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THE KIDS ARE ALRIGHT: CHILD MIGRANTS AND WAGE GAPS WITHIN GENDER AND ETHNICITY GROUPS IN THE UK

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Abstract

Foreign-born employees in the UK earn less than comparable UK-born employees. We ask whether this penalty also applies to migrants who arrived as children, and how it differs by gender and ethnicity. Estimating wage gaps separately within gender–ethnicity groups, we find sizeable penalties for foreign-born employees overall. But migrants who arrived before age 16 face little or no penalty relative to UK-born employees of the same gender and ethnicity. Wage-gap convergence is substantially stronger for years spent in the UK during childhood than for years spent here as an adult, although the strength and timing of convergence do vary across groups. Age-at-arrival profiles show essentially no gap for those arriving before age 10. The migrant wage penalty in the UK is therefore concentrated among those who arrived later in life. In this sense, the kids are indeed alright: those who arrive during childhood largely avoid the wage penalties faced by later-arriving migrants.

Keywords: migrant wage gap, gender, ethnicity, child migrants.
JEL codes: J15, J16, J31, J61

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1. Introduction

An important question for scholars on the economics of immigration, as well as for policy makers dealing with the integration of increasingly important immigrant populations, is whether migrants who arrive as children catch up with their native-born peers. Because child migrants are typically schooled in the host country and acquire its language early, their labour market outcomes speak directly to the transferability of human capital, the timing of integration, and the extent to which childhood exposure to the host country can offset the wage disadvantages that migrants face (e.g., Bleakley and Chin, 2004, 2010; Algan et al., 2010). We study this question in the UK, where migrants typically earn less than UK-born workers with similar observable characteristics (e.g., Hall et al., 2024; Kaya, 2025). Around one in six workers in the UK was born abroad, and the composition of migrant inflows has changed markedly since the 2016 referendum on EU membership and the introduction of a points-based immigration system in 2021 (e.g., Portes, 2016; Migration Advisory Committee, 2018). Whether migrants and their families become economically integrated is therefore a central policy question. Most of the evidence on this question concerns the average migrant and how the wage penalty evolves with the time spent in the UK (e.g., Lemos, 2013; Bell and Johnson, 2023; Kaya, 2025).

This paper asks a more focused question: are the kids alright? That is, do people who were born abroad but arrived in the UK as children face a wage penalty as adults, relative to comparable UK-born workers? And does the answer depend on gender and ethnicity? Child migrants, sometimes called the '1.5 generation' (Rumbaut, 2004), are an important and growing part of the foreign-born workforce: around one in five foreign-born employees in our data arrived before the age of 16. They are highly likely to attend school in the UK and obtain UK qualifications, and usually acquire English relatively early. If the migrant wage penalty reflects imperfectly transferable human capital, limited language skills or unrecognised foreign qualifications, then child migrants should face little or no penalty. If instead it reflects factors that do not fade with early exposure, such as discrimination or differences in social capital and networks, then the penalty may persist.

Answering this question requires comparing, as far as possible, like with like. Wages differ substantially across ethnicity groups among the UK-born (Froud et al., 2023), and the ethnic composition of the foreign-born differs substantially from that of the UK-born. Comparisons of foreign-born and UK-born workers that pool across ethnicity groups therefore mix migrant-specific penalties with ethnic wage gaps that exist irrespective of where people were born. We avoid this by comparing foreign-born and UK-born employees within twelve gender–ethnicity groups (men and women; white, Indian, Pakistani, Bangladeshi, Chinese and black), allowing the associations of education, age and region with wages to differ across these groups. Within minority ethnic groups, most UK-born adults are the children

of migrants, so our comparison for child arrivals is in effect between the 1.5 and second generations.

Using the Annual Population Survey (APS), with 2012–19 as our main sample period, we document five findings. First, there is a sizeable unexplained hourly wage penalty for foreign-born employees, conditional on education levels, age, and region of the UK: around 12 log points for men and 8–10 log points for women over most of the period, narrowing somewhat toward 2019. Second, the penalty remains within most gender–ethnicity groups, ranging from around 5 log points for Indian men to around 15 log points for Pakistani and Bangladeshi men, with no significant penalty for Chinese men or women. Third, and our main result, among those who were foreign-born but arrived in the UK before age 16, the hourly wage penalty is close to zero and statistically insignificant within ten of the twelve gender–ethnicity groups, and small (1–3 log points) in the remaining two. Fourth, the conditional wage gap narrows considerably faster with years spent in the UK before age 16 than with years spent there as an adult in most groups: among Bangladeshi men, for example, each additional childhood year is associated with a gap around 2 log points smaller, compared with 0.4 log points for each adult year. Fifth, the penalty is not simply a step change for arrivals at age 16. Estimating it separately for finer age-at-arrival bands shows essentially no gap for those who arrived before age 10 in any group, but a penalty emerges for arrivals at ages 10–15 in some groups: Bangladeshi and black men, and Indian, Chinese and black women. Those arriving at 16 or older face penalties of 7–27 log points in every group, with the exception of Chinese employees. Our central findings are all robust to extending the main sample through 2023, with or without the pandemic years 2020–21, to region-by-year fixed effects, and to using only one observation per individual.

Our study thus makes four contributions to the literature. First, it estimates migrant wage penalties entirely within gender–ethnicity groups. This matters empirically: for men who arrived as children, the pooled penalty (3.7 log points) is larger than the penalty in any of the six ethnicity groups taken separately, because pooling attributes part of the more general ethnicity wage gap among the UK-born to migrant status. Second, our study provides evidence that child migrants in the UK do not on average face a conditional wage penalty relative to UK-born individuals of the same gender and ethnicity, and that this holds, with at most small penalties, across all 12 gender–ethnicity groups we can study. Third, we show that wage-gap convergence is substantially stronger for years spent in the UK during childhood than for years spent here as an adult, although its strength and timing vary across groups. Fourth, we show how the penalty depends on age at arrival separately for each group. In a closely related recent study, Hall et al. (2024) find that migrants to the UK face a pay penalty over and above ethnicity pay gaps, which is largest for those arriving at older ages and small for those arriving before age 10. We show that this pattern holds within each gender–ethnicity group, and that the age at which a penalty emerges, and its size among adolescent arrivals, differ across groups.

Importantly in our analysis, we do not interpret differences by age at arrival as the causal effect of arriving younger. With repeated cross-sections, age at arrival is correlated with arrival cohort, the unobserved characteristics of migrant families, and the probability of having left the UK again before being surveyed (e.g., Dustmann and Weiss, 2007; Adda et al., 2022). Instead, we document where in the foreign-born population the wage penalty is concentrated, and where it is absent. Although our evidence is for the UK, these patterns bear directly on the broader questions about child migrants raised at the start of this section.

The rest of the paper is organised as follows. Section 2 reviews the related literature, including looking beyond the UK case. Section 3 describes the data and our empirical approach. Section 4 presents the results, and Section 5 discusses them and concludes.

2. Background

A large literature studies and compares the labour market outcomes of migrants and natives. One strand asks whether immigration affects the wages and employment of native workers. Much of the early evidence on this comes from the United States (e.g., Card, 1990, 2001; Borjas, 2018). For the UK, studies focused on the period around the 2004 EU enlargement, and the ensuing increased immigration, generally find small average wage effects, concentrated toward the bottom of the wage distribution (Dustmann and Fabbri, 2005; Dustmann et al., 2013; Lemos, 2017; Nickell and Saleheen, 2015).

This paper relates to a second major strand of the literature, which studies migrants' own wages relative to those of comparable natives. In a standard human capital framework, migrants arrive with skills that are imperfectly transferable, such as limited host-country language proficiency and incomplete information about the local labour market, so that they initially earn less than comparable natives (e.g., Friedberg, 2000; Dustmann and Fabbri, 2003). As they accumulate host-country experience, language proficiency and qualifications, their wages are expected to converge. How fast this happens is contested. Cross-sectional studies of the UK suggest rapid convergence (e.g., Dustmann, 1993; Bell, 1997), but such estimates confound assimilation with differences between arrival cohorts (Borjas, 1995, 2015). Panel and linked data, which follow the same individuals, show substantial entry penalties in the UK, followed by wage growth that varies considerably across groups (e.g., Lemos, 2013, 2017; Bell and Johnson, 2023; Lemos and Portes, 2025). Kaya (2025), using linked administrative data, finds that immigrants with fewer than ten years of UK residence earn less than comparable UK-born employees, while long-term immigrants have outcomes much closer to those of natives, and that gaps are wider for women, non-white immigrants and those from countries more distant from the UK.

The age at which migrants arrive is a natural dimension along which the transferability of human capital varies. People who arrive as children attend host-country schools, obtain

host-country qualifications and acquire the host-country language while young. Bleakley and Chin (2004, 2010) show that, among US immigrants from non-English-speaking countries, English proficiency declines sharply with age at arrival after early childhood, consistent with a critical period for language acquisition, and that this accounts for a large part of the relationship between age at arrival and earnings. Studies of first- and second-generation immigrants in Europe also show that the children of migrants often achieve educational outcomes similar to or better than those of natives, but that labour market gaps can persist for some ethnic groups (e.g., Algan et al., 2010; Dustmann et al., 2010). Using the Labour Force Survey, Xu and Zhu (2026) study returns to qualifications among UK-educated ethnic minorities and immigrants, restricting the immigrant sample to those who completed their full-time education in the UK. They find that minority immigrants obtain larger returns to higher UK qualifications than white natives, largely explained by differences in degree subject, university selectivity and occupational sorting. Their approach conditions on UK education; ours instead conditions on age at arrival, which captures exposure to UK schooling, language and society more broadly, and does not require attributing each qualification to a country.

For the UK, the study closest to ours is Hall et al. (2024). They document ethnic minority and migrant pay gaps over the life cycle, finding that migrants face an additional penalty beyond ethnicity pay gaps, which is largest for those who arrived at older ages, while those arriving before around age 10 face little or no additional penalty. We build on their analysis in three ways. First, rather than adding a migrant penalty to ethnicity gaps estimated across the whole population, we estimate all parameters separately within each gender–ethnicity group. The migrant gap is therefore identified only by comparing foreign-born and UK-born employees of the same gender and ethnicity. Second, we focus explicitly on child migrants, asking whether they face any penalty relative to UK-born employees of the same gender and ethnicity, who in minority groups are largely second-generation individuals. Third, we estimate how the penalty varies with age at arrival separately for each of the twelve gender–ethnicity groups, which shows how far the patterns are common across groups.

Much of the recent evidence on migrant wage gaps uses panel or linked administrative data, which follow the same individuals over time and are therefore well suited to studying wage growth, selective return migration and individual heterogeneity (e.g., Lemos, 2013; Bell and Johnson, 2023; Kaya, 2025). Our question is different. We ask how the level of the wage gap varies with age at arrival within narrowly defined gender–ethnicity groups, and for this purpose large repeated cross-sections have two advantages. First, age at arrival does not vary over time for a given individual, so following the same people over time adds relatively little variation for our main question, and individual fixed effects would absorb age at arrival entirely. Second, estimating gaps separately for twelve gender–ethnicity groups, and for child migrants within them, requires large samples with detailed information on ethnicity, country of birth, year of arrival and qualifications. Large household surveys such as the APS provide

all of these and, especially when pooled multiple years, yield sufficiently large samples for most groups. Administrative earnings records often lack detailed ethnicity and country of birth information, unless they are linked to census or survey data.

3. Data and method

3.1. Data

We use the January–December person files of the UK Annual Population Survey (APS) for 2012–23 (Office for National Statistics, 2023). The APS combines the Labour Force Survey (LFS) with boost samples and is a large annual household survey in the UK, with around 300,000 person observations per year on average. For our main analysis, we end our main sample period in 2019 because hours and pay from 2020 onwards were heavily affected by the COVID-19 pandemic and the furlough scheme, which affected migrants and natives differently, and because APS response rates and achieved sample sizes fell sharply after 2020 (Office for National Statistics, 2026b). Nevertheless, Section 4.4 shows that our main results are robust to extending the sample period to 2023.

