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Contents

The role of inflation subcomponents: applying maximally forward-looking core inflation to euro area countries

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For well-informed monetary policy decisions, central banks gather a wide range of data on the state of the economy, including several inflation measures. When pursuing a forward-looking monetary policy, policymakers ideally rely on measures that indicate where inflation is heading in the medium term, e.g. when shocks to the economy will have disappeared. To complement the set of inflation measures commonly used in the decision-making process, we construct maximally forward-looking core inflation, as proposed by Goulet Coulombe et al. (2024), for the euro area and its seven largest economies. Since the euro area aggregate summarizes diverse economic conditions and responses to shocks within the region, constructing maximally forward-looking core inflation for individual member states provides additional insights into the heterogeneity and commonalities across countries. Overall, our results confirm our measure's strong performance in predicting medium-term inflation developments, which holds for all economies in the set. We identify key economic sectors that provide useful signals for future headline inflation and find a broad consistency across the seven largest euro area economies.

JEL classification: C53, E31, E37, E52
Keywords: underlying inflation, inflation forecasting, inflation subcomponents, euro area

Major central banks routinely monitor various measures of inflation to understand prevailing price movements. Typically, they are more concerned about the persistent sources of inflationary pressures rather than about temporary fluctuations. For example, the inflation surge that started in 2021 sparked a crucial debate on whether the observed pressures were a transitory phenomenon or whether they would translate into a persistent increase in prices. Since inflation data are exposed to multiple sources of noise, aggregate inflation (or "headline" inflation) is usually not the primary choice when it comes to answering such fundamental questions. Instead, policymakers typically rely on underlying (or core) inflation measures, whose purpose is to signal medium-term inflationary trends.

Especially when pursuing a forward-looking monetary policy, separating informative signals from highly volatile data helps indicate where headline inflation will settle in the medium term. This task, however, becomes particularly complex in the euro area, where the aggregate inflation rate is influenced by multiple sources of noise arising from both different sectors and individual countries. Given that each euro area economy exhibits unique inflation dynamics because of its individual structural and historical characteristics and responses to economic shocks vary across countries, the aggregate constitutes a melting pot of heterogeneous inflationary pressures. Consequently, it can be informative to consider individual euro area economies and identify the most important subcomponents of their cross-sectional price data when considering the medium-term developments of their headline inflation rates.

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In this paper, we construct predictive core inflation measures for the seven largest euro area economies[2] based on Goulet Coulombe et al. (2024). The methodology they propose uses inflation subcomponents to forecast the headline rate and reweights these subcomponents to be maximally forward-looking. As such, their methodology directly targets the predictability of a core inflation measure for the headline rate, which is highly desirable when pursuing a forward-looking monetary policy. Moreover, by taking a cross-sectional perspective, it allows for evaluating the role of inflation subcomponents across countries.

Our results show that using inflation components helps improve the predictive accuracy for headline inflation across euro area countries in the medium term. This holds for pre- and post-COVID-19 pandemic periods. Our analysis yields valuable insights into which sectors provide forward-looking signals, which are less informative, and into whether these characteristics vary across the seven largest economies in the euro area. We find that, for all countries under observation, maximally forward-looking core inflation gives low weight to highly volatile subcomponents such as energy and food, while assigning high weight to goods and services like housing, recreation and other services. This suggests a broad alignment with commonly used core inflation measures. Moreover, our weighting schemes for the different economies are broadly consistent and do not show signs of significant heterogeneity.

This paper is structured as follows: In section 1, we discuss the relevance of core inflation for policy decisions in central banking and review the literature on existing measures and the role of inflation subcomponents. Section 2 presents the methodology used to construct the maximally forward-looking core inflation measure for the seven largest euro area economies. Section 3 summarizes our forecasting results and identifies sectors indicative of medium-term developments in each country. Section 4 concludes.

1 Core inflation and its relevance for monetary policy

Core inflation measures serve as key input for monetary policy assessment in major central banks since they are built on the goal of signaling the direction in which inflation is heading in the medium term. Ehrmann et al. (2018) describe the role of measures of underlying inflation as follows, “The central bank faces the problem of distinguishing in real time the ‘signal’ on medium-term inflationary pressure contained in the HICP inflation data from the ‘noise’ stemming from temporary or idiosyncratic factors. To this end, measures of underlying inflation are routinely monitored. Generally, their purpose is to obtain an estimate of where headline inflation will settle in the medium term after temporary factors have vanished.”

That being said, creating a measure of underlying inflation requires isolating persistent developments from highly volatile behavior. The resulting inflation series should be free of effects from idiosyncratic factors and transitory shocks that dissipate in the near term. That means a well-behaved core inflation measure has the following properties (see, e.g., Clark, 2001): (1) a small bias with respect to headline inflation and (2) low variance. Moreover, with regard to pursuing a forward-looking monetary policy, it should have (3) strong predictive power with respect to headline inflation. Such a measure serves to indicate in which direction inflation will be heading in the medium term.

[2] Germany, France, Italy, Spain, Netherlands, Belgium and Austria.

1.1 Existing core inflation measures

Inflation measures central banks commonly monitor are either based on simple exclusion rules or rely on modeling techniques that extract underlying developments in the data. The most prominent inflation measure, which is usually reported as "core inflation," permanently excludes food and energy components. Since commodity prices are highly volatile and their fluctuations are often induced by supply shocks, it is difficult for monetary policymakers to frame a proper response to these specific inflationary pressures (Gordon, 1975; Eckstein, 1981; Motley et al., 1997). Based on these arguments, the concept of permanent exclusion is often extended to additional subcomponents such as those related to housing or tourism, or subcomponents are excluded from the measure on the basis of other criteria. These include overall price volatility (see Clark, 2001; Acosta, 2018), cyclical volatility (see Dolmas, 2009) and persistence (see Bilke and Stracca, 2007). Other studies take more structural approaches into account and focus on subcomponents that are sensitive to the economic business cycle. These approaches include Supercore for the euro area (see Ehrmann et al., 2018) and the Federal Reserve Bank (FRB) San Francisco Cyclical Core Personal Consumption Expenditures (PCE) Inflation (see Mahedy et al., 2017; Stock and Watson, 2020).

Permanently excluding specific subcomponents from the aggregate has a number of drawbacks. Excluded subcomponents may provide useful signals for future inflation despite being highly volatile, e.g. by potentially inducing second-round effects on inflation expectations and wages, of which policymakers should be aware (Cecchetti and Moessner, 2008). Included subcomponents, on the other hand, may carry substantial amounts of noise and/or be subject to transitory shocks that blur the overall trend (Verbrugge, 2022). As an alternative, the literature suggests reducing volatility and extracting the medium-term trend via temporary exclusion. Trimmed mean inflation and median inflation (Bryan and Pike, 1991; Bryan and Cecchetti, 1993; Bryan et al., 1997) address the aforementioned issues by ensuring cross-sectional smoothing over time. Given that the distribution of monthly price changes is hardly ever symmetric but features substantial skeweness, a symmetrically trimmed core inflation measure may deviate from the underlying trend over short time horizons. This motivates an asymmetric trimming approach as in, e.g., Bryan et al. (1997) and Dolmas (2005), who exclude a higher share of the upper tail of the monthly price change distribution from their trimmed mean inflation measure.

Moving along the spectrum of econometric complexity, we find model-based inflation measures built to detect the underlying trend in numerous inflation components. A well-established concept is to extract the common component of all subindices with a dynamic factor model that identifies shared factors influencing the data. For example, the European Central Bank (ECB) monitors the persistent and common component of inflation (PCCI; Banbura and Bobeica, 2020), whereas the Federal Reserve Bank of New York constructs the multivariate core trend (MCT; Stock and Watson, 2016).

1.2 Using inflation subcomponents for a predictive core inflation measure

Many studies have shown that using inflation subcomponents is beneficial for predicting the aggregate inflation rate (see i.a. Marcellino et al., 2003; Espasa and Albacete, 2007; Giannone et al., 2014; Fulton and Hubrich, 2021; Boaretto and Medeiros, 2023). Using inflation subcomponents allows for capturing heterogeneous factors to which the aggregate is exposed. Moreover, using various price series provides additional information, e.g. on trends, short-term fluctuations or structural breaks that can potentially be extracted by a forecasting model (Espasa et al., 2002; Bermingham and D'Agostino, 2014). Other studies find small or muted improvements when applying disaggregated approaches (Benalal et al., 2004; Hubrich, 2005; Hendry and Hubrich, 2011, Chalmovianský et al., 2020). Difficulties may arise due to the accumulation of misspecifications, estimation uncertainty, instabilities and innovation errors, all of which influence the forecasting accuracy of the aggregate.

