1. Background

In France, major progress has been made in child health. For instance, it had an under-5 mortality rate of less than 4‰, which is below the European average of 5‰ in 2018 (UN IGME, 2019). However, children are facing widespread ethnic disparities in mortality depending on certain social categories, such as the origin or socio-professional category of their parents (Barbieri & Toulemon, 2005; Niel, 2011; Wallace et al., 2020).

Numerous studies that have examined whether birth outcomes vary according to parental origin have shown that these outcomes depend on several factors such as the type of indicator used, the country of origin and/or host country (Gagnon et al., 2009). For example, excess infant mortality among children of immigrant women from Africa and Asia has been documented in Norway (Kinge & Kornstad, 2013). While an infant mortality advantage was observed among children born to Mexican women in USA (Hummer et al., 2007), Maghrebi women faced a lower risk of Low Birth Weight (LBW) in Belgium (Sow et al., 2019). In addition, in France, excess infant mortality has been documented among children of North African immigrants, although an advantage is observed in terms of health (LBW, preterm birth) for children of the same immigrant group (Florian et al., 2021). More recently, an analysis of reproductive health (preterm birth, unplanned C-section, episiotomy and spontaneous vaginal birth) by migrant origin in Finland showed that this indicator, on which child health may depend, is unfavorable for women from low-income countries (Väisänen et al., 2022).

Despite these advances in research on the health of children according to parental origin, some questions deserve further investigation especially in France where a significant increase in infant mortality rate was observed from 2012 onwards (Claris, 2022; Trinh et al., 2022). To this end, the following research questions were identified: How have the differences in under-5 mortality (U5M) between native-born and immigrant changed from one period to the next, particularly from 2012 onwards? What are the factors driving these gaps?

In line with these research questions, we will test two hypotheses. Based on the cumulative disadvantage theory (DiPrete & Eirich, 2006), we hypothesize that the infant mortality gap between immigrant and native-born will increase from 2012 onwards. This theory suggests that structural inequalities, particularly accumulated socio-economic disadvantages, can have a growing impact on individuals' health, especially vulnerable populations such as immigrants. The rise in infant mortality among children of immigrants may therefore be explained by the convergence of unfavorable economic factors (precarious employment, limited access to healthcare) and the recent increase in the proportion of children born to immigrant parents with at-risk profiles in France (Insee, 2021).

Drawing on the theory of fundamental cause, which argues that social conditions, such as socio-economic status, are the root causes of health inequalities, impacting access to resources such as money, knowledge, and social connections, which, in turn, influence health outcomes across populations (Link & Phelan, 1995), we anticipate that socio-economic status will account for a significant portion of the under-5 mortality gap between immigrant and native-born, although the largest share will be attributable to unobserved factors. These unobserved factors may include a structural discrimination (Krieger, 2012), the prolonged impact of migration-related stress on children's health and other factors, which are not always captured in available data (Powers, 2016; DeSisto et al., 2018; Stanek et al., 2021).

2. Methodology

2.1. Data

We used the French Permanent Demographic Sample (EDP), France's largest socio-demographic panel. It contains individual-level anonymized records on life events from civil registers and censuses. Eligibility for the sample is based on date of birth. Prior to 2004, the sample consists of individuals born on 1-4 October, and from 2004 onwards, of births occurring in the first four days of the first month of each quarter. For our study, we linked the birth and death files between 1990 and 2020. Our sample contains 687,535 births representative of all births in France. The number of deaths under age 5 is 3,024.

2.2. Variables

The outcome variable is a binary variable indicating whether a child died before reaching age 5 or not. The independent variable is the mother's or father's country of birth. Two categories are identified: French-born as native and foreign-born as immigrant. Alongside the independent variable, we adjusted for several other predictor variables. They included the child's sex, multiple birth, region of birth in France, distinguishing between children born in Mainland France and those born in oversea territories., Variables related to parents such as the age of the mother or father at the child's birth, the father's socio-professional category (SPC)[1] grouped as higher (SPC+) vs lower (SPC-) and marital status of parents, indicating whether married or not, were included in the two models, in which the mother's migratory origin was analyzed separately from that of the father. The mother's SPC is not considered due to the poorer quality of this variable, linked in particular to the uncertainty of the "inactive" and "unknown" categories, which are over-represented at the time of childbirth, when many women are on maternity leave (Niel, 2011).