Our APS analysis sample consists of all employees aged 16–64 (i.e., employed but not self-employed) with valid information on pay, hours, education, country of birth and, for the foreign-born, year of arrival in the UK. Hourly pay is derived as the gross weekly pay in the main job divided by actual weekly hours worked in the main job.[1] To limit the influence of measurement error in constructed hourly pay, we drop observations below the 0.5th and above the 99.5th percentile of log hourly pay within each estimation sample. The LFS follows sampled households for up to five consecutive quarterly waves, but earnings questions are asked only at Waves 1 and 5. The APS annual person files are mostly constructed using these Wave 1 and Wave 5 observations from the underlying LFS, so the same individual can appear in more than one annual APS file (Office for National Statistics, 2026a). The end-user files contain no person identifier, so these repeated observations cannot be linked; in Section 4.4, we therefore also estimate all models using only LS wave 1 observations, in which each individual appears once.

An individual is designated as *foreign-born* if their recorded country of birth is outside the UK. For the foreign-born, we calculate *years since arrival* as the survey year minus the year in which the person reports having first come to the UK to live, and *age at arrival* as age at interview minus years since arrival.[2] We classify individuals into six ethnicity groups using the APS ethnicity variable: white (including White British, Irish and other white), Indian,

[1] Hours above 99 per week are set to missing. Measurement error in LFS and APS pay variables is well known (Skinner et al., 2002).

[2] Age at arrival is therefore measured with an error of up to one year. We drop the small number of observations whose reported year of arrival implies arrival before birth.

Pakistani, Bangladeshi, Chinese, and black (African, Caribbean and Black British). The remaining groups (mixed, other Asian and other) are too small and heterogeneous to analyse separately, but they are included in our pooled 'All' and 'Non-white' estimates. Education is measured by the highest qualification held, in six categories (degree, other higher education, A-level or equivalent, GCSE or equivalent, other qualifications and none). Finally, our geographical controls are at the level of the 12 UK government office regions of residence (e.g., London, West Midlands, Scotland).

3.2. Empirical approach

We first estimate a Mincer-style wage regression separately for each year $t \in \{2012, \ldots, 2023\}$ and gender (the latter not denoted), with an added indicator for a person being foreign-born and region fixed effects:

$$\ln w_{it} = \alpha_t + \beta_t F_{it} + f_t(E_{it}, A_{it}) + \rho_{R_{it},t} + \varepsilon_{it} \ , \tag{1}$$

where $\ln w_{it}$ is log hourly pay, F_{it} is an indicator for being foreign-born, $f_t(E_{it}, A_{it})$ contains indicators for the six education categories interacted with a quadratic in age, and $\rho_{R_{it},t}$ are region fixed effects. The coefficient β_t thus gives the conditional average log wage difference between foreign-born and UK-born employees with the same education, age and region. This estimate is typically referred to in the literature as an adjusted or unexplained wage gap (e.g., Bell, 1997; Lemos, 2013; Hall et al., 2024).

Having first described how the overall foreign-born wage gap varies over time, we next turn to differences within gender–ethnicity groups. We pool the 2012–2019 data and estimate the model separately within each gender–ethnicity group. For each gender (g) and ethnicity group (e) we estimate:

$$\ln w_{it} = \alpha^{ge} + \beta^{ge} F_{it} + f^{ge}(E_{it}, A_{it}) + \rho^{ge}_{R_{it}} + \tau^{ge}_{t} + \varepsilon_{it} \ , \tag{2}$$

where τ^{ge}_t are year fixed effects. All coefficients, including the returns to education and age, are thus specific to each gender–ethnicity group. We estimate Equation (2) first including all foreign-born employees, and then including only the foreign-born who arrived before age 16. In the second case, β^{ge} gives the conditional average wage gap between child migrants and UK-born employees of the same gender and ethnicity, who in minority ethnic groups are mostly the children of migrants. We use age 16 as the threshold because it approximately corresponds to the end of compulsory schooling in the UK: those arriving before 16 will typically have arrived as dependants and are therefore likely to have experienced at least some formal UK schooling.

To examine how the conditional wage gap on average varies with time spent in the UK before and after age 16, we decompose, for the foreign-born, the total years since arrival into the

years spent in the UK before age 16, C_{it}, and years spent in the UK from age 16 onwards, D_{it}. We then estimate:

$$\ln w_{it} = \alpha^{ge} + \beta^{ge} F_{it} + \lambda^{ge} \widetilde{C}_{it} + \delta^{ge} \widetilde{D}_{it} + f^{ge}(E_{it}, A_{it}) + \rho^{ge}_{R_{it}} + \tau^{ge}_{t} + \varepsilon_{it} \,. \tag{3}$$

For the foreign-born, $\widetilde{C}_{it}$ and $\widetilde{D}_{it}$ give the demeaned values within each gender–ethnicity estimation sample, and both are zero for the UK-born. This centring preserves the interpretation of β^{ge} as the average conditional wage gap between foreign-born and UK-born employees within the gender–ethnicity group. The coefficients λ^{ge} and δ^{ge} then describe how this gap varies around that average according to the number of years migrants have spent in the UK before or after age 16. Positive values of either coefficient indicate convergence toward the wages of otherwise comparable UK-born employees. For migrants arriving before age 16, an additional year of C_{it} corresponds to arriving one year younger, so λ^{ge} gives the change in the conditional wage gap associated with an additional year spent in the UK before age 16. In contrast, δ^{ge} gives the change in the conditional wage gap associated with an additional year spent in the UK from age 16 onwards. Our main interest is therefore in whether λ^{ge} and δ^{ge} differ: a larger λ^{ge} would indicate that years spent in the UK during childhood are associated with faster convergence toward otherwise comparable UK-born employees' wages, relative to years spent in the UK from age 16 onwards.

Finally, we relax the piecewise linear relationship between the conditional wage gap and time spent in the UK imposed by Equation (3), replacing the foreign-born indicator and the years-since-arrival terms with indicators for bands of age at arrival:

$$\ln w_{it} = \alpha^{ge} + \sum_{b} \theta^{ge}_{b} \mathbb{1}[F_{it} = 1,\ \text{age at arrival}_i \in b] + f^{ge}(E_{it}, A_{it}) + \rho^{ge}_{R_{it}} + \tau^{ge}_{t} + \varepsilon_{it}, \tag{4}$$

with bands $b \in \{0\text{–}4,\ 5\text{–}9,\ 10\text{–}12,\ 13\text{–}15,\ 16+\}$ and UK-born individuals of the same gender–ethnicity group as the omitted category. Each θ^{ge}_{b} therefore gives the average log wage gap relative to UK-born employees for migrants who arrived in age band b, conditional on age, education, region, and year. As a robustness check, the Online Appendix also reports estimates using single years of age at arrival.

There are two important points about the interpretation of the estimates obtained from these equations. First, because, conditional on current age, age at arrival determines years since arrival, the profiles in Equation (4) compare people of the same current age who arrived at different ages and have consequently spent different lengths of time in the UK. Second, all our estimates are conditional on education, which may itself partly be an outcome of age at arrival.[3] The estimated penalties we report should, therefore, be interpreted as unexplained

[3]The APS does not record where qualifications were obtained. This is a common difficulty in UK studies of migrant human capital, where foreign qualifications are not always directly comparable with UK qualifications (e.g., Manacorda et al., 2012). One approach is to compare the age at which individuals left full-time education

gaps among employees with the same current age and qualifications, rather than as total differences in pay.

3.3. Descriptive statistics

Our pooled annual APS 2012–19 estimation samples contain 283,710 employee observations for men and 301,355 for women. Within the six ethnicity groups, there are 67,983 foreign-born employees, of whom almost 22% arrived in the UK before age 16. Table 1 reports, for each gender–ethnicity group, the number of foreign-born employees, the share who arrived before 16, their age at arrival and years since arrival, and the number of foreign-born employees in each age-at-arrival band used in the final part of our analysis below.

The groups differ markedly: the share of foreign-born employees who arrived as children is between 16% and 24% in most groups, but 37% among Bangladeshi men and Pakistani women and 48% among Bangladeshi women, reflecting both the historical timing of migration patterns to the UK from these countries and differences in employment rates among women who arrived as adults. Most groups have several hundred foreign-born employee observations in each age-at-arrival band, but some cells are small: for example, only 30 Chinese men arrived aged 0–4, and only 21 Bangladeshi women arrived aged 13–15. We therefore report age-at-arrival estimates in bands in the main text.

TABLE 1: Foreign-born employees by gender and ethnicity: age at arrival and years since arrival in the UK, 2012–19

	Foreign-born employees					Number arriving at age				
	N	% arrived aged 0–15	Mean age at arrival	Median age at arrival	Mean years since arrival	0–4	5–9	10–12	13–15	16+
Men										
White	21,367	23.0	22.6	24	16.1	3,042	1,048	441	376	16,460
Indian	4,921	18.6	24.7	26	17.3	284	272	175	185	4,005
Pakistani	2,121	23.6	22.4	23	17.2	171	153	76	101	1,620
Bangladeshi	1,055	37.3	20.2	22	19.9	135	137	73	49	661
Chinese	707	21.4	22.9	22	17.1	30	34	33	54	556
Black	3,693	16.6	26.0	26	16.0	105	179	151	179	3,079
Women										
White	23,433	21.6	22.3	23	16.6	2,968	1,068	484	531	18,382
Indian	3,884	20.8	22.6	24	19.5	250	266	136	155	3,077
Pakistani	983	37.1	18.1	19	21.2	168	109	46	42	618
Bangladeshi	391	47.6	15.3	17	22.6	86	54	25	21	205
Chinese	979	16.2	23.4	23	16.9	38	45	33	43	820
Black	4,449	18.8	24.7	25	17.0	115	286	194	241	3,613

Notes: Foreign-born employees aged 16–64 in the estimation samples of Figure 2A, Annual Population Survey (APS), January–December files 2012–19, pooled and unweighted. Age at arrival is age at interview minus years since arrival in the UK. Years since arrival by five-year bands are reported in Online Appendix Table A4.

Table 2 reports raw foreign-born wage gaps and sample sizes by gender–ethnicity group. Among all foreign-born employees, mean log hourly pay is lower than among UK-born

with their age at arrival (as in Xu and Zhu, 2026); for our purposes, this would largely re-express age at arrival, so we work directly with age at arrival.

employees of the same gender and ethnicity in most groups. The largest raw shortfalls are among Bangladeshi men and black women, at around 14 and 15 log points, respectively, while white women have a small positive gap. For those who arrived before age 16, raw gaps are closer to zero in most groups, although sizeable negative gaps remain among Chinese and black women. These are unconditional differences in mean log hourly pay; Section 4.2 presents the corresponding adjusted estimates.

TABLE 2: Raw wage gaps between foreign-born and UK-born employees, within gender–ethnicity groups, 2012–19

	Any age at arrival			Arrived aged 0–15	
	N UK-born	*N* foreign-born	Raw gap	*N* foreign-born	Raw gap
Men					
White	235,916	21,367	−0.047	4,911	0.030
Indian	2,087	4,921	−0.003	922	−0.009
Pakistani	1,341	2,121	−0.099	501	−0.005
Bangladeshi	357	1,055	−0.144	395	−0.016
Chinese	282	707	0.001	150	−0.040
Black	1,581	3,693	−0.107	615	−0.077
Women					
White	252,240	23,433	0.009	5,054	0.040
Indian	2,186	3,884	−0.051	808	−0.052
Pakistani	1,268	983	−0.056	365	−0.015
Bangladeshi	332	391	−0.031	186	0.045
Chinese	236	979	−0.063	160	−0.148
Black	2,400	4,449	−0.151	837	−0.128

Notes: Employees aged 16–64, APS 2012–19, pooled and unweighted. The raw gap is the difference in mean log hourly pay between foreign-born and UK-born employees of the same gender and ethnicity group, before any controls. *N* UK-born refers to the sample including all foreign-born; it differs slightly in the child-arrival sample because of trimming (see Online Appendix Tables A2 and A3).