Leaving plain forecasting performance aside, building on inflation subcomponents comes with several benefits. First, it allows for a breakdown of the aggregate into inflationary versus noninflationary (or even deflationary) components. As such, it offers policymakers more detailed information on the origins of prevailing price pressures. Since inflation subcomponents vary in their reactions to monetary policy in terms of extent and speed, a disaggregated perspective is essential for informed monetary policy decision-making. As Aruoba and Drechsel (2024) show, the aggregate response of headline inflation to a monetary policy shock differs substantially from individual responses across the range of inflation subcomponents. While some components respond quickly and in the expected direction, others exhibit long lags or may even react in the opposite direction. Hence, examining cross-sectional inflation data provides valuable insights into the transmission of monetary policy shocks, while relying on aggregate indices only may blur the picture.

Core inflation measures that are based on inflation subcomponents and that directly target the predictive performance with regard to headline inflation are rather rare. Suggestions in the literature include Ravazzolo and Vahey (2009), who propose a forecast-based core inflation measure based on each individual subcomponents' performance in density predictions, and Gamber and Smith (2019), who combine disaggregated inflation subindices in a standard linear regression model to formulate a core inflation measure. In a recent study, Goulet Coulombe et al. (2024) propose using a regularization-based approach which aggregates inflation subcomponents based on their explanatory power with respect to future headline inflation. It allows for incorporating high levels of disaggregation and ensures interpretability through constraints on the coefficients. In the following, we apply the concept of maximally forward-looking core inflation proposed by Goulet Coulombe et al. (2024) to the euro area aggregate and the seven largest euro area economies and provide useful insights into the predictive power of the different subcomponents.

2 Methodology: maximally forward-looking core inflation

We base our analysis on Albacore (adaptive learning-based core inflation), a method proposed by Goulet Coulombe et al. (2024). It linearly aggregates inflation subcomponents so that the resulting series is maximally predictive of future headline inflation. By focusing on the forward-looking criterion, Albacore combines the benefits of using inflation subcomponents for predicting aggregate inflation and at the same time provides a trackable measure for underlying inflation. That is, the goal is not to perform a plain forecasting exercise which yields the best possible forecast for headline inflation but to determine the weights of subcomponents so that the resulting aggregate is a good medium-term predictor, and to thus provide a measure of underlying inflation.

This goal is achieved by using a simple machine-learning algorithm called "assemblage regression," which is a generalization of the popular ridge regression model.[3]

The authors propose two versions of maximally forward-looking core inflation: Albacore (components) in components space, which means that the algorithm uses the disaggregated inflation subcomponents and assembles them according to their predictability, and Albacore (ranks) in ranks space, which means that we rank inflation subcomponents from the lowest to the highest values at each point in time, like in a trimmed mean inflation, and the algorithm is allowed to decide what weight to assign to each of the ordered time series ("ranks").

The first case is a supervised weighting approach, in which the algorithm assembles disaggregated inflation subcomponents and directly targets future headline inflation. Following Goulet Coulombe et al. (2024), we let $\pi_{t+1:t+h}$ denote the h-step headline inflation rate averaged over $t+1$ to $t+h$ and $\mathbf{\Pi}_t$ the K-dimensional vector of inflation subcomponents, both in quarter-on-quarter changes at time t (for $t = 1, \ldots, T$). To obtain the optimized weights for Albacore (components), $\widehat{w}_c$, for the basket of components we minimize the following loss function:

$$\widehat{w}_c = \arg\min \sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w'\mathbf{\Pi}_t)^2 + \lambda \| w - w_{headline} \|_2 \qquad (1)$$
$$st\ w \geq 0, w_l' = 1.$$

Note that instead of shrinking coefficients toward 0, the penalty term ($\lambda \| w - w_{headline} \|_2$), with the quadratic Euclidian norm between both weight vectors, pushes the solution toward the official Eurostat headline inflation weights ($w_{headline}$). Also, the two constraints introduced in the assemblage regression make sure that coefficients sum to 1 and are nonnegative. As such, the methodology ensures that the resulting weights are (1) interpretable as weights, (2) optimized to be forward-looking while they (3) remain aligned with the official headline weights in the limit (i.e., when $\lambda \rightarrow \infty$).

The second version is a supervised trimming approach. Here, the monthly growth rate of inflation subcomponents is ordered from the lowest to the highest values at each point in time before they enter the minimization problem as regressors. To achieve this, $\boldsymbol{O}_t$ defines the K-dimensional vector of ordered inflation subcomponents and we obtain the optimized weights for Albacore (ranks), $\widehat{w}_r$, as follows:

$$\widehat{w}_r = \arg\min \sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w'\mathbf{O}_t)^2 + \lambda \| Dw \|_2 \qquad (2)$$
$$st\ w \geq 0,\ \ \bar{\pi}_{t+1:t+h} = \bar{\pi}^*_{ranks,t}.$$

The penalty term ($\| Dw \|_2$) opts for a smooth distribution of the weights, with D being the difference operator (i.e., $\sum_{r=1}^{K} (w_r - w_{r-1})^2$). For Albacore (ranks), weights are constrained to be nonnegative and the resulting inflation series needs to have the same long-run mean as headline inflation. Again, these restrictions are designed to optimize the regression problem with respect to predictability and at the same time ensure interpretability as an underlying inflation measure.

[3] Ridge regressions belong to the class of regularization-based techniques. They are used to improve predictive accuracy by adding a penalty term which prevents the model from fitting too closely to the data. This is particularly important when using a large number of regressors in an estimation.

Being inspired by trimmed mean inflation, this approach focuses on the cross-sectional distribution of inflation subcomponents. For further details, please refer to Goulet Coulombe et al. (2024).

3 Albacore for euro area countries

We use monthly HICP data from Eurostat, disaggregated at the four-digit Classification of Individual Consumption by Purpose (COICOP) level. We construct the series for the euro area and for its seven largest economies: Germany, France, Italy, Spain, Netherlands, Belgium and Austria. To address substantial irregularities in some subindices, we either remove them from our set or replace them with their three-digit or two-digit aggregates. This leaves us with 92 subindices for the euro area, 66 for Germany and France, 67 for Austria, 62 for Belgium, the Netherlands and Italy, and 55 for Spain. All data series are seasonally adjusted and run from April 2002 until March 2024.[4]

For our analysis, we focus on the 12-months-ahead horizon, which allows us to take a medium-term perspective and use quarter-on-quarter changes of the series. Following Goulet Coulombe et al. (2024), our evaluation is based on two out-of-sample test sets, one covering the pre-pandemic period (January 2010 to December 2019) and the other the post-pandemic period (January 2020 to March 2024). Given that euro area HICP data are typically not subject to significant revisions, our analysis is based on a pseudo-out of sample evaluation. For countries with revised price data, it may be of interest to conduct a real-time exercise. To determine whether the resulting inflation series is indeed a reliable indicator of future headline inflation developments, we evaluate the point forecasting performance of Albacore with root mean squared errors (RMSEs) against a set of benchmarks. These include the headline inflation rate, the core inflation rate (excluding energy and food) as well as the 30% trimmed mean inflation rate for each country in our sample. Benchmarks are combined in a nonnegative ridge regression including and excluding the intercept. This strategy resembles a forecasting combination scheme, which is often found to beat simple univariate benchmarks (Diebold and Shin, 2019; Hauzenberger et al., 2023).

3.1 Forecasting performance

Overall, both Albacore series yield a good point forecasting performance with regard to the euro area aggregate as well as the individual euro area economies (see table 1). We find substantial gains for both the pre- and post-pandemic periods, with improvements for the pre-pandemic period being higher for most countries (except for the Netherlands). Additionally, we observe that including an intercept in the benchmark specification is beneficial, if at all, only for the pre-pandemic sample. Compared to the euro area aggregate, we find similar (or even stronger) performance with regard to the individual countries, suggesting that Albacore can effectively manage potentially more volatile subcomponents than those reflected in the weighted average across countries. These results suggest a potential for constructing the euro area aggregate by optimizing weights across both countries and components. As shown by Goulet Coulombe et al. (2024), a geographical assembling of inflation series can indeed improve the model's performance; such a step, however, is outside the scope of the present study.

[4] For seasonal adjustment, we use the Census X-13ARIMA-SEATS Seasonal Adjustment Program from the seasonal package in R (Sax and Eddelbuettel, 2018). For series with heavy irregularities, we either remove severe outliers after the seasonal adjustment step or replace them with their two- or three-digit aggregates. Note that, depending on data quality, this data-wrangling step may affect the estimate and alter results.