2.3. Statistical analysis

i. Calculation of the U5MR

For this study, we analyze under-5 mortality for birth cohorts from 1990 to 2020, using death data covering the period from 1990 to 2020. We were able to observe birth cohorts up to the age of 5 for birth years 1990 to 2015. Birth cohorts after 2015 have not yet reached the age of 5 by 2020 and are therefore considered truncated. To address the truncated cohorts, we used survival models to estimate under-5 mortality rates (U5MR) accounting for censored data, in order to best incorporate the available information on the truncated cohorts. This methodology allows us to ensure the robustness of our conclusions while integrating the most recent data available.

ii. Segmented regression of an interrupted time series

To conduct our statistical analyses, we first estimate trend change in under-5 mortality rate (U5MR) from 2012 using segmented regression of an interrupted time series, a statistical method for estimating intervention effects (Wagner et al., 2002). We choose 2012 because that's the year when a reversal in infant mortality was detected at the national level. This allows us to study changes in the time series, effectively comparing slopes over time between pre- and post-intervention periods, and assessing whether there

[1] SPC+ includes agriculture, commerce, crafts, management and intermediate professions. Employees, workers, inactive people or people of unknown activity are included in SPC-.

was a discontinuity in outcomes when the intervention began (Wagner et al., 2002; Linden, 2015; Mascha & Sessler, 2019).

A basic segmented linear regression model using aggregated data (See **Appendix** for data structure) for a continuous outcome can be specified as follows:

$$y_t = \beta_0 + \beta_1 * time_t + \beta_2 * intervention_t + \beta_3 * time\_post_t + \varepsilon_t \quad (1)$$

Where

- y_t is the mean of the outcome (U5MR or U5MR gap) in year t which refers to the child's year of birth.
- time is a continuous variable indicating time in year at time t from 2004 (the year in which the sample size was changed), the start of the observation period,
- intervention is an indicator (dummy variable) for time t occurring before (intervention=0) or after (intervention =1) 2012 implemented at year 8 in the series;
- time_post is a continuous variable counting the number of years after the intervention at time t, coded 0 before 2012 and (time-8) after 2012;
- β_0 is the baseline level of the outcome, its mean per year at time 0;
- β_1 is the change in the mean of outcome that occurs with each year before the intervention (i.e. the baseline trend);
- β_2 is the level change in the mean yearly of outcome immediately after the intervention, that is, from the end of the preceding segment;
- β_3 is the change in the trend in the mean yearly outcome after 2012, compared with the yearly trend before 2012;
- The sum of β_1 and β_3 is the post-intervention slope

Using Equation 1, we estimate a change in the temporal trends associated with the year 2012, controlling for baseline level and trend, a major strength of segmented regression analysis (Wagner et al., 2002).

iii. Multivariate decomposition

In the multivariate section, we use the non-linear decomposition method for binary outcome variable. While the decomposition technique was originally applied only to linear models (Oaxaca, 1973; Blinder, 1973), many studies have extended its use to non-linear cases (Fairlie, 1999; Sinning et al., 2008; Arteaga et al., 2017; Lam et al., 2021; Fairlie, 2003, 2005, 2017). In non-linear models, the decomposition essentially consists of determining the difference between the predicted probability for one group using the coefficients of the other group and the predicted probability for that group using its own coefficients (Fairlie, 2017). Thus, following Fairlie (2003, 2005, 2017) and taking the native-born as a reference, the Twofold Oaxaca-Blinder (O-B) decomposition of a non-linear equation $Y = F(X\hat{\beta})$ can be written as follows:

$$\Delta\bar{Y} = \underbrace{\left[\sum_{i=1}^{N^{Na}} \frac{F(X_i^{Na}\widehat{\beta^{Na}})}{N^{Na}} - \sum_{i=1}^{N^{Im}} \frac{F(X_i^{Im}\widehat{\beta^{Na}})}{N^{Im}}\right]}_{Explained\ (EC)} + \underbrace{\left[\sum_{i=1}^{N^{Im}} \frac{F(X_i^{Im}\widehat{\beta^{Na}})}{N^{Im}} - \sum_{i=1}^{N^{Im}} \frac{F(X_i^{Im}\widehat{\beta^{Im}})}{N^{Im}}\right]}_{Unexplained\ (UC)} \quad (2)$$

Where *Y* is probability of dying before age 5, *X* is the average value of the predictors, $\hat{\beta}$ is the logit coefficient estimates, *Im* and *Na* are immigrant and native-born respectively, *F* is the cumulative distribution function from the logistic distribution.