4. Results

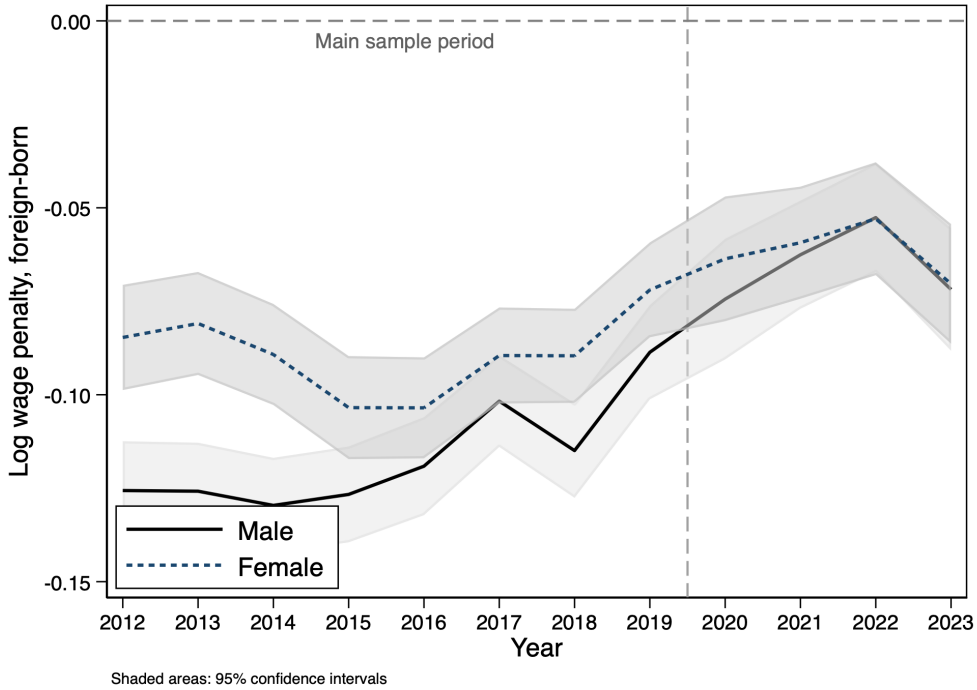
4.1. The average migrant wage penalty

Figure 1 shows the average unexplained wage penalty for all foreign-born employees, by year and gender, β_t, from Equation (1). Foreign-born men earned around 12.5–13 log points less than comparable UK-born men between 2012 and 2015. The penalty generally narrowed after 2016, reaching 8.9 log points in 2019. For women, the penalty was smaller at the start of the period, at 8.5 log points in 2012, rose to around 10 log points in 2015–2016 and fell to 7.2 log points in 2019. The penalty is precisely estimated in every year (Online Appendix Table B1). After 2019, outside our main sample period, the penalty continued to narrow, to around 5 log points for both men and women in 2022, before widening to around 7 log points in 2023.

These later estimates are less precise, as the number of employees with pay data roughly halved between 2019 and 2023, and we do not interpret their year-to-year movements.

The narrowing toward 2019 coincides with substantial changes in the composition of UK immigration, including the fall in migration from the EU after the 2016 referendum (e.g., Portes, 2016; Migration Advisory Committee, 2018), and so may partly reflect changes in who migrated to and remained in the UK. With repeated cross-sections we cannot separate these changes in composition from changes in the penalty faced by given individuals. What matters for the rest of the paper is that the penalty is sizeable throughout, and that it is an average over very different groups.

FIGURE 1: Unexplained log hourly wage gaps between foreign-born and UK-born employees, by year and gender



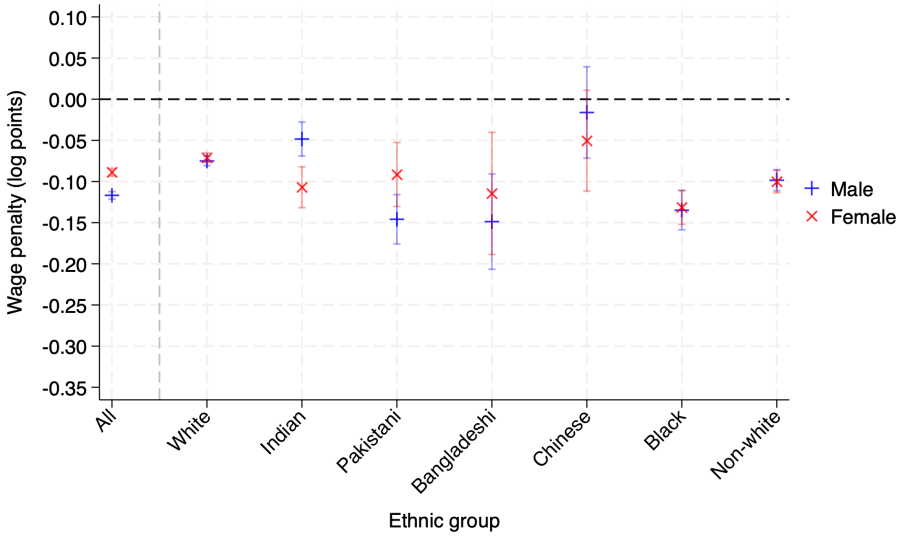
Notes: coefficient on the foreign-born indicator from Equation (1), estimated separately by year and gender. Employees aged 16–64, APS 2012–2023, unweighted. The dashed vertical line marks the end of the main sample period (2012–2019); sample sizes fall from around 32,000 men and 34,000 women in 2019 to around 15,000 men and 16,000 women in 2023. Controls: education categories interacted with a quadratic in age, and region. Shaded areas are 95% confidence intervals using robust standard errors. See Online Appendix Table B1.

4.2. Penalties within gender–ethnicity groups

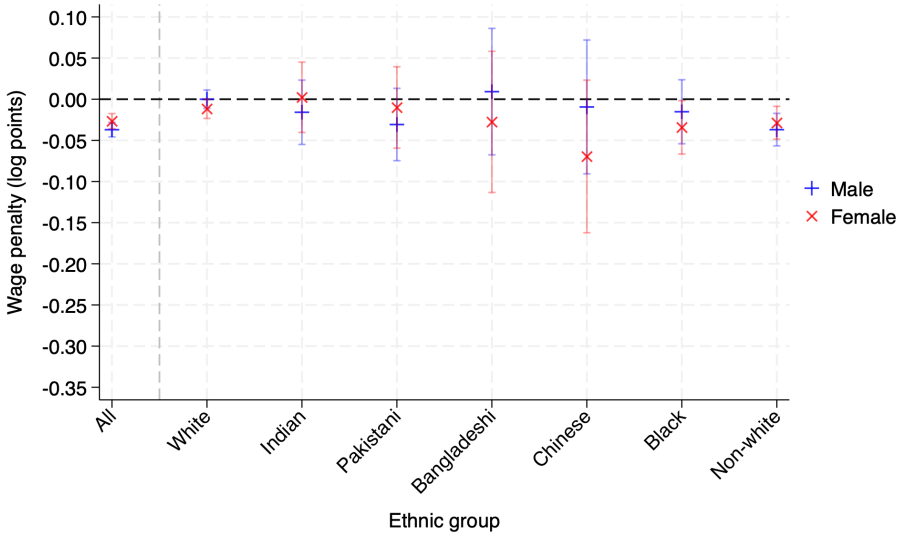
Figure 2 shows the unexplained hourly wage gap estimated separately within each gender–ethnicity group from Equation (2), pooling 2012–2019, for all foreign-born employees (panel A) and for those who arrived before age 16 (panel B). The first estimate for each gender, labelled 'All', pools all ethnicity groups, as in Figure 1. Table 2 reports the corresponding raw gaps and sample sizes.

FIGURE 2: Unexplained log hourly wage gaps between foreign-born and UK-born employees, within gender–ethnicity groups, 2012–19

A. Any age at arrival



B. Arrived aged 0–15



Notes: coefficient on the foreign-born indicator, β^{ge}, from Equation (2), estimated separately by gender–ethnicity group, pooling 2012–2019, with region and year fixed effects. Panel A includes all foreign-born employees; panel B excludes those who arrived in the UK aged 16 or older. 'All' pools all ethnic groups; 'Non-white' pools all groups other than white. Both panels have the same vertical scale. Bars are 95% confidence intervals using robust standard errors. For the estimates and sample sizes see Online Appendix Tables B2-B3.

Comparing the raw gaps in Table 2 with the adjusted estimates in Figure 2 shows how conditioning on observable characteristics changes the foreign-born wage gaps. The raw differences in mean log hourly pay between foreign-born and UK-born individuals of the same ethnicity are smaller than the adjusted gaps in ten of the twelve groups (see also Online Appendix Tables A1–A3). For example, foreign-born white women earn slightly more per hour on average than UK-born white women. The foreign-born therefore tend to have

characteristics, such as their qualifications, age and region of residence, that are associated with higher pay, and the penalties we report are conditional on these. For those who arrived as children, the pattern is reversed: in ten of the twelve groups the adjusted gap is closer to zero than the raw gap. Among black and Chinese women who arrived as children, for example, raw gaps of 13 and 15 log points shrink to 3 and 7 log points once education, age, region and year are held constant.

The foreign-born wage penalty persists within most groups. Among men, it is 7.5 log points for white men, 4.8 for Indian men, 14.6 for Pakistani men, 14.9 for Bangladeshi men and 13.5 for black men. Among women, it is 7.1 log points for white women, 10.7 for Indian women, 9.2 for Pakistani women, 11.4 for Bangladeshi women and 13.1 for black women. For Chinese men and women, the estimates are small and statistically insignificant. The size of the penalty therefore differs considerably across groups, as does its gender pattern: for example, foreign-born Indian women face a penalty more than twice as large as foreign-born Indian men, while for Pakistani men the penalty is larger than for Pakistani women.

Pooling across ethnicity groups can therefore give a misleading summary. The pooled estimate of the average conditional wage gap over all men, 11.7 log points, is substantially above the 7.5 log point penalty for white men, who make up the large majority of the sample. This difference arises because the pooled regression compares the foreign-born population, which is disproportionately from ethnic minority groups, with a UK-born population that is mostly white. Without conditioning on ethnicity, the foreign-born coefficient therefore also reflects between-ethnicity differences in wages that are correlated with foreign-born status. For the rest of the paper, we therefore compare foreign-born and UK-born employees only within gender–ethnicity groups.

Panel B of Figure 2 repeats the exercise, but includes only the foreign-born who arrived in the UK before age 16. Within every gender–ethnicity group, the estimated penalty for child migrants is much smaller than for the foreign-born as a whole, and in most cases it is statistically indistinguishable from zero. For men, the estimates range from -3.1 log points (Pakistani) to $+0.9$ (Bangladeshi), and none is statistically significant; for white men, the estimate is exactly zero to three decimal places. The estimates for Indian, Pakistani, Bangladeshi and Chinese women are statistically insignificant, and those for white women (-1.2 log points) and black women (-3.4 log points) are small and only marginally significant. Compared with panel A, the estimated wage penalty for child migrants is around one-tenth of that for all foreign-born among black men, and around one-fifth among Pakistani men.

Overall, these estimates show that foreign-born employees who arrived in the UK as children earn, on average, about the same as UK-born employees of the same gender, ethnicity, education, age and region. Within ethnic minority groups, the UK-born comparators are

largely second-generation individuals, specifically the UK-born children of migrants. The 1.5 generation therefore does not face a wage penalty relative to them.[4]

The pooled estimates again illustrate the potential problem with ignoring ethnicity. Among men, the pooled penalty for child migrants is 3.7 log points and statistically significant, larger in magnitude than the estimate for any of the six ethnicity groups considered on their own. Among women, the pooled estimate is 2.7 log points, larger than the estimates for three of the six ethnicity groups, including white women, who make up most of the sample.

4.3. Age at arrival

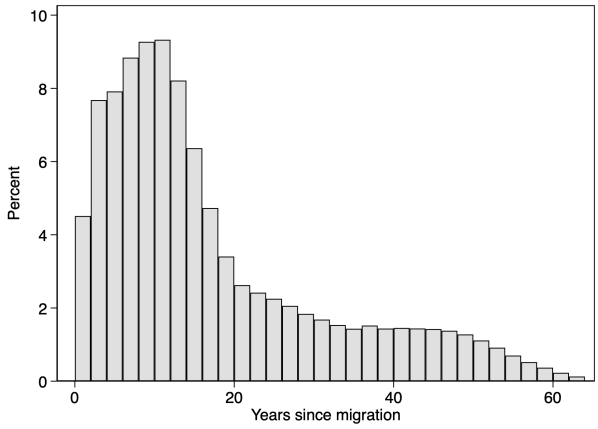
The contrast between the two panels of Figure 2 shows that the average unexplained migrant wage penalty is concentrated among those who arrived as adults. We now examine how the penalty varies with age at arrival and years since arrival.