Table 1

Forecasting performance of Albacore

	Euro area	Austria	Belgium	Germany	Spain	France	Italy	Netherlands
Pre-pandemic sample								
Albacore (components)	0.9	0.9	0.8	0.7	0.9	0.8	0.8	0.7
Albacore (ranks)	1.0	0.8	0.9	0.8	0.9	0.8	1.0	0.8
Predictive combinations with intercept	1.0	0.8	0.9	0.7	1.1	0.9	1.1	0.8
Post-pandemic sample								
Albacore (components)	0.9	0.9	0.9	0.9	0.9	1.2	1.0	0.7
Albacore (ranks)	1.0	0.9	0.9	1.0	0.9	1.0	1.0	0.7
Predictive combinations with intercept	1.0	1.1	0.8	1.2	0.9	1.1	1.0	0.9

Source: Authors' calculations.

Note: The table gives root mean-squared errors (RMSEs) relative to the predictive combinations without intercept. The benchmarks combine HICP headline inflation, HICP core inflation and the 30% trimmed mean in a nonnegative ridge regression. Values below one show forecasting improvements over the benchmark, while values above one indicate inferior performance. The pre-pandemic sample covers the period from January 2010 to December 2019. The post-pandemic sample covers January 2020 to March 2024.

When evaluating the model's performance with regard to each country before the outbreak of the COVID-19 pandemic, we find a remarkable performance of Albacore (components) for Germany and the Netherlands and of Albacore (ranks) for Austria against our main benchmark without intercept. Note, however, that including the intercept for this set of countries makes the benchmark hard to beat. This is due to the low and stable inflation rates these countries experienced before the pandemic, which caused the constant in the model to become more important. This effect is amplified because we chose a relatively long forecasting horizon.

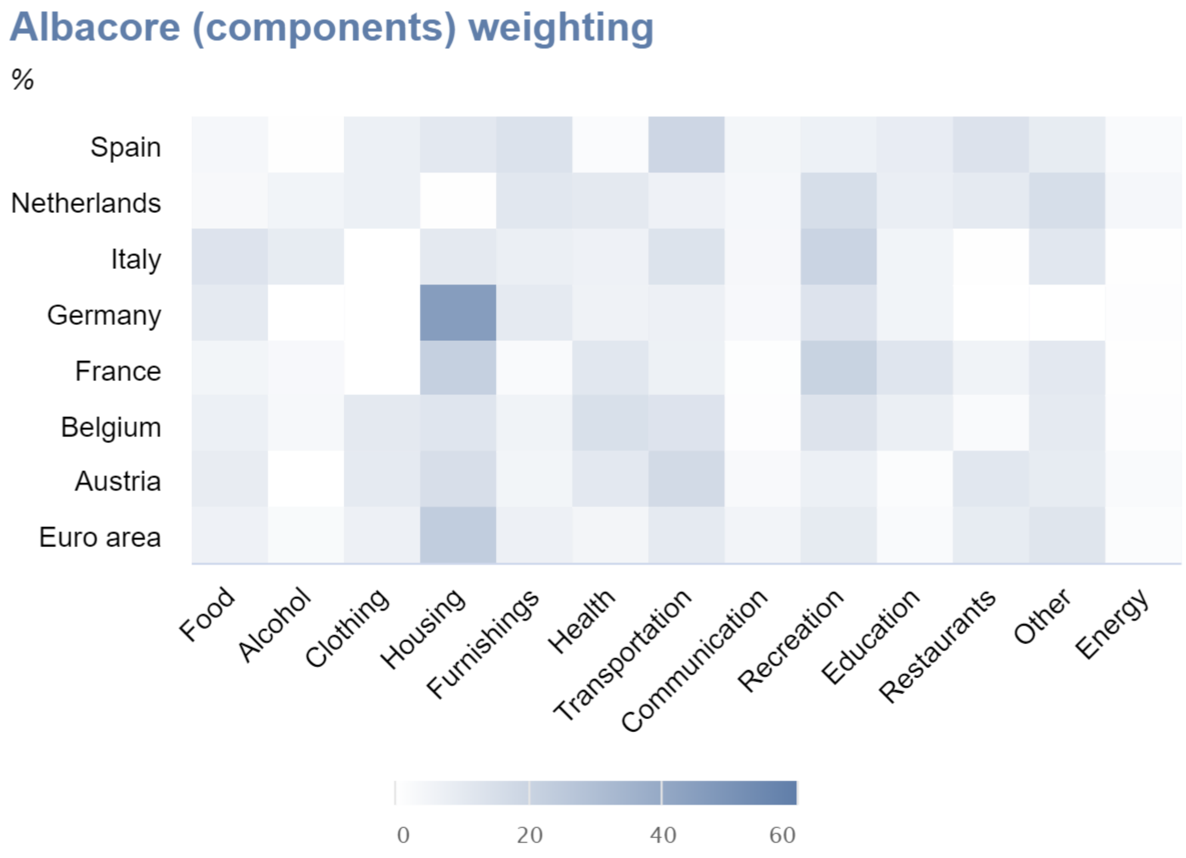
For the post-pandemic sample, the strongest improvements against both benchmarks can be achieved for the Netherlands. Given that the Netherlands saw a strong surge in their headline inflation rate, peaking at 17.1% in September 2022, simple benchmarks have difficulties to predict these strong dynamics. Conversely, we find that simple benchmarks perform well for economies like France, which saw a less severe increase in its headline inflation rate during 2022/2023. Belgium is the only country for which the benchmark outperformed both Albacore measures by considerable margins for the post-pandemic period. We find that Albacore mainly loses ground during the rebound of headline inflation observed in late 2023.

The resulting inflation series can be found in chart A2 in the annex. We summarize key findings for the post-pandemic period. First, for all countries in our sample, both Albacore measures reduce volatility compared to headline inflation, especially for 2020 and 2021. For the surge of inflation, we find early signs of upward pressures from both Albacore measures for Austria, Belgium and Italy. For all other countries as well as the euro area aggregate, Albacore (ranks) is the first to point toward upward tendencies. For the turning point, we find harmony across all core inflation measures. Finally, our results for recent months reveal some heterogeneity between countries. While for all countries in our set, the newly built underlying inflation measure is still above pre-pandemic levels, it remains particularly elevated for France, Austria and Belgium. This can be traced to exceptionally low levels of inflation recorded before the pandemic in France and to strong underlying pressures that are fading out more slowly in Austria and Belgium. Yet, our Albacore measures point toward an ongoing disinflationary process for all countries observed.

3.2 The role of inflation subcomponents across euro area countries

In this subsection, we explore the role of inflation subcomponents for the predictive performance of Albacore across the different euro area countries. We identify key economic sectors that are important for predicting inflation trends in the medium term and highlight those that receive less weight due to the low signal they produce. To do this, we summarize the final weights Albacore (components) assigns to the various disaggregated inflation series presented in chart 1 as well as the differences to the official weights given in chart 2. A more detailed illustration can be found in chart A3 in the annex. For the purpose of illustration, we aggregate the weights of the subcomponents back to level 2.

Chart 1



Source: Authors' calculations.
Note: We aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

As we would expect from a core inflation measure that reduces noise and signals medium-term developments, the energy component is assigned low to zero weight. Moreover, we find low weight for the subcomponents "food including nonalcoholic beverages" and "alcohol including tobacco and narcotics," subcomponents that are excluded from official core inflation.[5] Another

[5] While energy and food prices can certainly have predictive power during specific periods, their high volatility limits the usefulness of their signals for longer-term forecasting. As demonstrated by Goulet Coulombe et al. (2024), both components

group of subcomponents that is deemed unimportant by Albacore (components) is communication. While energy and food are characterized by high volatility, communication services and equipment are components with constant or even deflationary paths. As such, the former is too volatile and the latter too persistent (or downward bound) to signal medium-term trends.

In general, higher importance is assigned to services and goods related to housing, recreation and other services (which include, i.a., insurance and financial services). For Germany and France, housing clearly receives the highest weight, while recreation is most important in the Netherlands and Italy. In Austria and Spain, we find transportation to be the top-weighted component. Note that these observations are broadly reflected in the official Eurostat weighting scheme (see chart A1 in the annex). Even more interesting are, thus, the differences between our results and the official weights, as these suggest which components deserve greater attention than usual when monetary policy aims to be forward-looking.

