77			
	(3.49)			
[Year = 2014]	-1.65			
	(4.26)			
[Year = 2015]	-33.81			
	(20.91)			
Size control	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Establishment fixed effects	Yes	Yes	Yes	Yes
Number of observations	2751	1732	396	1732
R^2	0.89	0.96	0.98	0.96
Establishment (fixed effects)	198	198	198	198

Note: Size control includes log size and cumulative decrease in log size.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, robust standard errors clustered at the firm level in parentheses.

Table S9.5 Panel B Impact of subcontracting intensity between 2011 and 2019 on top 10% isolation in France

	Model 1	Model 2	Model 3	Model 4
S_{event} × [year = 2008]	1.65			
	(8.95)			
S_{event} × [year = 2009]	9.76			
	(6.96)			
S_{event} × [year = 2010]	-6.37	-6.46		-6.96
	(4.95)	(4.89)		(5.11)
S_{event} × [year = 2011]	0	0		0
S_{event} × [year = 2012]	0.17	0.78		0.22
	(6.33)	(6.43)		(6.11)
S_{event} × [year = 2013]	17.56	17.10^{*}		14.43^{**}
	(11.22)	(10.01)		(6.91)
S_{event} × [year = 2014]	14.64^{**}	15.71^{**}		16.29^{*}
	(7.30)	(7.11)		(8.66)
S_{event} × [year = 2015]	19.28^{*}	20.22^{*}		20.48^{*}
	(10.63)	(10.45)		(11.86)
S_{event} × [year = 2016]	32.78^{*}	32.07^{*}		31.66^{*}
	(18.13)	(17.28)		(17.83)
S_{event} × [year = 2017]	43.14^{**}	43.48^{**}	44.68^{**}	43.30^{**}
	(18.72)	(18.32)	(19.01)	(19.21)
S_{event} × [year = 2018]	43.21^{*}	45.14^{**}		46.27^{**}
	(22.25)	(22.01)		(23.78)
S_{event} × [year = 2019]	-55.79			
	(55.38)			
Size control	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Establishment fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,282	3,235	726	3,235
R2	0.90	0.92	0.95	0.92
Establishment (fixed effects)	363	363	363	363
S_{event} =	Share of value added subcontracted	Share of value added subcontracted	Share of value added subcontracted	Share of value added subcontracted

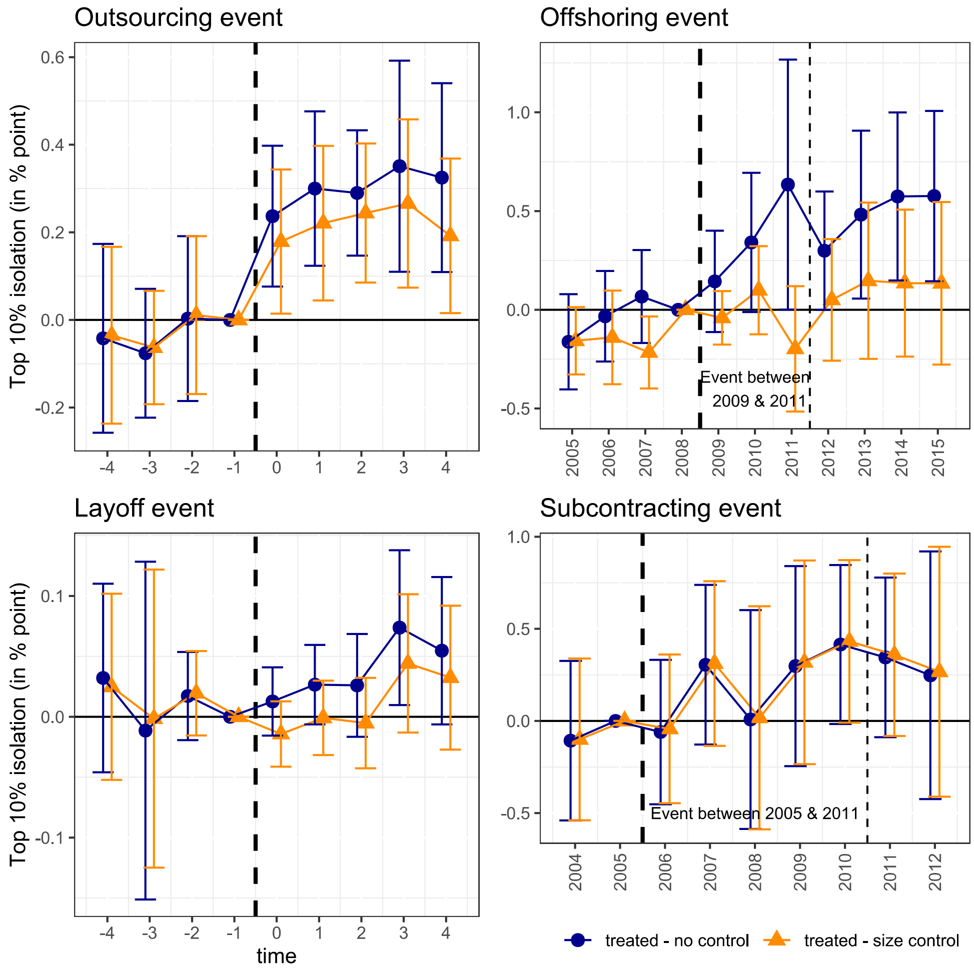
Note: Size control includes log size and cumulative decrease in log size.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, robust standard errors clustered at the firm level in parentheses.