Figure 3 shows the observed distributions of years since arrival and age at arrival among foreign-born employees in the pooled 2012–19 APS. Both vary widely. Age at arrival has a clear bimodal shape: there is a mass of arrivals in early childhood, a lower and roughly flat density between ages 5 and 15, and a much larger peak among young adults in their twenties. Years since arrival ranges from recent arrivals to employees who have lived in the UK for several decades, with a median of 11–23 years across gender–ethnicity groups (Online Appendix Table A4). Panel C shows the joint distribution of the two variables. The largest observed concentration is among employees who arrived in their twenties and have been in the UK for 5–15 years: in other words, the migrant employee pool is relatively concentrated among young to middle-aged adults who arrived as young adults. Child arrivals, to the left of the dashed line in Panel C, are spread over much longer durations since arrival, typically 15 years or more. Because age at arrival plus years since arrival approximately equals current age, and our sample is aged 16–64, the observations fill a triangle; within it, there is substantial variation in years since arrival at a given age at arrival. This variation allows us to compare employees who arrived at different ages but are now the same age, as in Equation (4).

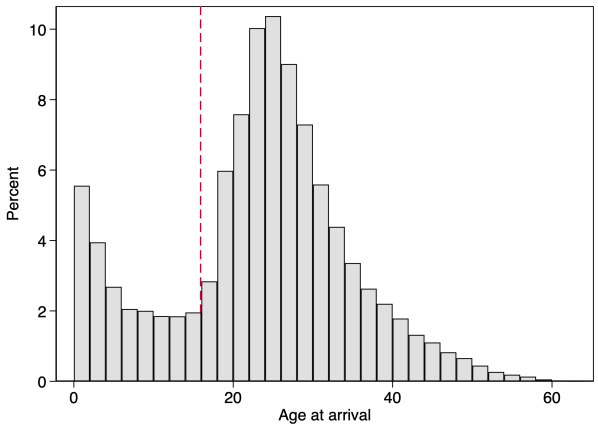
Figure 4 summarises the estimated average conditional relationship between wages and years spent in the UK before and after age 16, λ^{ge} and δ^{ge} respectively from Equation (3) (see also Online Appendix Tables B4-B5). Positive coefficients indicate convergence toward the wages of otherwise comparable UK-born employees. Among men, the point estimates indicate faster convergence for years spent in the UK during childhood than for years spent here as an adult among Pakistani, Bangladeshi, black and white men. The contrast is largest for Bangladeshi men: each additional year spent in the UK before age 16, equivalent to arriving

[4]For standard usage of the terms second generation and 1.5 generation in the academic literature, see Algan et al. (2010) and Rumbaut (2004), respectively.

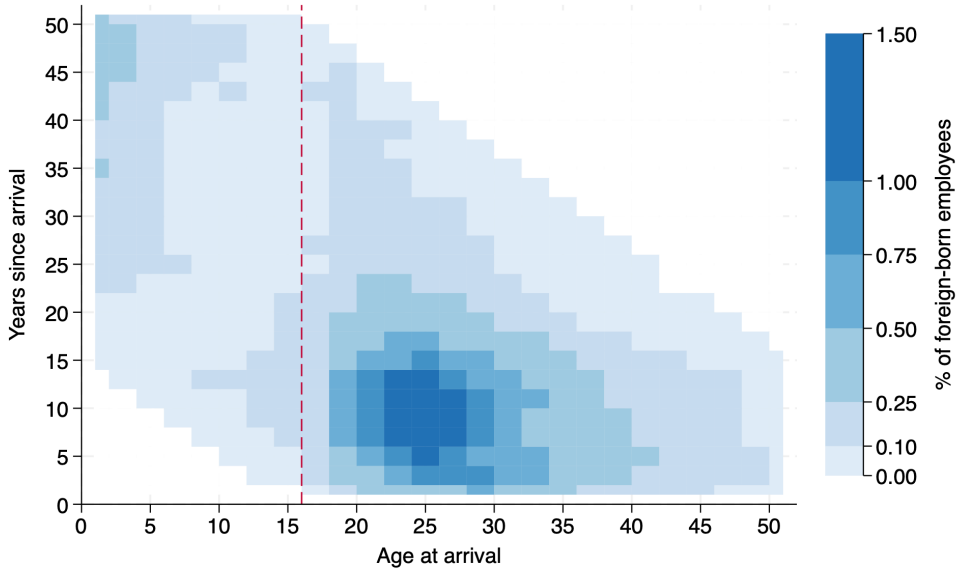
FIGURE 3: Distribution of years since arrival and age at arrival among foreign-born employees in the UK, 2012–19



A. Years since arrival



B. Age at arrival



C. Joint distribution

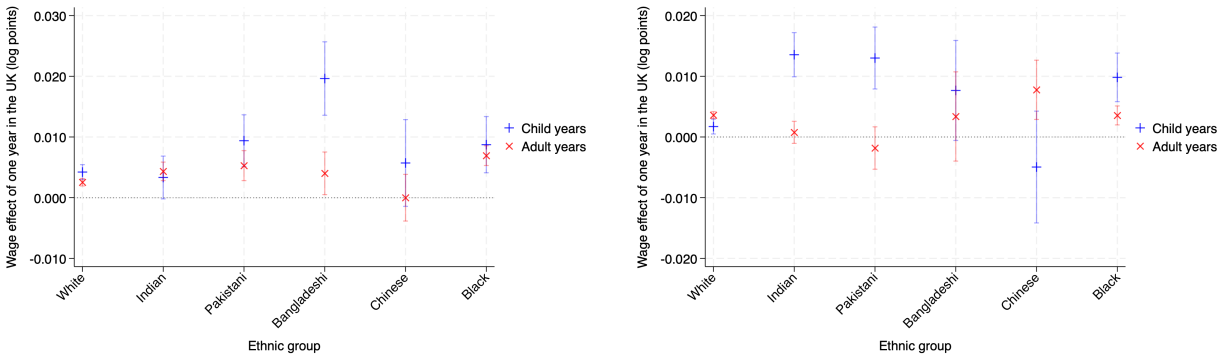
Notes: foreign-born employees in the six ethnicity groups used in the estimation samples of Figure 2A, APS 2012–19, pooled and unweighted, two-year bins. The dashed lines in panels B and C mark age 16. In panel C, the shading shows the percentage of foreign-born employees in each two-year by two-year cell, for ages at arrival and years since arrival up to 51. See Table 1 and Online Appendix Table A4 for accompanying statistics by gender and ethnicity.

one year younger, is associated with a narrowing of the conditional wage gap by around 2 log points, compared with only 0.4 log points for an additional year spent in the UK from age 16 onwards.

Among women, convergence associated with years spent in the UK during childhood is particularly strong for Indian, Pakistani and black migrants, at around 1.0–1.4 log points per year. By contrast, there is little evidence of convergence with additional years spent in the UK as an adult for Indian or Pakistani women. For white women, the point estimates suggest the

opposite pattern, with faster convergence associated with adult rather than childhood years. For Chinese men, neither slope is statistically distinguishable from zero; among Chinese women, only the adult-years slope is statistically significant.

FIGURE 4: Conditional foreign-born wage-gap convergence with years in the UK before and after age 16, within gender–ethnicity groups



A. Men B. Women

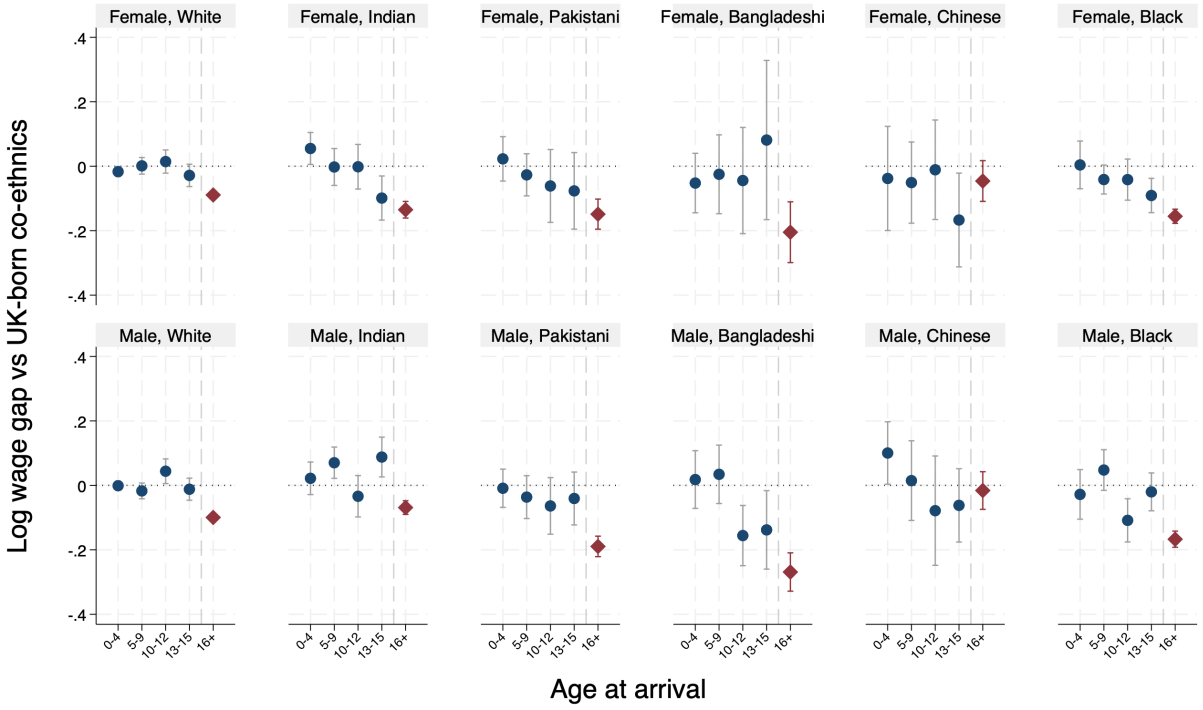
Notes: coefficients λ^{ge} (child years) and δ^{ge} (adult years) from Equation (3), estimated separately by gender–ethnicity group, pooling 2012–19. Bars are 95% confidence intervals using robust standard errors. See Online Appendix Tables B4-B5.

The piecewise linear specification in Equation (3) imposes a constant rate of conditional wage-gap convergence for each additional year spent in the UK during childhood. Figure 5 relaxes this restriction, showing the unexplained wage gap relative to UK-born of the same gender and ethnicity for age-at-arrival bands, estimated from Equation (4). Three patterns stand out. First, for those who arrived before age 10, there is essentially no foreign-born penalty within any gender–ethnicity group. Of the 24 estimates for the 0–4 and 5–9 bands, only one is significantly negative: white women who arrived aged 0–4 (−1.7 log points). The few other statistically significant estimates are positive: Chinese men and Indian women who arrived aged 0–4, and Indian men who arrived aged 5–9.

Second, a penalty emerges for arrivals at ages 10–15 in some, but not all, groups. Bangladeshi men who arrived aged 10–12 and 13–15 have conditional wage gaps 15.6 and 13.8 log points, respectively, relative to UK-born Bangladeshi men, while black men who arrived aged 10–12 have a gap of 10.9 log points. Among women, arrivals aged 13–15 have gaps of 9.9 log points among Indian women, 16.7 among Chinese women and 9.1 among black women. In the other groups, the estimates for arrivals at ages 10–15 are not significantly negative, although those for Pakistani men and women are negative and imprecisely estimated. The emergence of penalties from around age 10 is consistent with evidence that language proficiency deteriorates with later childhood arrival after the critical period for language acquisition (Bleakley and Chin, 2004, 2010). For those arriving in their early teens, later arrival also implies substantially less exposure to UK secondary schooling before GCSEs at around age 16.