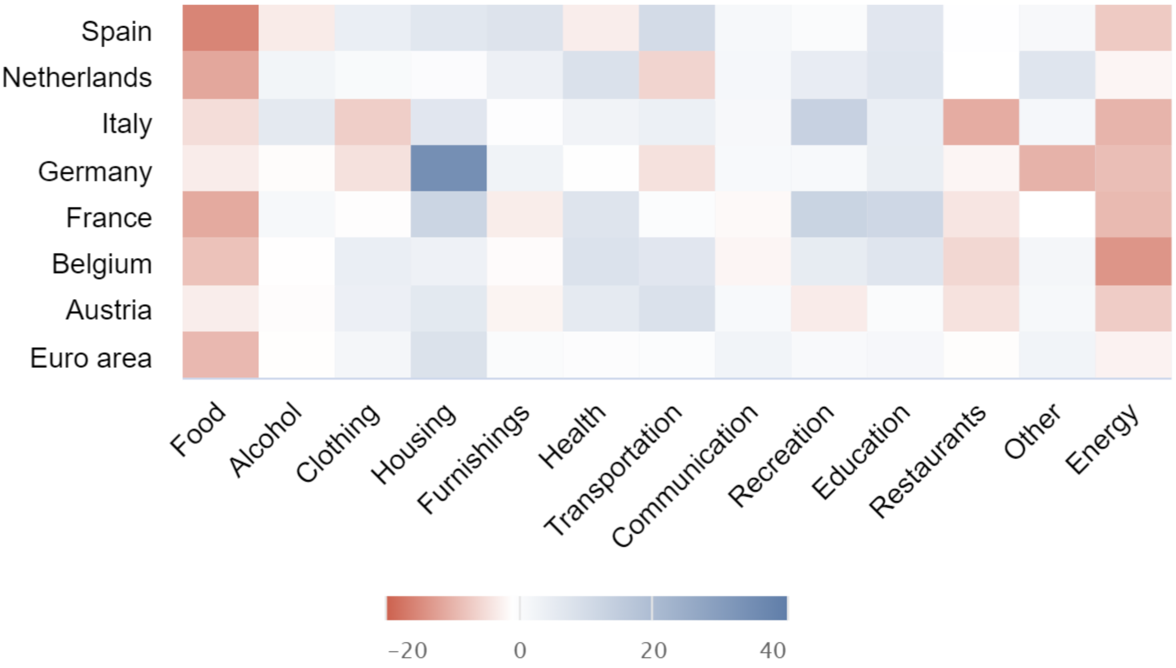
A comparison of our outcomes to the official weights reveals that assigning a low weight on energy and food constitutes a substantial downweighting of the corresponding subcomponents (see chart 2). Services and goods related to communication, on the other hand, already have a low weight in the official headline inflation aggregate, so our outcome would not suggest a major change. Even though subcomponents in the restaurants category receive substantial weights for several countries (Austria, Spain, the Netherlands) in our measure, their high weight in the official aggregate reduces their importance for the aggregate across all countries. Our calculation assigns higher importance to housing, recreation, education and health in all countries. This supports an intuitive finding, which is also shown in Goulet Coulombe et al. (2024): Albacore (components) reduces the focus on highly volatile subcomponents and on overly persistent ones, while, at the same time, it increases the importance of core goods and services that indicate the overall growth trend of various price series. Notably, this holds for all seven economies under review, which suggests that they show little heterogeneity with respect to the forward-looking features of their inflation subcomponents.

receive positive weights in the very short run, but these weights diminish rapidly as the forecasting horizon extends. Furthermore, their predictive power is highly dependent on the nature of the prevailing shock, which reduces their general adequacy.

Chart 2

Differences between Albacore (components) and official weighting

Percentage points



Source: Authors' calculations.
Note: This chart shows the difference between Albacore (components) weights and official Eurostat weights for each country and the euro area in percentage points. For Albacore (components), we aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

3.3 A cross-sectional trimming perspective

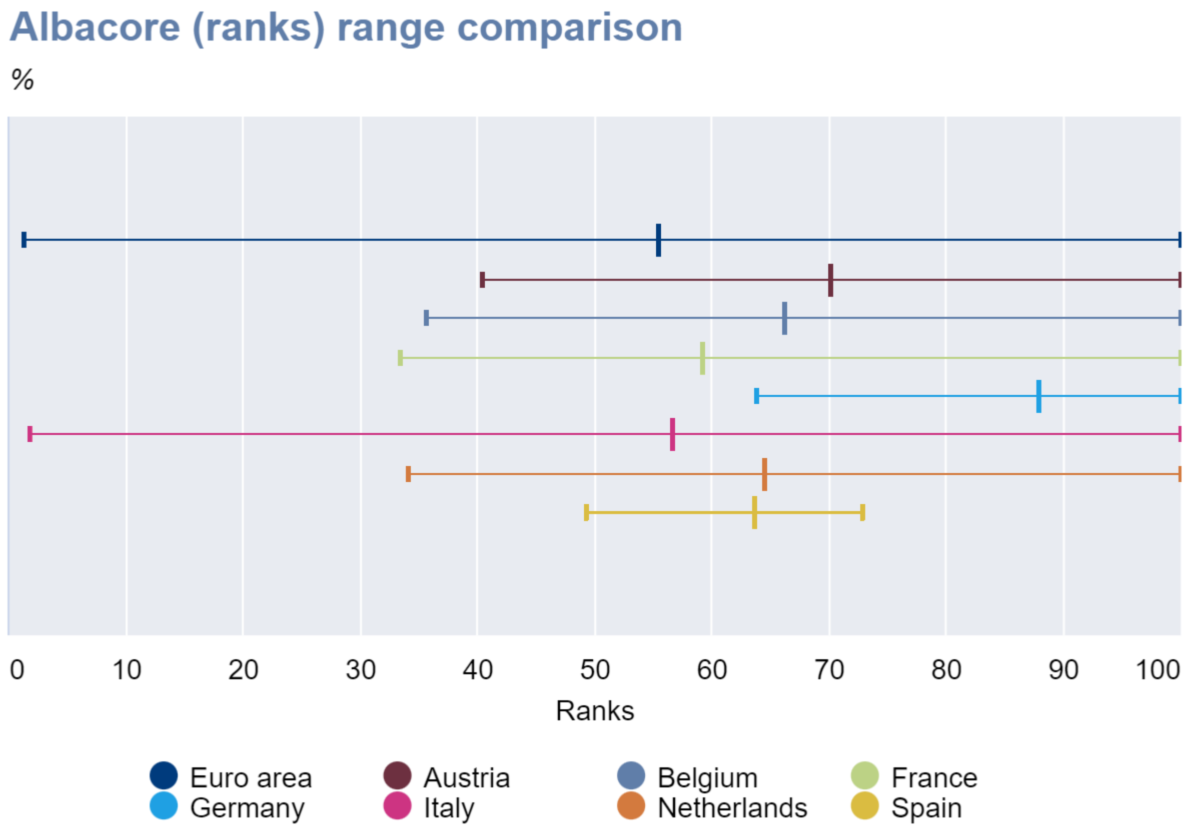
Inspecting the weights of the second measure, Albacore (ranks), allows us to shed light on similarities and differences between the various maximally forward-looking trimming schemes in place across the largest euro area economies. As an insightful add-on, Goulet Coulombe et al. (2024) demonstrate that it is possible to translate the trimming-based weights back into components space. This is particularly useful for our purpose, as it provides insights into the importance of subcomponents for the different countries, but from a time-varying perspective. In the trimming approach, the weight of each subcomponent depends on its location in the distribution at each point in time, implying that different subcomponents are assigned different weights over time (or are even excluded at some periods). Thus, we can identify subcomponents that are predominantly found in the tails or at the center of the distribution over time and see how this varies across our set of countries.[6]

First, we focus on the distributions resulting from the supervised weighting approach. For all countries, we see that the trimming is asymmetric and that it is left-skewed, upweighting the upper part of the distribution (see chart 3 and chart A4 in the annex for more details). While two

[6] In charts 3 and 4, we focus on the median of the components' weights over time.

countries, Germany and Spain, suggest a relatively sparse solution, weights for Italy are densely distributed. Apart from these countries, the norm seems to be a smooth, but highly asymmetric trim assigning weights to the upper two-thirds of the distribution.