Note that the sum of the contributions of the two components is always equal to 100%. Nevertheless, a component can have a negative contribution or a contribution greater than 100%. Thus, whenever the contribution of one component is negative, it is offset by the contribution of the other component which exceeds 100%. The contribution of each component corresponds to the sum of the contributions of each factor. A positive (or negative) coefficient of a factor implies a decrease (respectively an increase) in the mortality gap if the distribution of this risk factor were fixed to that of native-born but the effects of these risk factors among immigrant were unchanged. Here, the “explained” component (EC) corresponds to compositional effects, i.e. differences in mortality between immigrant and native-born that are explained by the different composition by SES and other variables. As far as the unexplained component is concerned, it indicates the part of the difference arising from the difference between the coefficients of the two groups weighted by the vector of average explanatory variables for immigrants. In other words, it indicates the average variation in the immigrant result if they had the coefficients of the native-born, while holding the explanatory variables or characteristics constant (Etezady et al., 2020). It quantifies the variation in the immigrants‘ Y indicator when the native-born coefficients are applied to the immigrants’ characteristics.

Twofold Oaxaca-Blinder (O-B) decomposition (Oaxaca, 1973; Blinder, 1973) of U5M using logit coefficient estimates from pooled sample were implemented. Analysis was performed using the Oaxaca package in Stata. Categorical variables are included as dummy variables (i.e. each categorical variable has been transformed into a set of binary variables). This is a solution proposed by Yun (2005) and widely adopted to address the index problem that may arise in detailed decomposition estimates when using categorical variables. Alongside the variables relating to parents such as the age of the mother or father at the child's birth, the father's SPC and the marital status of parents, the calendar year variable was introduced into the models to assess variations in the immigrant-native U5M gap from 2012.

3. Results

3.1. Mortality risk factors according to parents' migratory status

Tab 1 shows the distribution of mortality risk factors such as infant sex, multiple birth, place of birth, father's SPC, mother and father's age at infant birth and the marital status of parent, according to migration status.

Tab *1:* Covariates distribution according to parents' migratory status

Risk factors	Total	Mother's migratory status (%)		Father's migratory status (%)	
	N = 687,535 (100.00)	Immigrant N =132,581 (20.50)	Native-born N =546,614 (79.50)	Immigrant N = 136,593 (25.66)	Native-born N =517,979 (75.34)
Female (%)	48.85	48.84	48.84	48.91	48.79
Twins (%)	3.24	3.33	3.24	3.22	3.28
Oversea France (%)	4.77	5.58	3.78	3.83	3.57
Father's SPC+ (%)	67.8	66.35	68.82	67.82	71.85
Mean mother's age (SD)	30.00 (5.35)	30.75 (5.75)	29.82 (5.24)	30.50 (5.76)	29.99 (6.02)
Mean father's age (SD)	33.10 (6.45)	36.05 (7.61)	32.39 (5.92)	35.46 (7.42)	32.49 (4.60)
Married parent (%)	44.52	62.08	40.72	62.07	42.48

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

As shown in table 1, children of immigrants are more likely to be born in France's overseas territories, to married parents, or to older fathers compared to children of native-born, whatever the migratory origin of the mother or the father. Conversely, children of native-born mothers or fathers are more likely to have a father in higher SPC.

Tab 2 is the result of the intersection of three variables: migration status, mortality risk factors and U5M. This table shows that immigrant-born has excess U5MR calculated as ‰ dying below age 5, whatever the migratory origin of the mother or the father. However, there is no significant difference between the migratory origins of the father and mother as regards the immigrant-native U5M gap, which will be decomposed in the multivariate section.

Tab 2: U5MR (5q0) according to mortality risk factors and migratory status

	Mother's migratory status		Father's migratory status	
Risk factors	U5MR (‰)		U5MR (‰)	
	Immigrant	Native-born	Immigrant	Native-born
Female	5.65 (5.22-6.42)	3.45 (3.32-3.73)	5.37 (4.81-5.99)	3.25 (3.11-3.57)
Twins	20.37(16.59- 25.12)	17.11 (15.33-19.13)	19.46 (15.67-24.12)	16.32 (14.54-18.42)
Oversea France	11.45 (9.23-14.19)	9.56 (8.32-10.97)	9.12 (6.79-12.12)	9.82 (8.54-11.44)
Father's SPC+	5.77 (5.32-6.44)	3.67 (3.51-3.87)	5.49 (5.12-5.99)	3.78 (3.56-3.97)
Married parent	5.63 (5.10-6.11)	3.60 (3.42-6.07)	5.66 (5.21-6.18)	3.62 (3.33-3.88)
TOTAL	6.12 (5.71-6.58)	4.14 (3.96-4.33)	5.77 (5.43-6.22)	3.91 (3.74-4.10)