Third, those who arrived at 16 or older face substantial conditional wage penalties in every group except the Chinese: 10.0 log points for white men and 8.9 for white women, 6.9 for Indian men and 13.5 for Indian women, 18.9 and 14.9 for Pakistani men and women, 26.9 and 20.5 for Bangladeshi men and women, and 16.7 and 15.5 for black men and women. These penalties are larger than those in Figure 2A, which average over both child and adult arrivals.

FIGURE 5: Unexplained wage gap relative to UK-born co-ethnics, by age at arrival, within gender–ethnicity groups



Notes: coefficients θ_b^{ge} from Equation (4), estimated separately by gender–ethnicity group, pooling 2012–19. The reference category is UK-born employees of the same group. Bars are 95% confidence intervals using robust standard errors. Online Appendix Figure B1 shows estimates by single year of age at arrival. See Online Appendix Tables B6-B7.

Online Appendix Figure B1 shows the same profiles using single years of age at arrival. These are noisy for the smaller groups, but they show the same overall shape: estimates scattered around zero for early childhood arrivals, becoming more negative for some groups from around age 10, and a clear penalty for arrivals at 16 or older. Online Appendix Figure B2 shows the same comparison among the foreign-born only, relative to those who arrived at 16 or older.

4.4. Robustness

Our main sample ends in 2019 because of the pandemic-related disruption to hours and pay and the subsequent deterioration in APS sample quality discussed in Section 3.1. As a

robustness check, we re-estimate the main results over 2012–23, both including and excluding 2020–21.

Online Appendix Figure B3 compares the conditional wage gap for foreign-born employees who arrived before age 16 across the three samples. The results are very similar. Using 2012–23, the estimated average penalty for child migrants is statistically insignificant in eleven of the twelve gender–ethnicity groups, and small in the remaining one (black women, 3.3 log points). Among men, the estimates range from −2.9 log points (Pakistani) to +1.0 (Chinese); among women, from −3.3 (Bangladeshi and black) to −0.2 (Indian). The estimate for white women, which was marginally significant in the main sample, is 0.9 log points and no longer statistically significant. Excluding 2020–21 gives almost identical results. The penalties for all foreign-born employees are also similar across the three samples (Online Appendix Table B8): they change by at most around 3 log points, and the Chinese remain the only group with no significant penalty.

The age-at-arrival profiles are also robust (Online Appendix Figure B4). In the extended sample, no estimate for arrivals before age 10 is significantly negative. Penalties for arrivals at ages 10–15 remain for Bangladeshi men (17.4 and 14.9 log points for arrivals aged 10–12 and 13–15), black men aged 10–12 (10.4 log points), and Indian and black women aged 13–15 (8.1 and 6.9 log points). The penalty for Chinese women who arrived aged 13–15, which rests on only 43 observations in the main sample, is smaller and no longer statistically significant. Penalties for those who arrived at 16 or older are very similar.

We also restrict the estimation samples to LFS wave 1 observations, so that no individual appears more than once. The results show that this leaves the point estimates for all foreign-born employees and for child arrivals very similar. Standard errors rise by about 40%, consistent with using fewer than half of the observations, and the estimated penalty for child arrivals is then statistically insignificant in all twelve groups. The estimates for arrivals at ages 10–15 become less precise (Online Appendix Figure B6): the penalties for Bangladeshi and black men arriving at ages 10–12 and for black women arriving at 13–15 are no longer statistically significant, although most point estimates remain negative, while those for Indian and Chinese women arriving at 13-15 remain significant and that for Pakistani women arriving at 13–15 becomes significant. Moreover, replacing the separate region and year fixed effects in Equations (2)–(4) with region-by-year fixed effects changes no estimate by more than 3 log points.

Finally, as Figure 1 shows, the average penalty for all foreign-born employees continued to narrow after 2019, before widening again in 2023. Given the changes in the achieved APS sample over this period, we do not interpret these year-to-year movements. The key result, that child migrants face no sizeable wage penalty relative to UK-born employees of the same gender and ethnicity, is therefore robust across these alternative samples and specifications.

5. Discussion and conclusion

On average, foreign-born employees in the UK earn around 8–13 log points less per hour than UK-born employees with the same education, age and region of residence. This paper shows that this average hides two important sources of variation. The first is ethnicity: much of the unexplained difference between foreign-born and UK-born wages reflects gaps between ethnicity groups that also exist among the UK-born. Once foreign-born employees are compared with UK-born employees of the same gender and ethnicity, penalties remain for most groups but vary between about 5 and 15 log points, and are statistically insignificant for Chinese employees. The second is age at arrival: the migrant wage penalty is concentrated among those who arrived as adults. Foreign-born employees who arrived as children earn about the same as UK-born employees of the same gender and ethnicity, most of whom are the children of migrants. In that sense, the kids are alright. In most groups, the conditional wage gap narrows with each year spent in the UK more so as a child than as an adult, most clearly among Bangladeshi and Pakistani men, and Indian, Pakistani and black women.

The age-at-arrival profiles add further nuance to this picture. There is essentially no penalty for those who arrived before age 10: the only significantly negative estimate, for white women who arrived aged 0–4, is below 2 log points. For those arriving in early adolescence, there is some evidence of penalties in some groups, most clearly among Bangladeshi and black men, and Indian, Chinese and black women. These estimates rest on small samples and are less precise when each individual is counted only once. This is consistent with the importance of language acquisition in early childhood (Bleakley and Chin, 2004, 2010) and of completing secondary schooling in the host country. Arriving at age 13 or 14 leaves little time to acquire English and complete UK schooling. That these penalties differ across groups suggests that the costs of arriving in adolescence may depend on language background, the schools and areas in which children settle, and family circumstances.

Several caveats apply. First, with repeated cross-sections, differences by age at arrival also reflect differences across arrival cohorts, in the characteristics of migrant families and in who remains in the UK. Second, we condition on education, which is itself partly determined by age at arrival; the penalties we report are therefore gaps among people with the same qualifications. Third, we study employees with valid pay data. Employment rates differ substantially across groups, particularly among Pakistani and Bangladeshi women, and selection into employment may differ between child and adult migrants. Fourth, some cells are small, and the APS ethnicity categories are broad: the black group, for example, combines people of African and Caribbean heritage, whose migration histories to the UK differ substantially. As linked census and earnings records become available for recent migrant cohorts, it will be possible to revisit these questions with longitudinal data and more accurately measured earnings.

With these caveats in mind, the findings have two implications. First, analyses of migrant wage gaps should compare foreign-born and UK-born employees within the same ethnicity group. Pooled comparisons mix migrant-specific penalties with ethnicity wage gaps, and can imply a penalty for child migrants that is not in fact evident within any ethnicity group. Second, the migrant wage penalty in the UK appears to be linked to the circumstances of those who arrive as adults, such as the transferability of their qualifications, their language skills and the recognition of their experience, rather than to being foreign-born as such. This suggests that policies improving the recognition of foreign qualifications and supporting language acquisition among adult migrants, and among those who arrive in their early teens, are likely to be especially relevant for closing migrant wage gaps.

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The Kids are Alright: Child Migrants and Wage Gaps within Gender and Ethnicity Groups in the UK

Online Appendix

Appendix A. Further description of the data

TABLE A1: Estimation samples by year, gender and country of birth (Figure 1)

	UK-born				Foreign-born				Raw gap
Year	*N*	Mean log hourly pay	Mean hourly pay (£)	Mean age	*N*	Mean log hourly pay	Mean hourly pay (£)	Mean age	in mean log pay
Men									
2012	33,019	2.440	12.73	41.7	4,753	2.372	11.98	39.1	−0.068
2013	32,946	2.456	12.97	41.9	4,831	2.380	12.09	39.5	−0.076
2014	32,791	2.470	13.15	41.9	5,279	2.387	12.16	39.4	−0.083
2015	31,912	2.480	13.27	41.9	5,104	2.393	12.20	39.9	−0.088
2016	28,679	2.496	13.40	42.0	5,099	2.424	12.57	39.8	−0.072
2017	29,533	2.521	13.64	42.2	5,090	2.464	12.92	40.0	−0.058
2018	28,250	2.551	13.99	42.2	4,877	2.483	13.15	40.3	−0.068
2019	26,845	2.583	14.49	42.2	4,732	2.537	13.86	40.5	−0.046
Women									
2012	35,722	2.289	11.10	41.6	4,492	2.308	11.38	39.4	0.019
2013	35,393	2.305	11.31	41.7	4,750	2.309	11.41	39.6	0.004
2014	35,036	2.326	11.57	41.9	5,048	2.329	11.63	39.6	0.003
2015	33,666	2.343	11.76	42.0	5,118	2.329	11.64	39.7	−0.014
2016	30,822	2.366	11.93	42.1	4,921	2.332	11.53	39.5	−0.034
2017	31,493	2.397	12.26	42.3	5,284	2.379	12.05	39.9	−0.018
2018	30,335	2.431	12.60	42.4	5,129	2.416	12.41	40.4	−0.016
2019	29,064	2.463	13.04	42.5	5,092	2.459	12.93	40.1	−0.003

Notes: Employees aged 16–64 in the estimation samples of Equation (1), APS 2012–19, unweighted, after trimming the top and bottom 0.5% of log hourly pay in each year-gender sample. Hourly pay is in nominal terms. The raw gap is the foreign-born minus the UK-born mean of log hourly pay, before any controls.

TABLE A2: Estimation samples by gender, ethnicity and country of birth, all foreign-born (Figure 2A)

	UK-born			Foreign-born			Raw gap
	N	Mean log hourly pay	Mean age	*N*	Mean log hourly pay	Mean age	in mean log pay
Men							
White	235,916	2.498	42.2	21,367	2.450	38.7	−0.047
Indian	2,087	2.537	35.6	4,921	2.535	42.0	−0.003
Pakistani	1,341	2.379	32.4	2,121	2.280	39.6	−0.099
Bangladeshi	357	2.307	30.2	1,055	2.163	40.1	−0.144
Chinese	282	2.528	35.3	707	2.529	40.0	0.001
Black	1,581	2.478	40.0	3,693	2.371	41.9	−0.107
Women							
White	252,240	2.359	42.3	23,433	2.368	38.9	0.009
Indian	2,186	2.467	35.4	3,884	2.416	42.1	−0.051
Pakistani	1,268	2.282	32.3	983	2.226	39.2	−0.056
Bangladeshi	332	2.294	29.5	391	2.263	37.9	−0.031
Chinese	236	2.493	34.4	979	2.430	40.3	−0.063
Black	2,400	2.473	40.9	4,449	2.321	41.7	−0.151

Notes: Employees aged 16–64 in the estimation samples of Equation (2), APS 2012–19, pooled and unweighted. The raw gap is the foreign-born minus the UK-born mean of log hourly pay, before any controls.

TABLE A3: Estimation samples by gender, ethnicity and country of birth, foreign-born who arrived aged 0–15 (Figure 2B)

	UK-born			Foreign-born			Raw gap
	N	Mean log hourly pay	Mean age	*N*	Mean log hourly pay	Mean age	in mean log pay
Men							
White	236,062	2.498	42.2	4,911	2.529	41.0	0.030
Indian	2,094	2.539	35.6	922	2.530	47.8	−0.009
Pakistani	1,342	2.377	32.4	501	2.372	41.1	−0.005
Bangladeshi	360	2.301	30.3	395	2.285	38.7	−0.016
Chinese	279	2.546	35.4	150	2.506	37.5	−0.040
Black	1,586	2.481	40.0	615	2.403	38.3	−0.077
Women							
White	252,272	2.359	42.3	5,054	2.400	40.9	0.040
Indian	2,194	2.468	35.4	808	2.416	46.8	−0.052
Pakistani	1,267	2.283	32.3	365	2.268	38.0	−0.015
Bangladeshi	332	2.294	29.5	186	2.339	37.3	0.045
Chinese	237	2.484	34.4	160	2.336	36.9	−0.148
Black	2,402	2.474	40.9	837	2.346	38.7	−0.128

Notes: As Table A2, but excluding foreign-born employees who arrived in the UK aged 16 or older. UK-born sample sizes differ slightly from Table A2 because the trimming of log hourly pay is applied within each estimation sample.