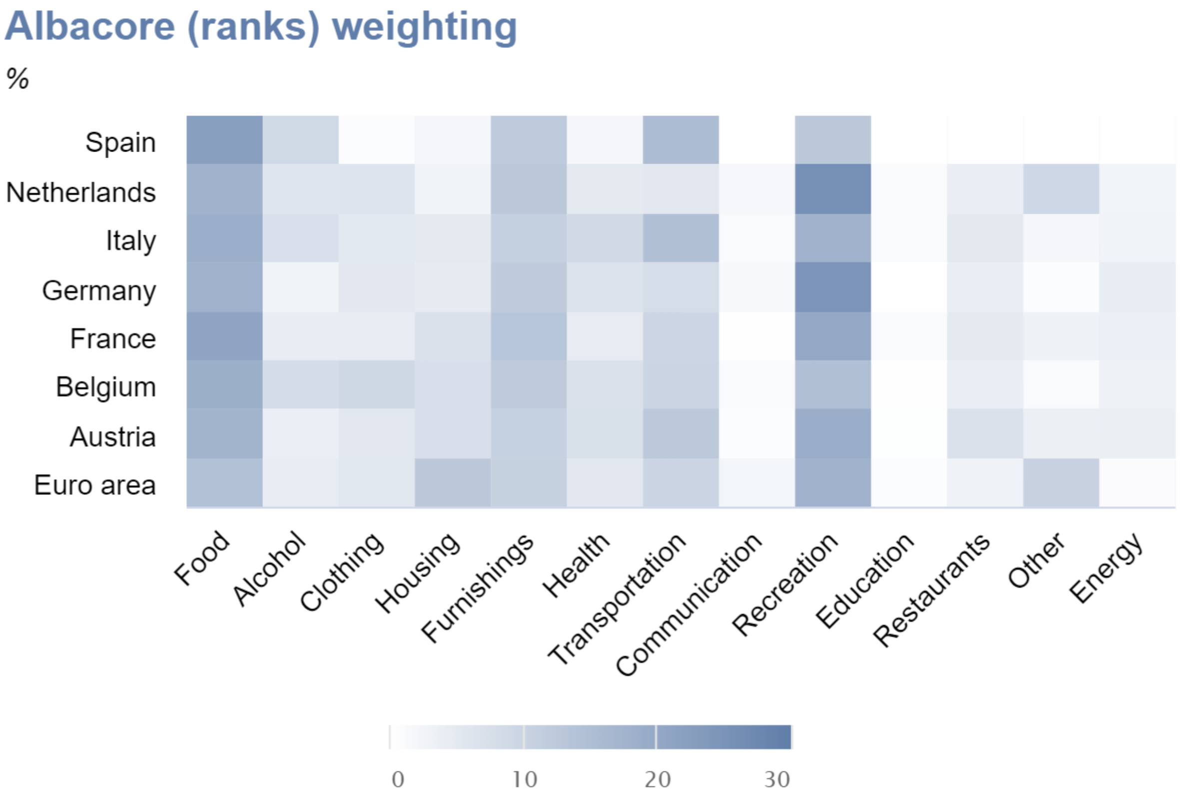
Chart 3



Source: Authors' calculations.
Note: This chart shows the distribution of Albacore (ranks) for each country and the euro area in percent. It indicates the range between the highest and lowest rank receiving a non-zero weight as well as the rank with the highest weight. Results are based on estimates for the period from April 2002 to December 2019.

Converting weights back to components reveals that components with the highest weights averaged over time belong to the food and recreation category (see chart 4). Moreover, furnishings and transportation frequently show up in those parts of the distribution that receive high weights. Low importance is assigned to services and goods in the communication and education category, which can be explained by their low to negative growth rates. This fact places them in the lower parts of the distribution, which receives little to no weight.

Chart 4



Source: Authors' calculations.
Note: This chart shows the median weights of Albacore (ranks) for each country and the euro area over time, transformed back to components space, in percent. For more details on the transformation process, see Goulet Coulombe et al. (2024). We aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

When evaluating our results relative to the official weights (see chart 5), some of our previous findings are confirmed while others are set aside. First, energy decreases in importance, which is something we find for all countries under review and both Albacore measures. Second, subcomponents related to communication are found not to be informative for forward-looking measures, while those related to recreation are. Food, however, tells a different story for Albacore (ranks). Being frequently located in the middle to upper parts of the distribution of monthly price growth, the corresponding subcomponents enter the aggregate with even higher weights than in the headline inflation rate. Similarly, housing flips its sign and is less important in Albacore (ranks) while it was upweighted in Albacore (components) for most economies in our set.

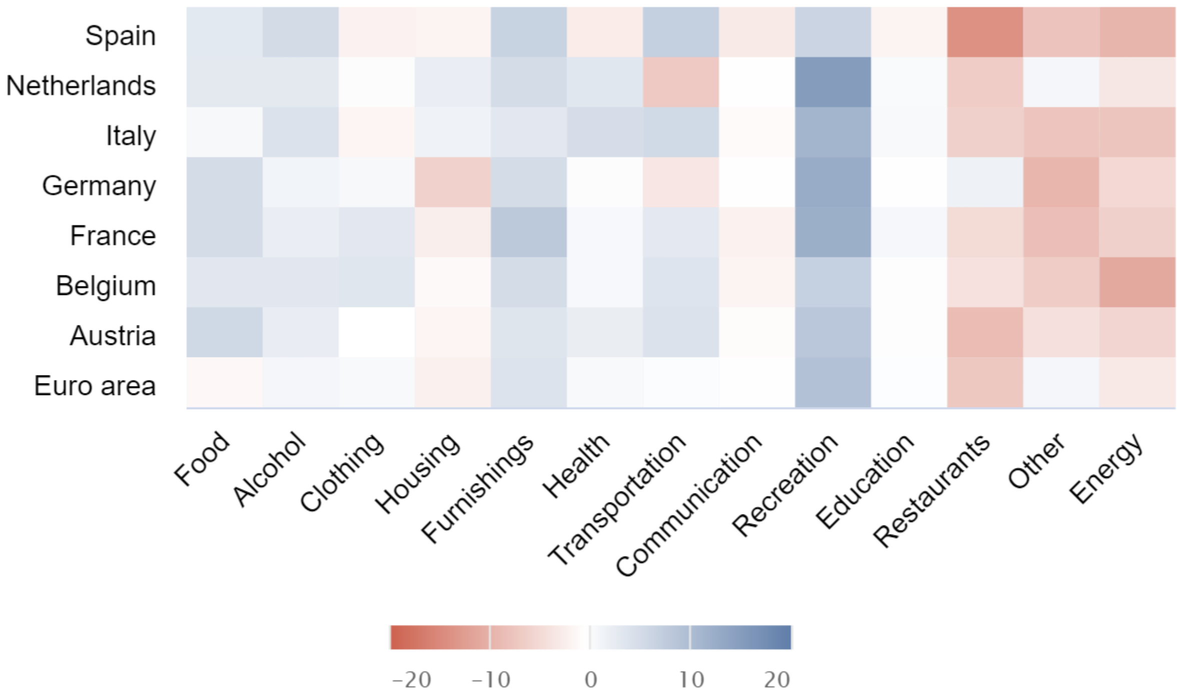
As in Albacore (components), we do not observe significant heterogeneity across countries, although some results are country specific. Examples include a higher weight on the restaurants category for Germany and a lower weight on the transportation category for the Netherlands and Germany. These observations, however, are not due to large differences between the results produced by Albacore (ranks) but can be explained by the fact that the corresponding official weights differ significantly from the other countries. Chart A1 in the annex reveals that Germany features a considerably lower weight on restaurants than all the other economies in our sample.

Conversely, transportation subcomponents in Germany and the Netherlands have relatively high weights. Albacore (ranks), in general, does not show any striking differences across countries.

Chart 5

Differences between Albacore (ranks) and official weighting

Percentage points



Source: Authors' calculations.
Note: This chart shows the difference between median Albacore (ranks) weights over time, transformed back to components space, and official Eurostat weights for each country and the euro area, in percentage points. For Albacore (ranks) in components space, we aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

4 Conclusion

Basing inflation forecasts on inflation subcomponents can be beneficial in terms of forecasting performance, and building a thorough analysis on inflation subcomponents can be highly informative with respect to different developments in individual sectors and countries. In this study, we constructed a maximally forward-looking core inflation measure for the seven largest euro area economies, which is found to perform well in terms of signaling inflation trends in the medium term. Components identified as important inflation drivers in the medium term are goods and services related to housing, recreation and other services. Energy subcomponents are found not to be informative due to their high volatility. Results for food subcomponents are somewhat ambiguous in the sense that they receive a low weight for the measure based on inflation subcomponents while, when we use the monthly price growth distribution for a supervised trimming approach, the corresponding results show up frequently in highly weighted parts of the distribution. Regarding country heterogeneity in the euro area, we do not find significant differences when it comes to forward-looking properties of inflation subcomponents.

From a central bank perspective, the homogenous nature of our findings supports the common narrative, i.e. discounting temporary supply shocks and concentrating on more persistent underlying pressures. Given their good forecasting performance, monitoring inflation measures based on maximally predictive inflation subcomponents offers valuable insights into sector-specific and country-specific inflation trends. By identifying commonalities across countries, this approach supports more targeted and effective policy interventions.