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

A bivariate analysis of under-five mortality (U5M) and associated risk factors according to migratory status reveals major disparities, largely favoring native mothers and fathers. These disparities are particularly evident in relation to the child's sex, the father's socio-professional category (SPC) and the parents' marital status. For example, the infant mortality rate for female children born to immigrant mothers is close to 6 ‰ whereas the same rate is almost 4‰ for children born to native mothers. If we consider the father's CSP, children born to an immigrant father with a higher CSP have a mortality rate of almost 6‰ while their counterparts born to native fathers with the same level of CSP have a rate of 4‰.

3.2. Segmented regression of an interrupted time

Tab 3 contains the parameter estimates from the linear segmented regression model of effects of the year 2012 on yearly U5MR and U5MR immigrant-native gap using mother's origin.

Tab 3: Segmented regression of an interrupted time using mother's origin

Parameters	Immigrant Estimates (95% CI)	SE	Native-born Estimates (95% CI)	SE	U5MR gap Estimates (95% CI)	SE
intercept, β_0	6.15*** (2.86 - 9.44)	1.52	4.14***(3.83- 4.46)	0.14	2.01 (-1.50- 5.51)	1.62
time, β_1	-0.01 (-0.62- 0.60)	0.28	-0.03(-0.14- 0.09)	0.05	0.02 (-0.66 -0.69)	0.31
intervention, β_2	-0.66 (-2.97- 1.64)	1.07	-0.04(-0.88- 0.80)	0.39	-0.62 (-3.15- 1.91)	1.17
time_post, β_3	0.15 (-0.53- 0.84)	0.32	0.01 (-0.12- 0.14)	0.06	0.15 (-0.56- 0.85)	0.33
β_1 + β_3	0.14 (-0.14- 0.43)	0.13	-0.02 (-0.11- 0.07)	0.04	0.16 (-0.04- 0.36)	0.09

Note: time= years since start of study (1–7 preintervention and 8–16 postintervention), intervention: 0 for preintervention, 1 for post, time_post: equals 0 in preintervention period and starts at 1 for first year in postintervention. ***=p<0.001, *SE*=Standard Error.

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

Our results indicate that just before the beginning of the observation period, immigrants exhibit an U5MR of 6‰ while that of native-born is 4‰, a gap of 2‰ between the two groups per year. Prior to 2012, there were no significant year-to-year changes in the under-five mortality rate for either group. Similarly, after 2012, no significant changes were observed, either in the annual levels or the trends in U5MR for both groups.

When using father's origin, it should be noted that the year-to-year trend in U5MR for immigrant increased by 0.4. The same applies to the U5MR Immigrant-native gap, where the year-to-year trend increased by 0.5. Furthermore, while the post-intervention slope also increased by 0.4 (β_1 + β_3) for immigrants, there was not a change in the post-intervention slope for native between the pre- and post-2012 periods.