TABLE A4: Years since arrival of foreign-born employees, by gender and ethnicity

		Share with years since arrival:					Median years
	N	0–4	5–9	10–14	15–19	20+	since arrival
Men							
White	21,367	0.20	0.24	0.19	0.08	0.28	11
Indian	4,921	0.16	0.21	0.24	0.10	0.29	12
Pakistani	2,121	0.13	0.21	0.23	0.12	0.31	13
Bangladeshi	1,055	0.10	0.13	0.18	0.14	0.45	18
Chinese	707	0.12	0.15	0.24	0.15	0.34	14
Black	3,693	0.10	0.19	0.26	0.20	0.25	14
Women							
White	23,433	0.17	0.24	0.20	0.09	0.30	11
Indian	3,884	0.11	0.19	0.23	0.11	0.36	14
Pakistani	983	0.07	0.17	0.14	0.16	0.46	18
Bangladeshi	391	0.05	0.16	0.10	0.13	0.57	23
Chinese	979	0.10	0.18	0.24	0.17	0.31	14
Black	4,449	0.08	0.16	0.28	0.22	0.28	14

Notes: See Table 1. Shares sum to one within each row.

Appendix B. Additional results

TABLE B1: Foreign-born wage penalty by year and gender (Figure 1)

	Men			Women		
Year	Estimate	95% CI	N	Estimate	95% CI	N
2012	-0.126^{***} (0.007)	[-0.139, -0.112]	37,772	-0.085^{***} (0.007)	[-0.099, -0.071]	40,214
2013	-0.126^{***} (0.007)	[-0.139, -0.113]	37,777	-0.081^{***} (0.007)	[-0.095, -0.067]	40,143
2014	-0.130^{***} (0.006)	[-0.142, -0.117]	38,070	-0.089^{***} (0.007)	[-0.103, -0.076]	40,084
2015	-0.127^{***} (0.007)	[-0.139, -0.114]	37,016	-0.103^{***} (0.007)	[-0.117, -0.090]	38,784
2016	-0.119^{***} (0.007)	[-0.132, -0.106]	33,778	-0.104^{***} (0.007)	[-0.117, -0.090]	35,743
2017	-0.102^{***} (0.006)	[-0.114, -0.089]	34,623	-0.090^{***} (0.007)	[-0.102, -0.077]	36,777
2018	-0.115^{***} (0.006)	[-0.128, -0.102]	33,127	-0.090^{***} (0.006)	[-0.102, -0.077]	35,464
2019	-0.089^{***} (0.006)	[-0.101, -0.076]	31,577	-0.072^{***} (0.006)	[-0.085, -0.059]	34,156
2020	-0.074^{***} (0.008)	[-0.091, -0.058]	22,307	-0.064^{***} (0.009)	[-0.080, -0.047]	24,207
2021	-0.063^{***} (0.007)	[-0.077, -0.048]	23,037	-0.059^{***} (0.008)	[-0.074, -0.044]	24,889
2022	-0.053^{***} (0.007)	[-0.067, -0.038]	20,283	-0.053^{***} (0.008)	[-0.068, -0.038]	21,919
2023	-0.072^{***} (0.008)	[-0.088, -0.055]	15,297	-0.070^{***} (0.008)	[-0.086, -0.054]	16,443

Notes: Coefficients on the foreign-born indicator, β_t, from Equation (1), estimated separately by year and gender. 2012–19 is the main sample period; estimates for 2020–23 are shown for comparison (see Section 4.4). Robust standard errors in parentheses. $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$.

TABLE B2: Foreign-born wage penalty within gender–ethnicity groups, all foreign-born (Figure 2A)

	Men			Women		
Group	Estimate	(s.e.)	N	Estimate	(s.e.)	N
All (pooled)	−0.117***	(0.002)	283,710	−0.089***	(0.002)	301,355
White	−0.075***	(0.003)	257,283	−0.071***	(0.003)	275,673
Indian	−0.048***	(0.011)	7,008	−0.107***	(0.013)	6,070
Pakistani	−0.146***	(0.015)	3,462	−0.091***	(0.020)	2,251
Bangladeshi	−0.149***	(0.030)	1,412	−0.114**	(0.038)	723
Chinese	−0.016	(0.028)	989	−0.050	(0.031)	1,215
Black	−0.135***	(0.012)	5,274	−0.131***	(0.011)	6,849
Non-white	−0.098***	(0.007)	18,154	−0.100***	(0.007)	17,108

Notes: Coefficients on the foreign-born indicator, β^{ge} from Equation (2), estimated separately for each gender and ethnicity group, pooling 2012–19. N is the number of employee observations (UK-born and foreign-born) in each regression. 'Non-white' pools all ethnicity groups other than white. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE B3: Foreign-born wage penalty within gender–ethnicity groups, foreign-born who arrived aged 0–15 (Figure 2B)

	Men			Women		
Group	Estimate	(s.e.)	N	Estimate	(s.e.)	N
All (pooled)	−0.037***	(0.004)	252,542	−0.027***	(0.005)	269,812
White	0.000	(0.006)	240,973	−0.012*	(0.006)	257,326
Indian	−0.016	(0.020)	3,016	0.002	(0.022)	3,002
Pakistani	−0.031	(0.022)	1,843	−0.010	(0.025)	1,632
Bangladeshi	0.009	(0.039)	755	−0.028	(0.044)	518
Chinese	−0.009	(0.041)	429	−0.070	(0.047)	397
Black	−0.015	(0.020)	2,201	−0.034*	(0.017)	3,239
Non-white	−0.037***	(0.010)	8,245	−0.029**	(0.010)	8,785

Notes: As Table B2, but excluding foreign-born employees who arrived in the UK aged 16 or older. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE B4: Conditional foreign-born wage-gap convergence with years in the UK before and after age 16 – Men (Figure 4)

	White	Indian	Pakistani	Bangladeshi	Chinese	Black
Foreign-born	−0.0775***	−0.0345**	−0.1350***	−0.1570***	−0.0178	−0.1400***
	(0.0029)	(0.0110)	(0.0159)	(0.0300)	(0.0291)	(0.0121)
Years in UK before age 16	0.0042***	0.0033	0.0094***	0.0196***	0.0057	0.0087***
	(0.0006)	(0.0018)	(0.0022)	(0.0031)	(0.0037)	(0.0024)
Years in UK from age 16	0.0025***	0.0043***	0.0053***	0.0040*	0.0000	0.0069***
	(0.0003)	(0.0008)	(0.0013)	(0.0018)	(0.0020)	(0.0008)
N	257,283	7,008	3,462	1,412	989	5,274
R^2	0.277	0.310	0.348	0.338	0.399	0.231

Notes: Estimates of Equation (3), by ethnicity group, pooling 2012–19. Years in the UK before and after age 16 are demeaned among the foreign-born and set to zero for the UK-born, so the foreign-born coefficient is the gap at the mean years of each. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE B5: Conditional foreign-born wage-gap convergence with years in the UK before and after age 16 – Women (Figure 4)

	White	Indian	Pakistani	Bangladeshi	Chinese	Black
Foreign-born	−0.0735***	−0.1050***	−0.1030***	−0.1110**	−0.0229	−0.1360***
	(0.0030)	(0.0129)	(0.0205)	(0.0400)	(0.0333)	(0.0105)
Years in UK before age 16	0.0017**	0.0136***	0.0130***	0.0077	−0.0050	0.0098***
	(0.0006)	(0.0019)	(0.0026)	(0.0042)	(0.0047)	(0.0020)
Years in UK from age 16	0.0036***	0.0008	−0.0018	0.0034	0.0078**	0.0036***
	(0.0003)	(0.0009)	(0.0018)	(0.0037)	(0.0025)	(0.0008)
N	275,673	6,070	2,251	723	1,215	6,849
R^2	0.279	0.269	0.275	0.392	0.273	0.253

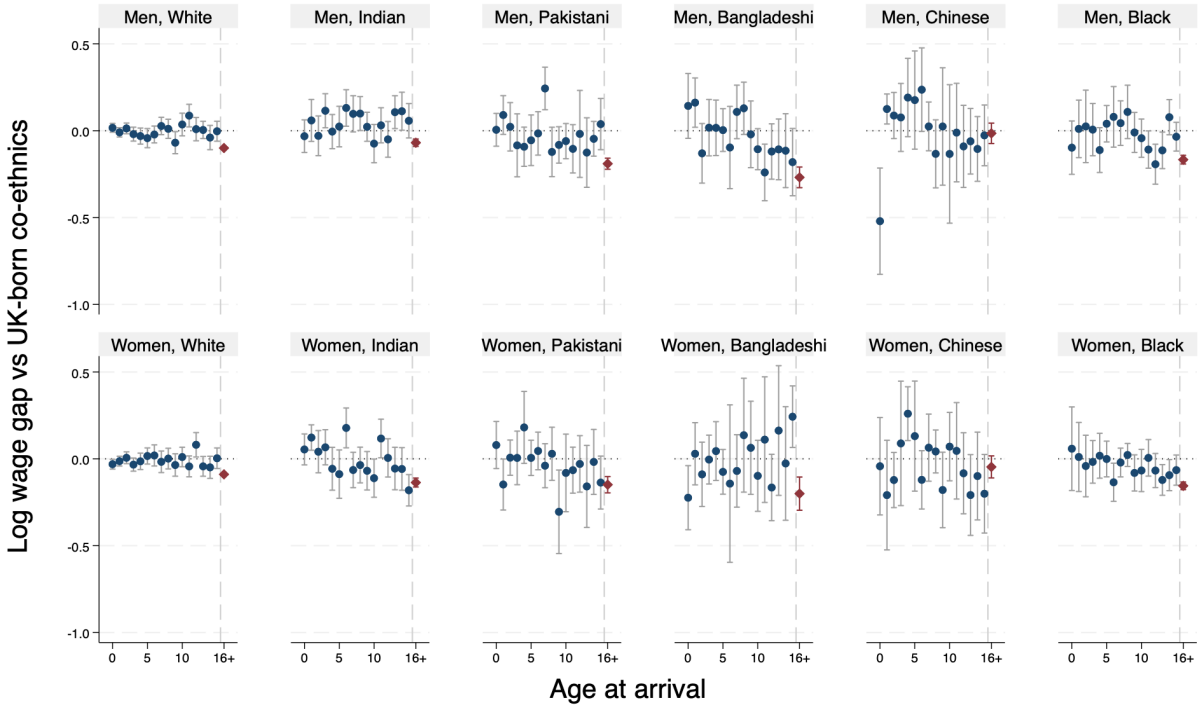
Notes: Estimates of Equation (3), by ethnicity group, pooling 2012–19. Years in the UK before and after age 16 are demeaned among the foreign-born and set to zero for the UK-born, so the foreign-born coefficient is the gap at the mean years of each. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE B6: Unexplained wage gap relative to UK-born co-ethnics, by age-at-arrival band (Figure 5)

	Men						Women					
Age at arrival	White	Indian	Pakistani	Bangladeshi	Chinese	Black	White	Indian	Pakistani	Bangladeshi	Chinese	Black
0–4	−0.001	0.022	−0.009	0.018	0.100*	−0.028	−0.017*	0.055*	0.023	−0.052	−0.038	0.004
	(0.007)	(0.026)	(0.030)	(0.046)	(0.049)	(0.039)	(0.008)	(0.025)	(0.035)	(0.047)	(0.082)	(0.038)
5–9	−0.017	0.070**	−0.036	0.034	0.015	0.048	0.001	−0.002	−0.027	−0.025	−0.051	−0.041
	(0.012)	(0.025)	(0.034)	(0.046)	(0.063)	(0.032)	(0.013)	(0.029)	(0.033)	(0.062)	(0.064)	(0.023)
10–12	0.044*	−0.034	−0.064	−0.156**	−0.079	−0.109**	0.015	−0.002	−0.061	−0.044	−0.011	−0.042
	(0.019)	(0.033)	(0.045)	(0.048)	(0.087)	(0.034)	(0.018)	(0.035)	(0.058)	(0.084)	(0.079)	(0.033)
13–15	−0.012	0.088**	−0.041	−0.138*	−0.062	−0.020	−0.029	−0.099**	−0.077	0.081	−0.167*	−0.091***
	(0.017)	(0.032)	(0.042)	(0.062)	(0.058)	(0.030)	(0.018)	(0.035)	(0.061)	(0.126)	(0.074)	(0.027)
16+	−0.100***	−0.069***	−0.189***	−0.269***	−0.016	−0.167***	−0.089***	−0.135***	−0.149***	−0.205***	−0.046	−0.155***
	(0.003)	(0.011)	(0.016)	(0.030)	(0.030)	(0.013)	(0.003)	(0.013)	(0.024)	(0.048)	(0.032)	(0.011)
N	257,283	7,008	3,462	1,412	989	5,274	275,673	6,070	2,251	723	1,215	6,849

