# Immigration and the distribution of income, consumption and wealth in the euro area: Implications for economic policies<sup>1</sup>

## Online appendix

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This version: February 2024

#### Abstract

We use representative data from household surveys in the euro area to describe differences in wages, income, consumption, wealth and liquid assets between households born in their country of residence ("natives") and those born in other EU and non-EU countries ("immigrants"). The differences in wealth and liquid assets are more substantial than the differences in wages, income and consumption: immigrants earn on average about 30% lower wages than natives and hold roughly 60% less net wealth. For all variables, only a small fraction of differences between natives and immigrants—around 30%—can be explained by differences in demographics (age, gender, marital status, education, occupation, sector of employment). Immigrants are more likely to be liquidity constrained: while we classify 17% of natives as "hand-to-mouth" (they hold liquid assets worth less than two weeks of their income), the corresponding share is 20% for households born in another EU country and 29% for those born outside the EU. Employment rates of immigrants are substantially more sensitive to fluctuations in aggregate employment. We discuss the implications of these findings for economic policies, including monetary, fiscal and pre-distribution policies.

Keywords: migration, inequality, distribution of income and wealth

JEL Codes: J15, D31 , E21, E24

<sup>&</sup>lt;sup>1</sup> First version: March 2022. All opinions expressed are personal and do not necessarily represent the views of the European Central Bank or the European System of Central Banks. This paper uses data from the Eurosystem Household Finance and Consumption Survey.

We thank participants in the Household Finance and Consumption Network research seminar and Niccolò Battistini, Claus Brand, Davide Debortoli, Davide Di Laurea, Virginia Di Nino, Michael Ehrmann, Nicola Fuchs-Schündeln, Johannes Gareis, Dimitris Georgarakos, Michael Haliassos, Arthur Kennickell, Geoff Kenny, Omiros Kouvavas, Luc Laeven, Philip Lane, Michele Lenza, Beatrice Pierluigi, Isabel Schnabel, João Sousa, Oreste Tristani and Guido Wolswijk for comments, and Omiros Kouvavas for sharing his code with us.

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#### Annex 1: Oaxaca–Blinder decomposition

Seminal work of Oaxaca (1973) and Blinder (1973) decomposes differences between groups of households into an observed and an unobserved part. The method divides the group mean difference ( $\mu_1 - \mu_2$ ) into two terms. The first one, commonly known as quantity effect, accounts for differences between the groups in observable characteristics (such as demographic variables). This term reflects that different compositions lead to unequal average outcomes. The second term captures the differences in coefficients, i.e., returns to observable characteristics. Given the same characteristics in individuals belonging to two distinct groups, the effects on the variable of interest are not the same. It is also known as coefficient effect, because it shows differences in returns for the two groups.

We apply the method considering two groups, natives and immigrants denoted by the index *i* = {*N*, *I*}, an outcome variable *Y*, logarithm of income, and a set of explanatory variables *X* containing demographic information like age, educational attainment and marital status. Let  $\mu_i$  denote the unconditional sample mean of group *i*. We want to understand what drives the difference between the means  $\mu_N - \mu_I$ . A positive difference indicates that natives have higher income than immigrants. Denoting the unconditional mean for each group as:  $\mu_i = E(Y_i) = \overline{X_i}\beta_L$ , their difference can be written as:

 $E(Y_N) - E(Y_I) = \left(E(\bar{X}_N) - E(\bar{X}_I)\right)' \beta_N + E(\bar{X}_I)' (\beta_N - \beta_I).$ 

The first term on the right hand side,  $(E(\bar{X}_N) - E(\bar{X}_I))' \beta_N$ , captures disparities in the composition of the underlying population evaluated with the coefficients of the reference group, natives in our analysis. For example, if natives are older than immigrants, according to the life-cycle theory, their earnings should be higher. The second term,  $E(\bar{X}_I)'(\beta_N - \beta_I)$  captures the differences in returns arising from the same set of characteristics. For example, if an additional year of experience has a higher impact on earnings of natives than immigrants, then  $\beta_N > \beta_I$ .

The size of the explained component is given by the first term; the rest of the gap is unexplained. The unexplained part reflects the effect of missing explanatory variables and other factors. In practice it is very hard to account for differences across households with observed characteristics only. This implies that the second, unexplained term is driven by factors, such as differences in preferences, beliefs, norms and cultural factors and discrimination or barriers.

### Annex 2: Additional charts





Chart 3: Age profiles of median gross hourly wages across countries

Sources: EU Statistics on Income and Living Conditions 2009-2018, Italy: 2009-2017. Notes: Hourly wages are calculated for employed individuals aged 18-64 (the self-employed are excluded). Due to data limitations the chart on hourly wages shows data for France, Italy and Spain. All reported numbers are medians.





#### Chart 5: Decompositions across the distribution, percentiles P25, P50 (median), P75

Note: The charts use the method of Chernozhukov et al. (2013) to decompose the gaps between native and immigrant households into a part explained by observable variables and an unobserved part at various quantiles of the distribution of the gaps. The observable variables are age, gender, marital status, education, presence of a child in the household, occupation, the sector of employment, employment dummy, self-employment dummy and time fixed effects. Net wealth and liquid assets were transformed using the inverse hyperbolic transformation (to account for the presence of zero and negative values). The top and bottom 5 percent of values were winsorised.



# Chart 6: Oaxaca-Blinder decomposition for net wealth—Robustness to excluding employment status and sector of employment from explanatory variables

Chart 7: Oaxaca-Blinder decomposition for net wealth—Robustness restricting the sample to the employed only

transformed using the inverse hyperbolic transformation (to account for the presence of zero and negative values). The top and bottom 5 percent

of values were winsorised.



Sources: Household Finance and Consumption Survey 2010, 2014, 2017. Germany, France, and Italy. Note: The right chart decomposes the average gap between native and immigrant households into a part explained by observable variables and an unobserved part. The sample is restricted to households whose reference person is employed and aged less than 65 years. For the baseline specification explanatory variables are: age, gender, marital status, education, presence of a child in the household, **occupation, the sector of employment, self-employment dummy** and time fixed effects. Net wealth and liquid assets were transformed using the inverse hyperbolic transformation (to account for the presence of zero and negative values). The top and bottom 5 percent of values were winsorised.