Tab *4:* Segmented regression of an interrupted time using father's origin

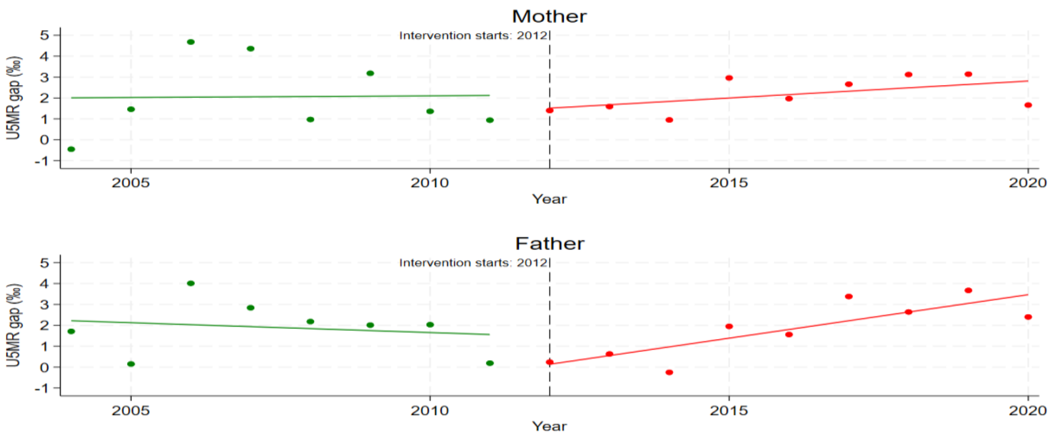
Parameters	Immigrant Estimates (95% CI)	SE	Native-born Estimates (95% CI)	SE	U5MR gap Estimates (95% CI)	SE
intercept, β_0	5.83*** (4.12- 7.54)	0.79	3.61*** (3.24- 3.99)	0.17	2.22* (0.17- 4.26)	0.95
time, β_1	-0.05 (-0.38- 0.27)	0.15	0.04 (-0.08- 0.16)	0.06	-0.10 (-0.52- 0.33)	0.20
intervention, β_2	-1.14 (-2.67- 0.38)	0.71	0.19 (-0.07- 1.09)	0.42	-1.33 (-3.32- 0.66)	0.92
time_post, β_3	0.40* (0.33- 0.52)	0.20	-0.11 (-0.25- 0.03)	0.17	0.51* (0.10- 0.97)	0.21
β_1 + β_3	0.35* (0.08- 0.61)	0.12	-0.07 (-0.17- 0.03)	0.05	0.42***(0.23-0.60)	0.10

Note: ***p<0.001; *p<0.05.

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

The unadjusted change in the immigrant-native U5M gap can be visualized in figure 1, which shows different trends depending on whether the mother's or father's origin is used. From 2004, the graph shows a downward trend to 2011, some stability 2011-2014 for mother’s origin only, and then an upward trend from 2015 (except perhaps in 2020) for the origin of the mother and father (for which the increase had already begun well before 2015).

Fig 1: Trend in immigrant-native gap in U5MR using the linear segmented regression of an interrupted time



Note: Data from 2004, the year in which the sample size was changed are used here to avoid erratic trends before this year

Source: Authors’ calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

3.3. Twofold O-B decomposition of under-5 mortality

Tab 5 displays results of the multivariate decomposition using the mother’s and father’s migratory status. Estimates are presented per 10,000 live births, instead of 1,000 live births given the small numbers from 1990 to 2020.

Tab *5 :* O-B decomposition of immigrant-native gap in U5M per 10,000 births

Difference	Mother’s migratory status		Father’s migratory status	
	Estimate (95% CI)	Percent Contribution	Estimate (95% CI)	Percent Contribution
Raw Difference	19.77 (14.98-24.56)	100.00	18.07 (13.43-22.71)	100.00
Explained (EC): Due to difference in characteristics	2.31 (0.51-4.12)	11.69	1.27 (-0.26-2.80)	7.03
Unexplained (UC): Due to other differences	17.46 (12.44-22.47)	88.31	16.80 (11.93-21.66)	92.97

Source : Authors’ calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

The results show that the average excess U5M among immigrant is around 20 per 10,000 live births when the mother's origin is used, compared with 18 when the father's origin is used. The confidence intervals of these two estimates overlap demonstrating no significant differences by mother's or father's origins. Only a small part of the disparities is explained by the composition or endowment effect, the major part being explained by factors not considered (unexplained components).

Comparing two cohort groups (2004-2011 and 2012-2020), as shown in tab 6, the results indicate that before 2012, the differences in mortality were due solely to unexplained components (UC). From 2012 onwards, the contribution of UC has decreased in favour of explained components (EC), which are also significant and still substantial. This result suggests that the differences in mortality gap between these two periods are due to the composition effect.