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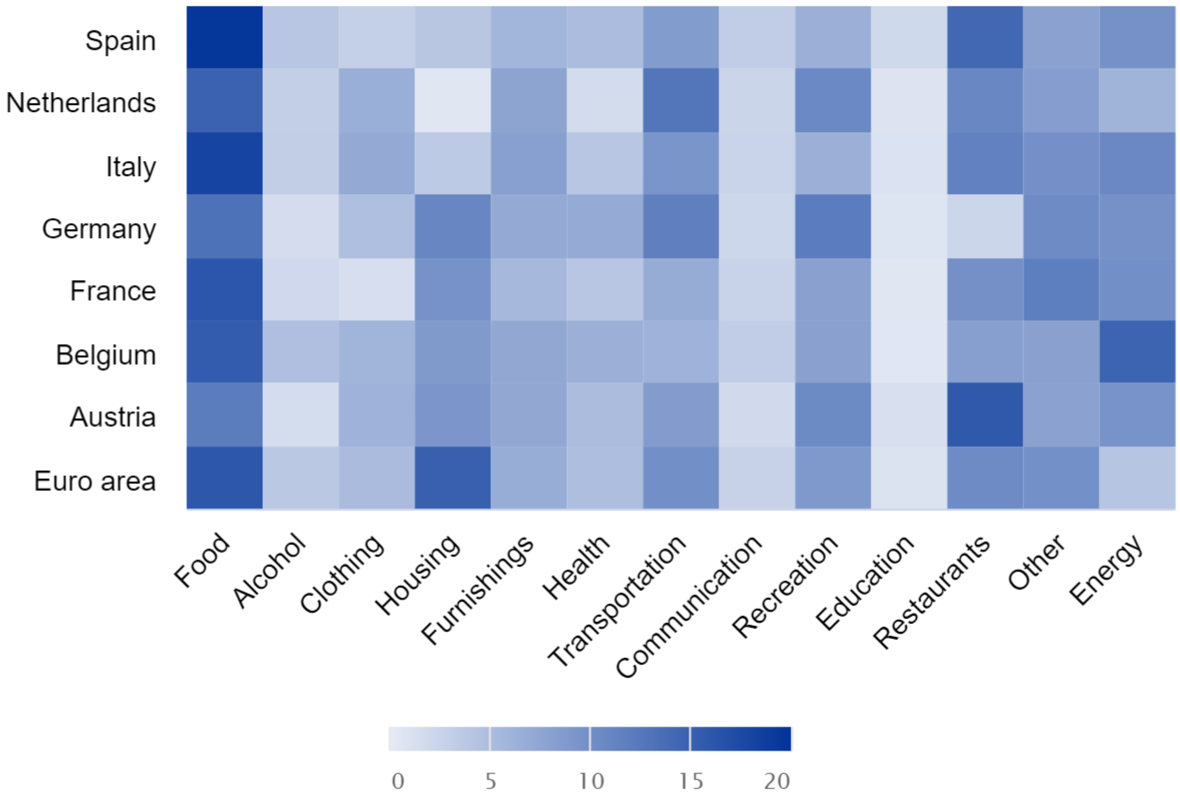
Annex

Chart A1

Official weighting (2023)

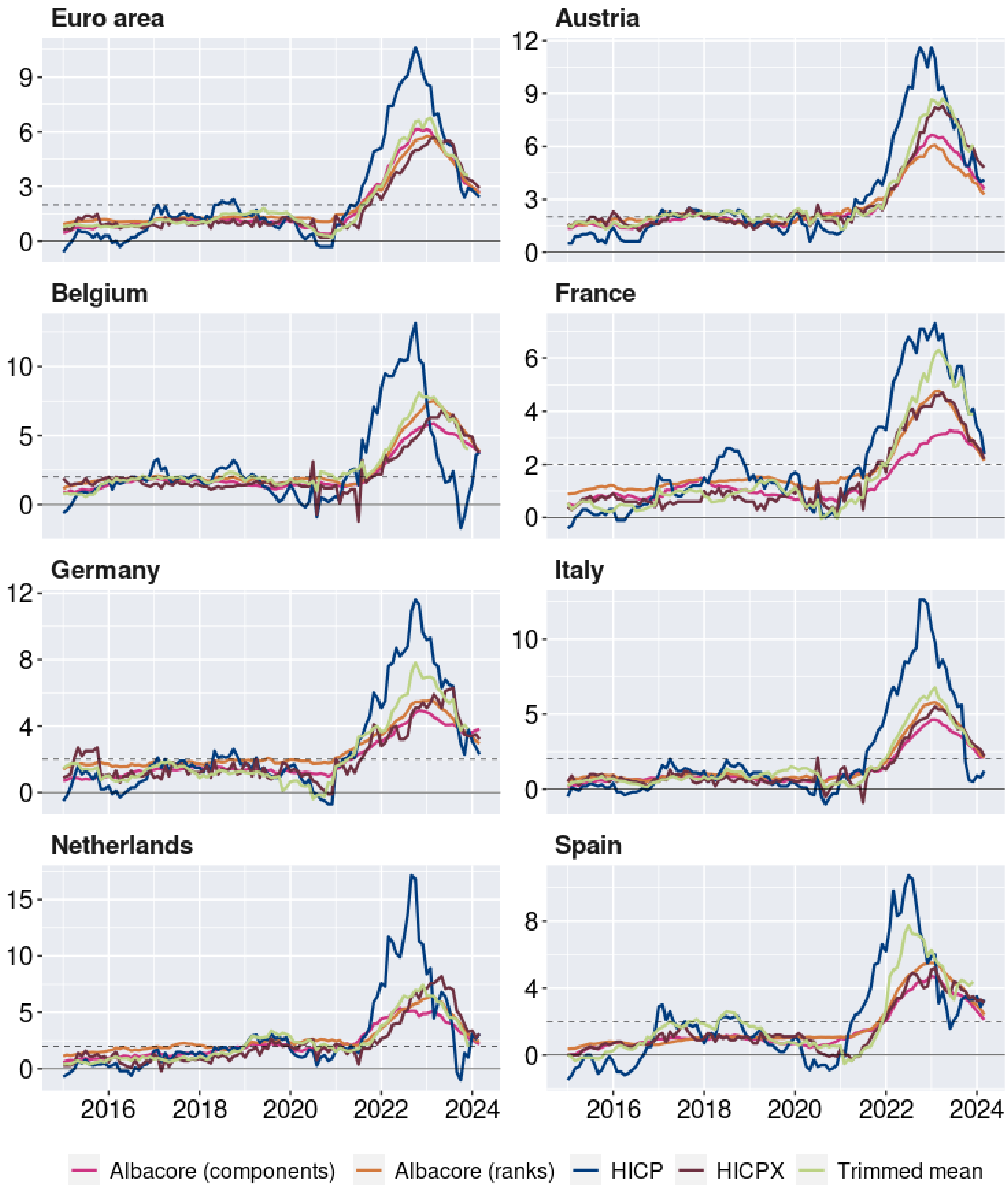
%



Source: Eurostat.