Table S9.6. Contribution of organizational events to the within workplace top 10 percent isolation trend

	Model 1	Model 2	Contribution to the trend	Field
Panel A				
Year linear trend	0.191^{***}	0.189^{**}	1%	All 2001-2017 BTS workplaces with n>1
Cumulative outsourcing events		3.484^{***}		
Number of observations	4,081,192	4,081,192		
Panel B				
Year linear trend	0.418^{***}	0.347^{***}	17%	2002-2014 BTS workplaces matched in MMO
Cumulative layoff events		0.396^{**}		
Number of observations	309,177	309,177		
Panel C				
Year linear trend	0.384^{***}	0.340^{***}	11%	2008 and 2012 BTS workplaces matched with CAM 2012 and present in 2008
2009-2011 offshoring event		2.20^{*}		
Number of observations	53,752	53,752		
Panel D				
Year linear trend	0.373^{**}	-0.09	123%	2005 and 2011 BTS workplaces present both in REPONSE 2005 and 2011, which had not subcontraced their activity in 2005
2006-20011 subcontracting event		3.254^{*}		
Number of observations	396	396		

Note: All regressions are OLS regressions, with workplace fixed effects and robust standard errors clustered at the firm level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Given the small number of workplaces involved in panel D (n=198), the apparent strong contribution of subcontracting to the segregation trend should be considered carefully.

Figure S9.1. Impact of workplace discrete restructuring events on top 10% isolation in France



Note: We measure the impact in France of four types of restructuring events (outsourcing, layoffs, offshoring, subcontracting) on top 10% isolation. Hence, an outsourcing event increases top earner isolation on year *t* by 0.24 percentage point more than in workplace which do not outsource. As workplace size decrease could be the mediator, we also estimate in separate models (triangle points) the impact of those events controlling for size. All models are OLS with workplace and year fixed effects, clustered at the firm level. We plot the 95% confidence interval. To avoid the issue of time-heterogeneity of treatment for the staggered outsourcing and layoff models, we use a stacked version of two-way fixed effects models, where database are constructed separately for each year of events and further aggregated.
Source: Figure 5 and Appendix A2.

S10. Digitalization and top earner isolation in France

To test the relationship between digitalization and top earner isolation at the micro level, we use the French COI (*Changement organisationnel et innovation*) 2006 survey on organizational change and innovation, which collects information on 14,508 firms in the private sector. The survey includes questions on the use of various forms of IT (intranet, extranet, website, databases, ERP software, etc.) both in 2006 and retrospectively for 2003. We consider a digitalization event to have occurred if the number of digitalized items (26 items in questions B11, B12, B14, B15 and C17) increased by at least one between 2003 and 2006, or if the firm undertook a major reorganization project involving IT (question G32). In Table S10.1, we use an event-study framework similar to the one developed for other workplace restructuring events.

Table S10.1. Impact of digitalization between 2003 and 2006 on top 10% isolation in France

	Model 1	Model 2
[Year = 2000]	0.67	0.83
	(1.39)	(1.24)
[Year = 2001]	-0.28	-0.25
	(1.33)	(1.17)
[Year = 2002]	-0.51	-0.70
	(1.32)	(1.15)
[Year = 2003]	0	0
[Year = 2004]	0.31	0.51
	(0.77)	(0.71)
[Year = 2005]	0.54	0.76
	(0.94)	(0.85)
[Year = 2006]	0.23	0.55
	(1.08)	(1.04)
[Year = 2007]	3.09^{**}	3.39^{**}
	(1.35)	(1.37)
[Year = 2008]	1.66	1.95
	(1.28)	(1.23)
[Year = 2009]	1.63	2.09^{*}
	(1.19)	(1.18)
Number of observations	265,791	265,791
R^2	0.90	0.92
Year fixed effects	10	10
Establishment fixed effects	39,469	39,469
Size control	No	Yes

Note: Size control includes log size and cumulative decrease in log size.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, robust standard errors clustered at the firm level in parentheses.

It shows that in 2007, just after the end of the 2003-2006 period during which digitalization is measured, top 10% isolation increased by 3 percentage points relative to 2003. The absence of a significant divergence between treated and counterfactual firms before 2003 supports a causal interpretation of the relationship between digitalization and workplace segregation.

S11. Replication Package

A replication package can be found at the following address:

http://olivier.godechot.free.fr/hopfichiers/Godechot_et_al_Great_Separation_Replication.zip

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