Tab *6: O-B decomposition of immigrant-native gap in U5M, 2004-2011 & 2012-2020*

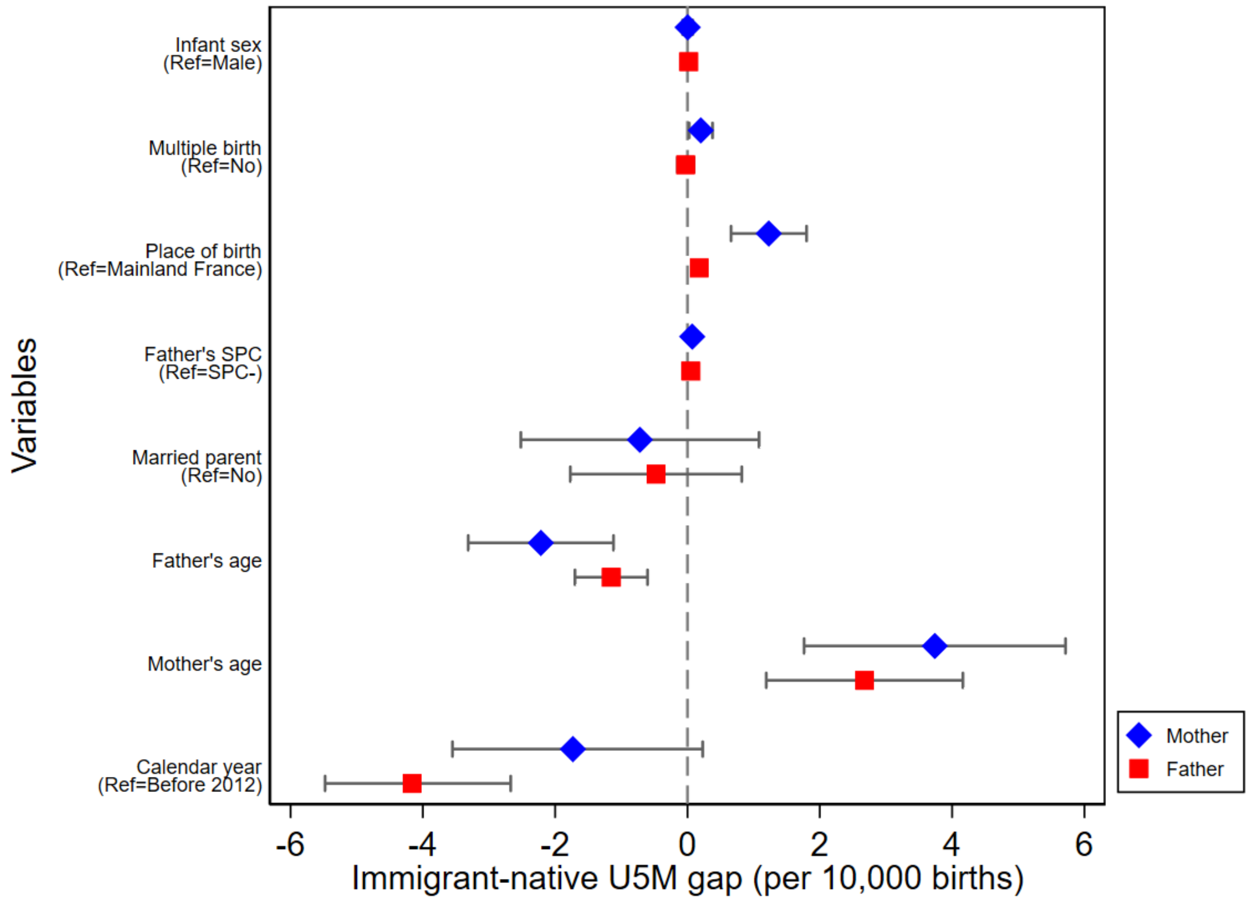
	Mother's migratory status				Father's migratory status			
	EC	%	UC	%	EC	%	UC	%
2004-2011	-0.20 (-2.74-2.33)	-1.20	17.08*** (8.71-25.46)	101.20	-1.08 (-3.41-1.25)	-7.00	16.51*** (8.38-24.64)	107.00
2012-2020	3.73 * (0.88-6.58)	16.67	18.64*** (11.85-25.43)	83.33	2.50* (0.19-4.80)	13.11	16.53*** (9.97-23.10)	86.89

Note: 95% CIs are in parentheses: ***p<0.001; *p<0.05.

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

A more detailed decomposition of the two models in which estimates are presented per 10,000 live births is shown in the figure 2.

Fig 2: Detailed contribution of the endowment effect to the immigrant-native U5M gap



Note: The horizontal dashed lines portray the 95% confidence interval. Mother indicates model using the mother's migratory origin and father for model using father's migratory origin Reading: Positive value indicates positive effect on survival of the child born to an immigrant.

Source: Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.