Notes: Estimates of Equation (4), by gender–ethnicity group, pooling 2012–19. The omitted category is UK-born employees of the same gender–ethnicity group. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

FIGURE B1: Unexplained wage gap relative to UK-born co-ethnics, by single year of age at arrival



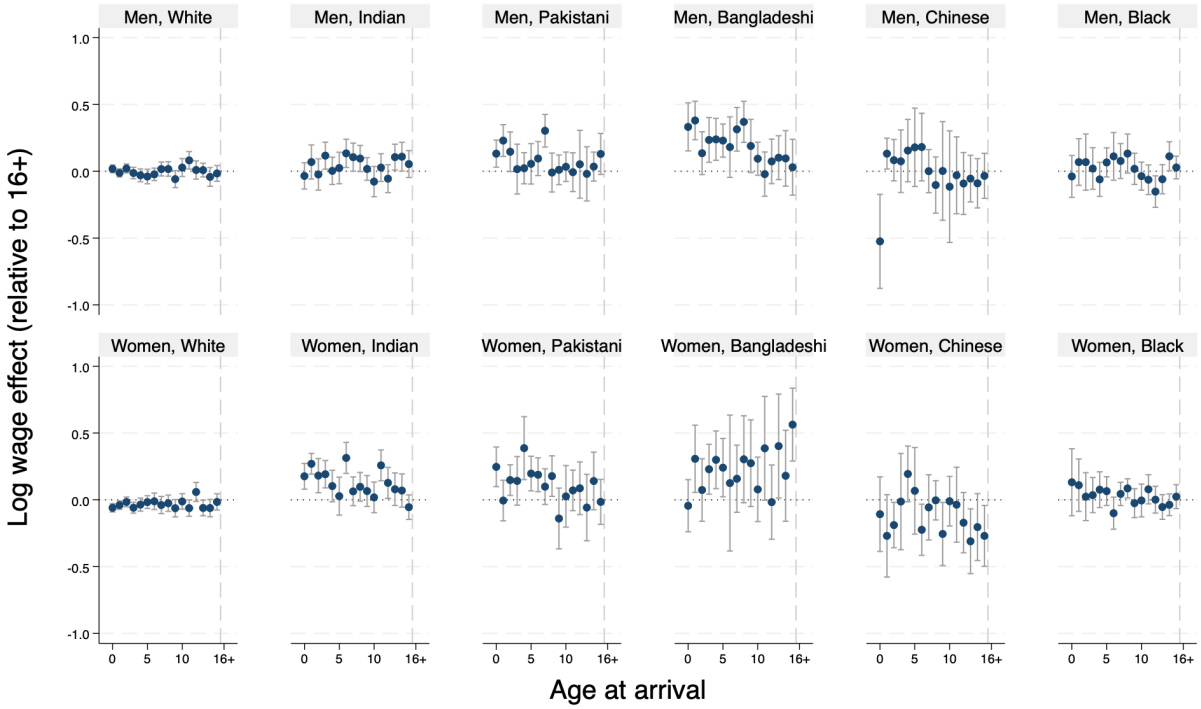
Notes: as Figure 5, but with a separate indicator for each year of age at arrival from 0 to 15; the last point in each panel is arrivals at 16 or older. See Table B7.

TABLE B7: Unexplained wage gap relative to UK-born co-ethnics, by single year of age at arrival (Online Appendix Figure B1)

	Men						Women					
Age at arrival	White	Indian	Pakistani	Bangladeshi	Chinese	Black	White	Indian	Pakistani	Bangladeshi	Chinese	Black
0	0.017	−0.031	0.005	0.143	−0.521***	−0.097	−0.031*	0.054	0.079	−0.224*	−0.042	0.058
	(0.013)	(0.048)	(0.048)	(0.095)	(0.156)	(0.078)	(0.014)	(0.045)	(0.069)	(0.094)	(0.143)	(0.123)
1	−0.009	0.059	0.090	0.162*	0.125**	0.010	−0.013	0.123**	−0.148*	0.029	−0.209	0.011
	(0.014)	(0.062)	(0.057)	(0.072)	(0.044)	(0.085)	(0.014)	(0.037)	(0.075)	(0.091)	(0.161)	(0.102)
2	0.013	−0.029	0.023	−0.130	0.088	0.025	0.006	0.041	0.007	−0.089	−0.122	−0.041
	(0.016)	(0.058)	(0.071)	(0.088)	(0.068)	(0.106)	(0.017)	(0.062)	(0.052)	(0.094)	(0.081)	(0.090)
3	−0.020	0.115*	−0.084	0.018	0.077	0.006	−0.033	0.066	0.005	−0.004	0.089	−0.017
	(0.020)	(0.050)	(0.093)	(0.083)	(0.100)	(0.077)	(0.019)	(0.052)	(0.079)	(0.072)	(0.183)	(0.063)
4	−0.031	−0.005	−0.092	0.017	0.191	−0.111	−0.014	−0.057	0.181	0.045	0.260***	0.018
	(0.024)	(0.050)	(0.058)	(0.081)	(0.115)	(0.066)	(0.024)	(0.063)	(0.106)	(0.086)	(0.079)	(0.066)
5	−0.043	0.024	−0.055	0.004	0.177	0.040	0.016	−0.088	0.006	−0.075	0.131	−0.001
	(0.028)	(0.060)	(0.074)	(0.063)	(0.144)	(0.054)	(0.024)	(0.071)	(0.052)	(0.066)	(0.162)	(0.053)
6	−0.022	0.131*	−0.015	−0.097	0.236	0.080	0.020	0.178**	0.045	−0.143	−0.121	−0.135*
	(0.025)	(0.054)	(0.064)	(0.121)	(0.123)	(0.089)	(0.031)	(0.059)	(0.055)	(0.231)	(0.086)	(0.056)
7	0.027	0.097	0.243***	0.108	0.025	0.044	−0.017	−0.064	−0.040	−0.070	0.064	−0.021
	(0.026)	(0.053)	(0.062)	(0.079)	(0.072)	(0.065)	(0.032)	(0.052)	(0.065)	(0.106)	(0.099)	(0.042)
8	0.011	0.099*	−0.122	0.129	−0.133	0.108	0.001	−0.036	0.029	0.136	0.042	0.022
	(0.028)	(0.050)	(0.073)	(0.077)	(0.100)	(0.079)	(0.030)	(0.053)	(0.078)	(0.167)	(0.063)	(0.034)
9	−0.069*	0.023	−0.082	−0.021	0.025	−0.010	−0.035	−0.069	−0.305*	0.064	−0.179	−0.081
	(0.032)	(0.043)	(0.053)	(0.098)	(0.172)	(0.059)	(0.033)	(0.057)	(0.123)	(0.137)	(0.111)	(0.053)
10	0.036	−0.074	−0.060	−0.106	−0.134	−0.043	0.011	−0.111*	−0.081	−0.098	0.070	−0.067
	(0.033)	(0.056)	(0.052)	(0.060)	(0.203)	(0.056)	(0.029)	(0.056)	(0.114)	(0.104)	(0.100)	(0.062)
11	0.087**	0.031	−0.104	−0.240**	−0.011	−0.108*	−0.043	0.117*	−0.065	0.111	0.046	0.006
	(0.033)	(0.052)	(0.071)	(0.083)	(0.145)	(0.055)	(0.031)	(0.057)	(0.068)	(0.185)	(0.142)	(0.054)
12	0.009	−0.050	−0.018	−0.120	−0.090	−0.193**	0.081*	0.005	−0.029	−0.165	−0.083	−0.067
	(0.034)	(0.052)	(0.128)	(0.081)	(0.121)	(0.059)	(0.036)	(0.056)	(0.083)	(0.098)	(0.119)	(0.050)
13	0.004	0.107*	−0.126	−0.107	−0.061	−0.113*	−0.043	−0.056	−0.159	0.163	−0.208	−0.122**
	(0.025)	(0.048)	(0.102)	(0.089)	(0.096)	(0.054)	(0.029)	(0.062)	(0.121)	(0.190)	(0.119)	(0.045)
14	−0.039	0.112*	−0.047	−0.115	−0.105	0.078	−0.049	−0.058	−0.018	−0.027	−0.099	−0.094*
	(0.036)	(0.056)	(0.051)	(0.109)	(0.095)	(0.052)	(0.032)	(0.063)	(0.095)	(0.167)	(0.129)	(0.046)
15	−0.003	0.057	0.038	−0.181	−0.027	−0.034	0.003	−0.181***	−0.137	0.243**	−0.201	−0.065
	(0.029)	(0.051)	(0.075)	(0.099)	(0.089)	(0.042)	(0.030)	(0.046)	(0.078)	(0.090)	(0.115)	(0.044)
16+	−0.100***	−0.069***	−0.190***	−0.269***	−0.015	−0.167***	−0.089***	−0.137***	−0.149***	−0.200***	−0.047	−0.155***
	(0.003)	(0.011)	(0.016)	(0.030)	(0.030)	(0.013)	(0.003)	(0.013)	(0.024)	(0.049)	(0.032)	(0.011)

Notes: As Table B6, but with a separate indicator for each year of age at arrival from 0 to 15. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

FIGURE B2: Unexplained wage differences by single year of age at arrival relative to arrivals at 16 or older, foreign-born only



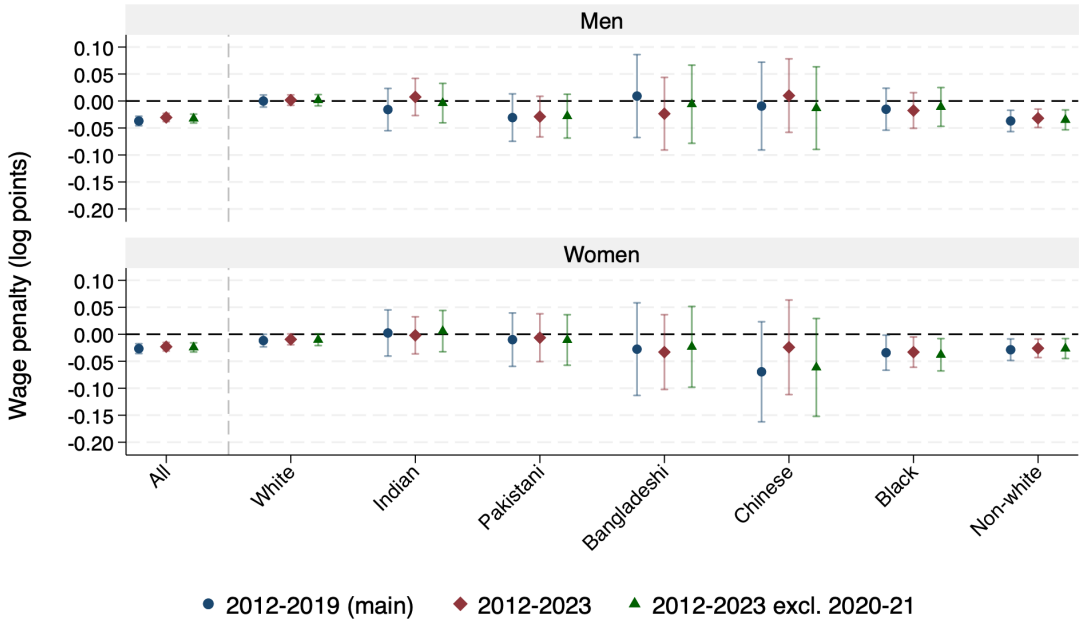
Notes: foreign-born employees only. Coefficients on indicators for each year of age at arrival from 0 to 15, relative to arrivals at 16 or older, controlling for (demeaned) years spent in the UK from age 16, education categories interacted with a quadratic in age, as well as region and year fixed effects, estimated separately by gender–ethnicity group, pooling 2012–19. Bars are 95% confidence intervals using robust standard errors.