Core inflation measures over time

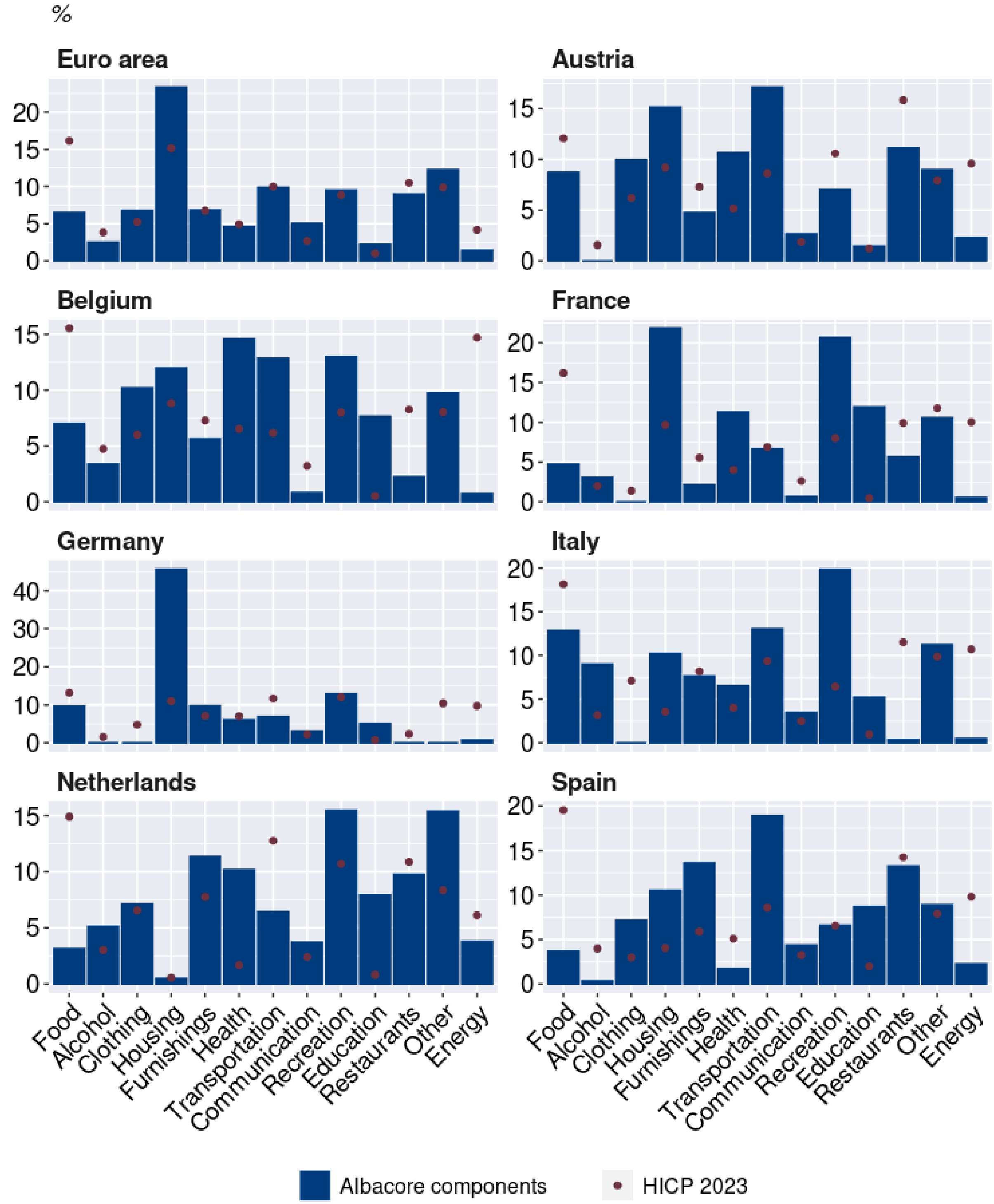
%



Source: Eurostat, authors' calculations.
Note: HICPX refers to HICP inflation excluding energy and food.

Chart A3

Albacore (components) weighting per country

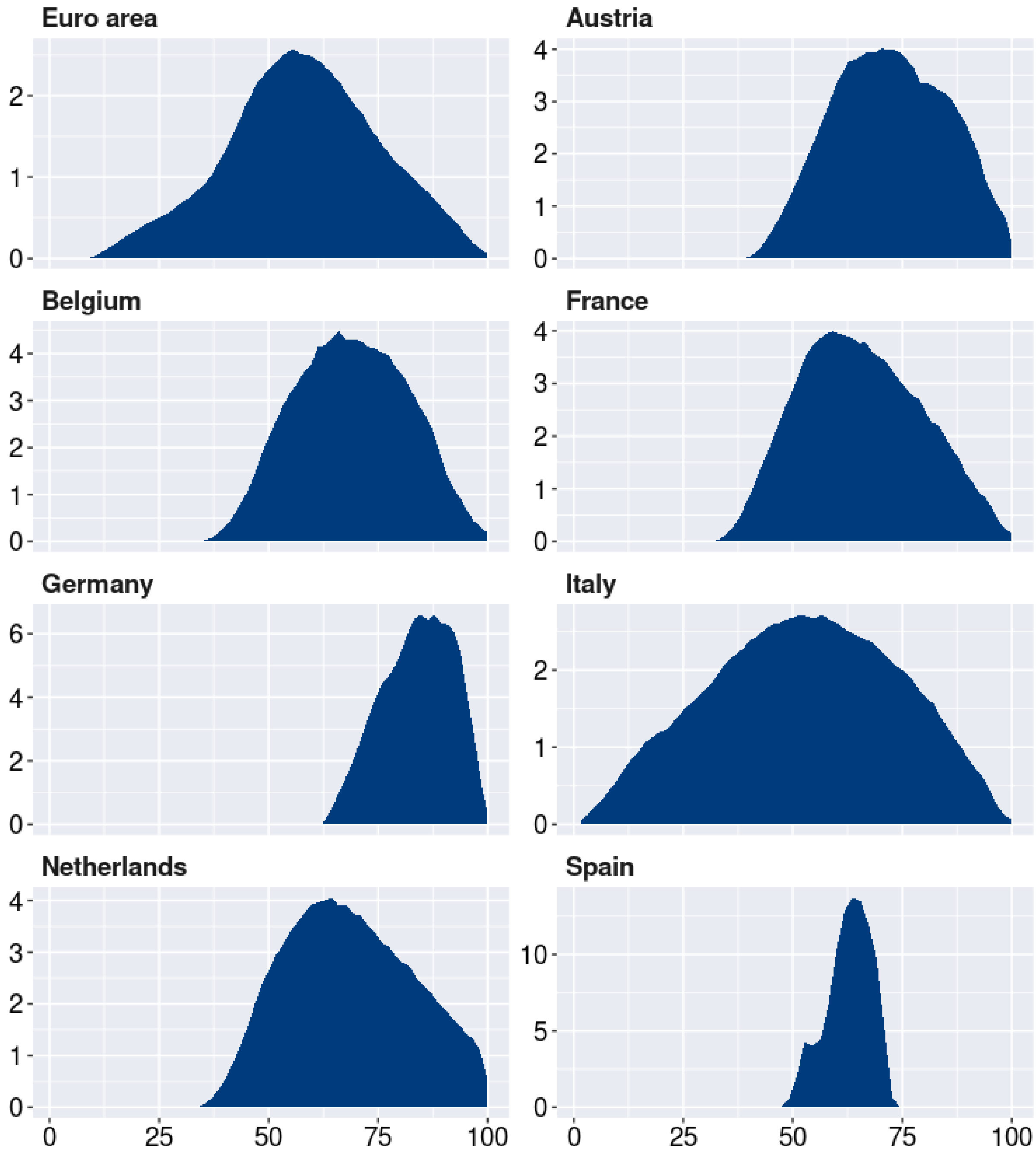


Source: Eurostat, authors' calculations.

Chart A4

Albacore (ranks) weighting per country

%



Source: Authors' calculations.

Macroeconomic effects of carbon prices – a cross-country perspective

Nađa Džubur,
Wolfgang Pointner[1]

In the fight against climate change, the EU has set ambitious targets for its member states to decarbonize their economies by 2050. While carbon prices are among the proposed policy instruments to reduce greenhouse gas emissions, the carbon taxes currently in place are nowhere near the levels that would reduce emissions sufficiently. We use a globally integrated forecast model to simulate the introduction of carbon prices that reduce emissions to the EU's targets, assuming that carbon prices are the only effective climate policy, while in reality, a bundle of policy measures will be necessary to reach these targets. Then we assess the effects of these prices on GDP and inflation as well as the potential tax revenues generated by these prices. The results highlight the multifaceted impact of high carbon prices within the euro area: We find that we would need a sharply increasing average carbon price – from the actual price of EUR 43/t CO2 in 2024 to EUR 668/t by 2030 – to achieve the planned reduction for the euro area aggregate, although the required price changes vary across member states. The macroeconomic effects seem manageable at the euro area level, with a cumulative GDP loss of –2.2% and a cumulative increase in the consumer price index (CPI) of 6.4 percentage points from 2024 to 2030. However, for countries with a low share of renewable energy capacities and a strong reliance on fossil fuels in production, combined with low incomes, the impact on GDP and inflation may be double the size of the euro area average. For countries that have already undertaken ambitious investments in the green transition the effect on GDP is only half of the euro area average and significantly lower for consumer prices. We show that carbon pricing may be a very powerful tool to reduce emissions. However, the heterogeneity of economic impacts across member states highlights the need for coordinated support and targeted investment in renewable energy capacities, which could be partially funded by the tax revenues obtained from carbon pricing.