The graph indicates that being a twin, being born in Overseas France, or having a father with a higher SPC is associated with child survival, thereby contributing to the disparities between immigrant and native-born. The calendar year exhibits a significant negative impact when the father is an immigrant, reflecting the increasing trend in U5M disparities according to father's origin from 2012, as previously highlighted in segmented regression of an interrupted time. As for the father's age, the more detrimental to survival is the immigrant origin. Unlike paternal age, maternal age has a positive impact on survival of immigrants' children. For instance, if we focus on the model using mother's migratory origin, these disparities would decrease by around 4 deaths per 10,000 live births. Based on the father's SPC, we note that equalizing it, i.e. increasing it to match that of native-born, decreases the disparities between the two groups by 0.1 deaths of children under five per 10,000 live births. As a reminder, immigrants are less represented in the higher socio-professional categories.

4. Discussion

Health disparities, particularly in under-5 mortality, remain a persistent challenge across various populations. While previous studies have documented a reduction in social inequalities in infant mortality in France between 1978 and 1998 (Barbieri & Toulemon, 2005), our findings reveal a contrasting trend beginning in 2012. Specifically, we observe a significant rise in mortality inequalities among children under 5, which supports our first hypothesis (H_1). This trend also corresponds with studies suggesting a deterioration in the health status of immigrants during the 2000s, reversing earlier improvements observed in the 1980s and 1990s (Dourgnon et al., 2008).

A number of explanations can be proposed to explain this result. As the comparative analysis of two cohort groups shows, there is a composition effect that could explain these results. The composition effect suggests a change in the composition of the immigrant population over time, with a greater proportion of risk groups with low SES and more African immigrants in the immigrant population...

However, this result does not call into question the effect of discrimination in these mortality inequalities, as shown by the greater contribution of the unexplained component in all our results. As indicated by Bazen et al. (2016), this unexplained component measures part of the discrimination even if Bartus (2006) and Rahimi & Hashemi Nazari (2021) call for caution in such an interpretation, given the small number of explanatory variables introduced into the models. While the residual method allows for an estimation of unobserved factors, it is important to recognize its limitations, as it cannot definitively distinguish between true discrimination and other unmeasured variables (Fortin et al., 2011) such as behavioral or contextual factor (The mother's state of health on arrival, her level of education, her eating and smoking habits, the number of births, access to care, monitoring of pregnancy and the first year of life by the health services, language barriers, cultural differences, endogamy in certain immigrant communities, etc.). Numerous ethnographic studies in France have documented discrimination against women of foreign origin in hospitals at gynecological and prenatal consultations and during or after childbirth (Fassin, 2000; Ouanhnon et al., 2022). This may contribute to the immigrant-native gap, as there is evidence linking discrimination and infant mortality across the world.

Indeed, racial discrimination or discrimination linked to migratory origin can affect children health through several mechanisms. It has been shown to, via the psychological stress and immunodepression it engenders, stimulate the production of corticotropin-releasing hormone in the placenta, which in turn may increase the risk of preterm delivery (Rich-Edwards et al., 2001). Also, discrimination in hospitals can exacerbate tensions during prenatal or postnatal consultations, leading to renouncing in pregnancy care and thus have a negative impact on pregnancy follow-up. Finally, risky behaviors (smoking, alcohol and psychoactive substance use, etc.) during pregnancy may be a response to the chronic stress generated by racial discrimination (Brondolo et al., 2009). Increased preterm births, high levels of LBW and poor gestational age outcomes are common among women who have experienced discrimination (Rich-Edwards et al., 2001; Mustillo et al., 2004; Giurgescu et al., 2011; Daalen et al., 2022). Risk behaviors and prematurity, LBW, and gestational age are important predictors of infant mortality (Evans & Alberman, 1989; Farré, 2016; Reichman & Teitler, 2006; Štípková, 2016; Ballon et al., 2019; Kihal-Talantikite et al., 2019).

The increase in inequality can also be explained by the implementation of successive immigration-related reforms. For example, the 1980s and 1990s were marked by the implementation of an integration policy, which was followed by a series of reforms to the right to citizenship in 1993, then in 1998, in 2003, in 2006, and again in 2011 (Duclos-Grisier, 2022a). These various reforms have profoundly reshaped the French legislative landscape in terms of the reception and integration of foreigners (Safon, 2018) and are said to have become stricter over time (Duclos-Grisier, 2022b). It is therefore possible to think that integration measures beneficial to immigrants until the late 1990s and less so after had an impact on the integration of immigrants and on their health and that of their children. In fact, some studies that have examined the link between migration policies and immigrant health supports this hypothesis. The findings of Juárez et al. (2019) in many European countries, including France, are illustrative of the link between restrictive entry policies and the deterioration of immigrants' mental health and perceived health, as well as of the reinforcement of health disparities among children of immigrant families following changes in immigration policy (Mendoza, 2009).