TABLE B8: Robustness: Unexplained foreign-born wage gap within gender–ethnicity groups, main and extended samples

	Men			Women		
	2012–19 (main)	2012–23	2012–23 excl. 2020–21	2012–19 (main)	2012–23	2012–23 excl. 2020–21
A. All foreign-born (Figure 2A)						
All (pooled)	−0.117***	−0.106***	−0.111***	−0.089***	−0.082***	−0.086***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White	−0.075***	−0.066***	−0.070***	−0.071***	−0.065***	−0.067***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Indian	−0.048***	−0.044***	−0.047***	−0.107***	−0.101***	−0.101***
	(0.011)	(0.009)	(0.010)	(0.013)	(0.011)	(0.011)
Pakistani	−0.146***	−0.123***	−0.135***	−0.091***	−0.102***	−0.105***
	(0.015)	(0.013)	(0.014)	(0.020)	(0.018)	(0.019)
Bangladeshi	−0.149***	−0.154***	−0.151***	−0.114**	−0.118***	−0.095**
	(0.030)	(0.026)	(0.028)	(0.038)	(0.031)	(0.034)
Chinese	−0.016	−0.019	−0.035	−0.050	−0.020	−0.046
	(0.028)	(0.024)	(0.026)	(0.031)	(0.027)	(0.029)
Black	−0.135***	−0.124***	−0.128***	−0.131***	−0.123***	−0.128***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.009)	(0.010)
Non-white	−0.098***	−0.090***	−0.095***	−0.100***	−0.095***	−0.098***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
B. Foreign-born who arrived aged 0–15 (Figure 2B)						
All (pooled)	−0.037***	−0.031***	−0.033***	−0.027***	−0.023***	−0.024***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
White	0.000	0.002	0.001	−0.012*	−0.009	−0.010
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Indian	−0.016	0.008	−0.004	0.002	−0.002	0.006
	(0.020)	(0.018)	(0.019)	(0.022)	(0.018)	(0.020)
Pakistani	−0.031	−0.029	−0.028	−0.010	−0.006	−0.011
	(0.022)	(0.019)	(0.021)	(0.025)	(0.023)	(0.024)
Bangladeshi	0.009	−0.024	−0.006	−0.028	−0.033	−0.023
	(0.039)	(0.034)	(0.037)	(0.044)	(0.035)	(0.038)
Chinese	−0.009	0.010	−0.013	−0.070	−0.024	−0.061
	(0.041)	(0.035)	(0.039)	(0.047)	(0.045)	(0.046)
Black	−0.015	−0.018	−0.011	−0.034*	−0.033*	−0.038*
	(0.020)	(0.017)	(0.018)	(0.017)	(0.014)	(0.015)
Non-white	−0.037***	−0.032***	−0.035***	−0.029**	−0.026**	−0.026**
	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)

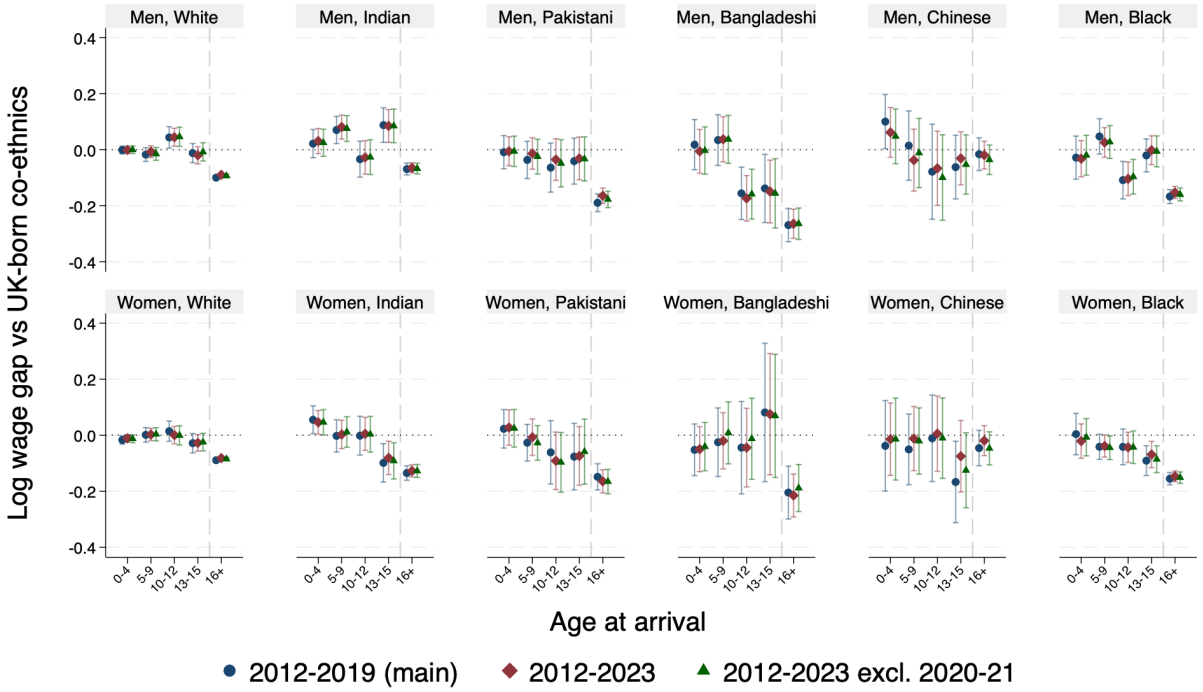
Notes: Coefficient on the foreign-born indicator from Equation (2), estimated separately by gender–ethnicity group on three samples of employees aged 16–64: the main sample (APS 2012–19), the extended sample (2012–23), and the extended sample excluding 2020 and 2021. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

FIGURE B3: Robustness: Unexplained wage gap between foreign-born employees who arrived aged 0–15 and UK-born employees, within gender–ethnicity groups, main and extended samples



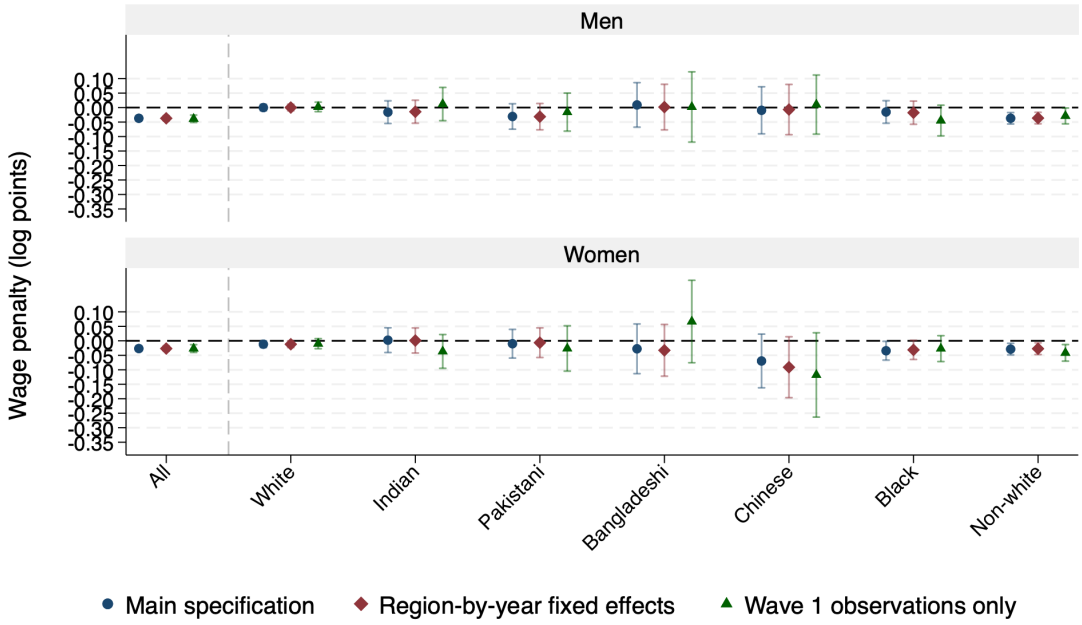
Notes: as Figure 2B, estimated on three samples: APS 2012–19 (main sample), 2012–23, and 2012–23 excluding 2020 and 2021. Bars are 95% confidence intervals using robust standard errors. See Online Appendix Table B8, Panel B.

FIGURE B4: Robustness: Unexplained wage gap relative to UK-born co-ethnics by age at arrival, main and extended samples



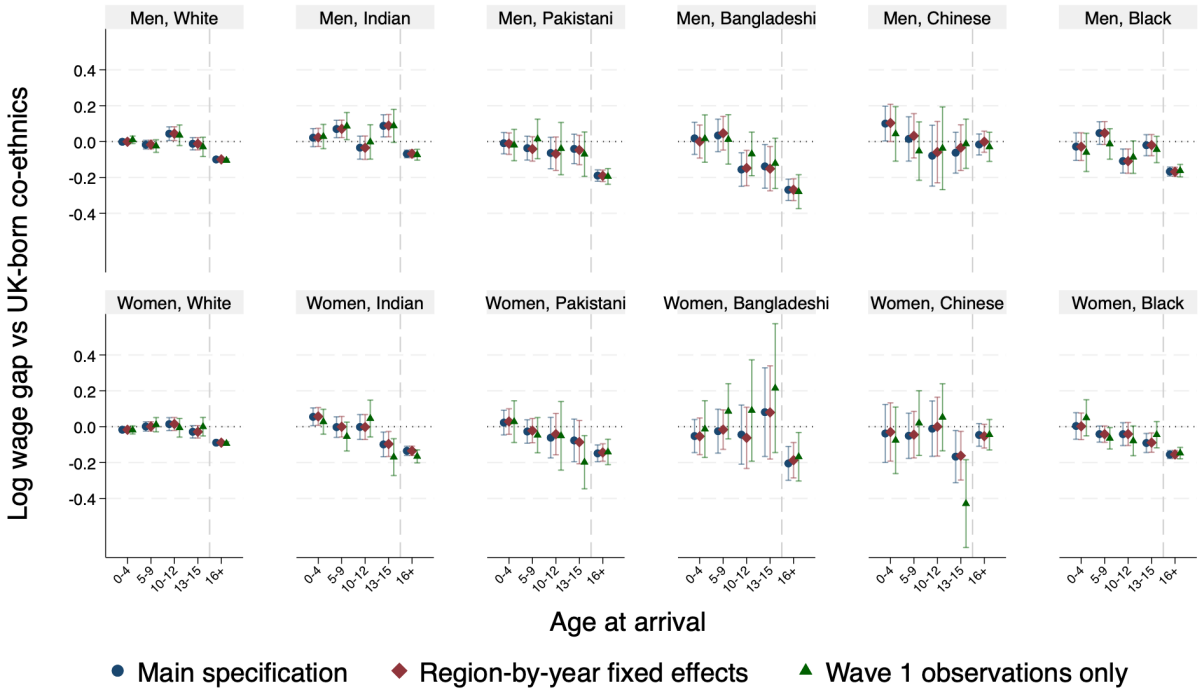
Notes: as Figure 5, estimated on three samples: APS 2012–19 (main sample), 2012–23, and 2012–23 excluding 2020 and 2021. Bars are 95% confidence intervals using robust standard errors.

FIGURE B5: Robustness: Unexplained wage gap for foreign-born employees who arrived aged 0–15, alternative specifications



Notes: as Figure 2B. Main specification; with region-by-year fixed effects; and using only LFS wave 1 observations, so that each individual appears once. APS 2012–19. Bars are 95% confidence intervals using robust standard errors.

FIGURE B6: Robustness: Unexplained wage gap relative to UK-born co-ethnics by age at arrival, alternative specifications



Notes: as Figure 5, for the three specifications described in Online Appendix Figure B5.