Our results indicating that the composition effect plays a minor role in explaining U5M immigrant-native disparities, consistent with previous studies, supports our second hypothesis (H_2). Examples include LBW gap between native-born and immigrant (African and Latin American) in Spain (Stanek et al., 2021), differences in preterm births between African-American and foreign-born black women (DeSisto et al., 2018), or infant mortality gap between women of Mexican-origin and non-Hispanic whites at higher maternal ages in U.S. (Powers, 2016).

Another result of this research is the important contribution of mother's age and father's age at the child's birth. This result provides further support for what is now a classic finding in infant mortality namely that paternal age is as significant as maternal age, when it comes to reproductive issues and infant health (Spiers, 1972; Janeczko et al., 2020). The contradictory effects of these two variables may be attributed to the biological effects of age. However, it cannot be excluded that age is correlated with social differences that cannot be captured by SPC.

Conclusion

Overall, we conclude that the migratory origin of the mother and father, like other parental characteristics, is a very important factor in child survival. A time decomposition of the increase in U5MR between two time periods among immigrants allows us to conclude that the increase in immigrant-native U5MR gap is due to a change in the composition of the immigrant group over time.

Our study also has some limitations. Like any statistical method, the O-B decomposition has some weaknesses. In addition to the so-called identification and the index problems which affects the estimates of the detailed decomposition (Lam et al., 2021; Horiuchi et al., 2008; Yun, 2005; Rahimi & Hashemi Nazari, 2021), there are difficulties in interpreting its results. Another limitation is that the method is constrained to two groups. Immigrants are a highly heterogeneous group, and lumping them together into one broad category may hide important disparities.

Despite its limitations, this research has a number of strengths. It is the first to estimate the contributions of individual variables to under-5 mortality of foreign-born women compared to French-born women. While some studies have attempted to explain these disparities using regression-based approaches, we have quantified the level and direction of contributions of unobserved factors. The O-B decomposition uses and extends the regression results to estimate the contribution of each individual variable. Our results add to the literature on the decomposition method by comparing birth cohorts over time and more importantly, highlighting how the immigrants-native gap has changed over time.

Although the factors associated with mortality disparities, such as parents' age, are not modifiable, the implementation of certain measures in relation to the health system and its actors, which are presumably forming most of the unobserved characteristics related to child health, can be successful in reducing inequalities in infant mortality.

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Appendix

Tab A-1: Structure of data for analysis of the impact of the year 2012 changes on U5MR

Observation	Year	U5MR_Na_f	U5MR_Im_f	Diff_f	U5MR_Na_m	U5MR_Im_m	Diff_m	time (year)	intervention (year 2012)	time_post
1	2004	3.62	5.33	1.71	4.32	3.87	-0.45	1	0	0
2	2005	4.09	4.24	0.15	4.13	5.59	1.46	2	0	0
3	2006	3.32	7.33	4.01	3.77	8.45	4.68	3	0	0
4	2007	3.79	6.63	2.84	4.31	8.67	4.36	4	0	0
5	2008	3.71	5.89	2.18	4.22	5.19	0.97	5	0	0
6	2009	3.62	5.63	2.01	3.58	6.76	3.18	6	0	0
7	2010	3.44	5.47	2.03	3.66	5.02	1.36	7	0	0
8	2011	4.47	4.66	0.19	4.44	5.38	0.94	8	0	0
9	2012	3.87	4.11	0.24	3.66	5.06	1.4	9	1	1
10	2013	3.97	4.6	0.63	3.88	5.47	1.59	10	1	2
11	2014	3.78	3.53	-0.25	3.57	4.52	0.95	11	1	3
12	2015	4.47	6.42	1.95	4.27	7.23	2.96	12	1	4
13	2016	3.88	5.44	1.56	3.79	5.76	1.97	13	1	5
14	2017	4.09	7.47	3.38	4.31	6.97	2.66	14	1	6
15	2018	3.78	6.42	2.64	3.72	6.84	3.12	15	1	7
16	2019	3.81	7.48	3.67	3.99	7.13	3.14	16	1	8
17	2020	3.04	5.44	2.4	3.22	4.88	1.66	17	1	9

Source : Authors' calculations based upon Permanent Demographic Sample (EDP), 1990–2020.