JEL classification: E31, H23, Q54
Keywords: carbon taxes, energy prices, inflation, GDP

Since the consequences of humanmade global warming are potentially catastrophic, the reduction of greenhouse gas (GHG) emissions has become an urgent policy objective. Economists have been assessing the economic and financial consequences of climate change and analyzing the contribution of economic activities to GHG emissions as summarized by Nordhaus (2019). Market mechanisms are not sufficient to rein in emissions, therefore Stern (2008) called climate change the biggest market failure the world has seen. The most prominent market failure in this context is the negative externality of GHG emissions: they cause severe damage, but emitters are not held responsible for the effects of their actions. An appropriate instrument to correct this kind of market failure is a carbon price that internalizes the externality by levying compensation for the social costs of GHG emissions on the emitters. This approach follows the so-called "polluter pays" principle. The calculation of the social cost of carbon depends on several variables that cannot be observed but only estimated, like the elasticity of demand or the discount rate as described in Stern and Stiglitz (2021). But even if we know the exact social cost of carbon, the implementation of a carbon price alone might be suboptimal because an excessively high carbon price triggers a huge negative supply shock. Therefore, Acemoglu et al. (2012) propose a mixed strategy combining carbon prices with targeted subsidies for green innovations. Krogstrup and Oman

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(2019) find that while carbon taxes are the most widely proposed measures, removing subsidies may be equally important to alter the relative prices between carbon-intensive and carbon-neutral goods. In a special report (IEA, 2021), the International Energy Agency (IEA) outlined a roadmap for the decarbonization of the global energy sector, which is responsible for ¾ of all GHG emissions. The report states that a swift implementation of several policies is required to reach global net zero by 2050 as pledged by most governments. In addition to carbon prices, the IEA emphasizes the need for regulations and mandates, like speed limits or energy efficiency standards. Current decisions by firms and households often depend on expectations about future prices. Cahen-Fourot et al. (2023) show that uncertainty about, and the heterogeneity of, expected carbon prices can delay firms' investment decisions. Ferrari and Nispi Landi (2022) present the effects of households' expectations on the inflationary impact of carbon taxes: to the degree that households anticipate lower future income because of the carbon tax, they will reduce their current demand.

Carbon prices can be enacted as taxes or as cap-and-trade schemes. Regardless of the institutional setup, a carbon price would make emission-intensive activities and their output more expensive. Under current production technologies, many sectors use emission-intensive inputs, hence carbon prices would cause widespread price increases. Moreover, these price increases may induce demand for higher wages, which could lead to inflationary second-round effects. Metcalf and Stock (2023) estimated the effects of existing carbon taxes in Europe and find no evidence for adverse impacts of these taxes on employment and GDP, and only modest effects on emissions. Brand et al. (2023) analyzed the macroeconomic effects of increasing carbon prices in the euro area using a suite of different models. They modeled the consequences of carbon prices increasing to EUR 140 per ton CO2 until 2030. The effect on the inflation rate is rather small in most cases, the median of their results does not exceed 0.2 percentage points in any given year. The impact on output is also rather contained, GDP falls to between 0.5% and 1.2% below the baseline in 2030. But not only are economic effects subdued, the reduction in emissions caused by higher carbon prices also significantly falls short of the EU's 2030 target. Running similar simulations for the euro area as a whole, Coenen et al. (2024) find that a carbon price of EUR 375 would be necessary to cut in emissions by 25% by 2030.

The aim of our research is twofold. First, we simulate the macroeconomic effects of carbon prices which are sufficiently high to reduce GHG emissions as targeted by the EU. As central bankers, we are genuinely interested in the inflationary effects of carbon prices and the economic adjustment process. Beyond that, the Eurosystem is committed to assessing how climate risks and the transition to a carbon-neutral society affect our economies. The introduction of significant carbon prices is a central element of the transition process. Second, we analyze the country-specific heterogeneity of these effects. ECB (2021) indicated that existing carbon pricing schemes in euro area countries differ significantly and that higher carbon prices might drive prices and inflation. Negative idiosyncratic shocks like different effects of carbon prices have to be addressed by national policies because the Eurosystem's monetary policy reacts only to aggregate changes in the euro area. We want to assess whether the macroeconomic impacts of high carbon prices pose a challenge to national policymakers.

The rest of this study is structured as follows: In the next section, we explain the price mechanisms that are currently in place and could be enhanced for the purpose of reducing GHG emissions. Then, we present our simulations made on the basis of the Global Economic Model of Oxford Economics, which was also used by Brand et al. (2023). The final section concludes our findings.

I The EU policy framework for carbon prices

In the Fit-for-55 package, the EU has defined its policies to reduce GHG emissions by at least 55% by 2030 in comparison to 1990 levels. The package includes legislative proposals and initiatives across various sectors to align the EU with its long-term climate objectives outlined in the Paris Agreement. A central part of the Fit-for-55 package is the EU Emissions Trading System (ETS-1), a carbon pricing mechanism operating as a cap-and-trade system by setting a cap on the total amount of GHG emissions allowed within a certain jurisdiction, covering mainly emission from energy, manufacturing, aviation and maritime transport. Emission allowances are assigned to specific industries, with each allowance representing the right to emit a given GHG amount. If a company emits less than its allocated allowances, it can sell the excess allowances to other companies. Conversely, if a company exceeds its allocated allowances, it must purchase additional allowances to cover the excess emissions.

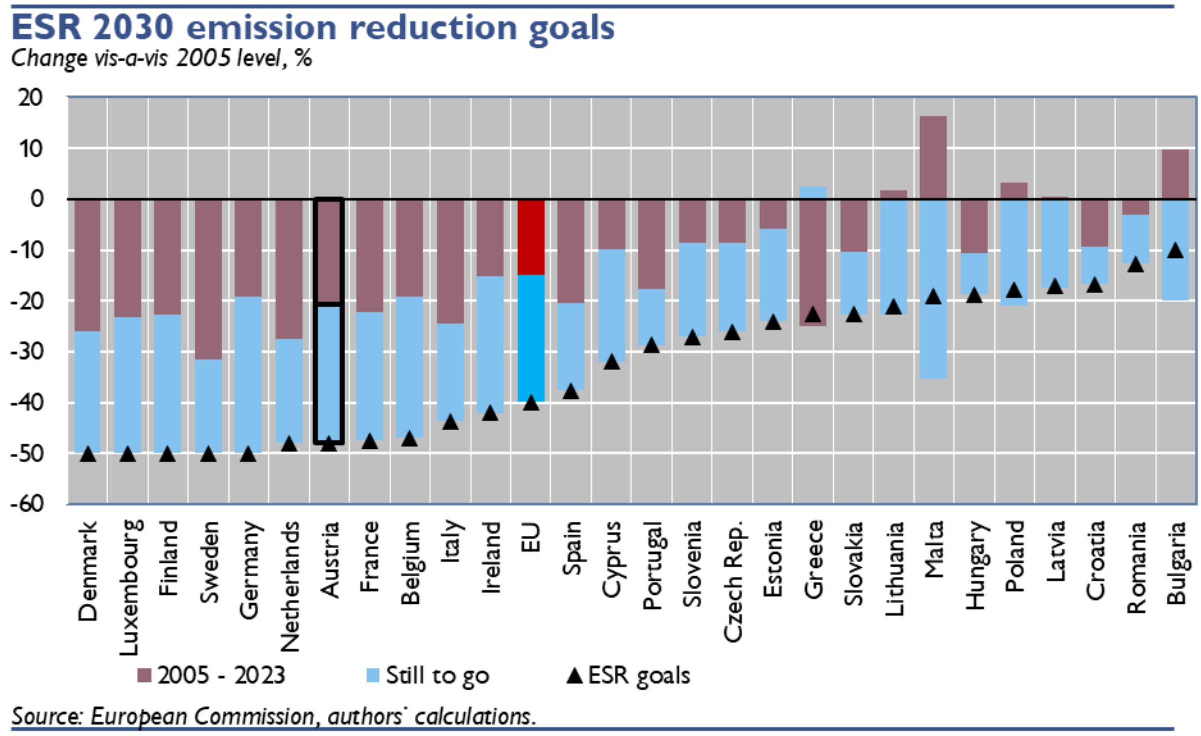
The trade in allowances establishes a carbon price for the capped emissions. Chart 1 depicts the development of the ETS-1 price per ton of carbon dioxide or the equivalent amount of other GHG over the last 15 years. Since the price was below EUR 20 per ton of emitted GHG and the EU's ETS was considered one of the more ambitious carbon pricing mechanisms, Dolphin et al. (2020) concluded that "most of the schemes introduced so far are associated with weak (average) price signals." Currently, ETS-1 is applied in all 27 EU member states, Iceland, Liechtenstein and Norway as well as Northern Ireland for electricity generation. Since its launch in 2005, it has generated revenues from auctions that amounted to more than EUR 150 billion[2].

Chart 1

[2] For more details, see the report on the functioning of the European carbon market by the European Commission (2023).

In addition, EU member states have also committed themselves to reduce emissions in sectors that are not governed by the ETS. The so-called Effort Sharing Regulation (ESR) defines national goals for reducing emissions in domestic transport, buildings, agriculture, small industry and waste. Together, these sectors emit almost 60% of all GHG in the EU. The objective of the ESR is to ensure fair and equitable contributions to the overall emission reduction objectives. Emission reduction goals are set in comparison to the 2005 emission levels. The EU revised the national ESR goals in June 2023 for the years up to 2025[3], in chart 2 we present the resulting national targets. In total, the EU is obliged to reduce its GHG emissions by 40% by 2030 compared to the 2005 level; by the year 2023, about one-third of the intended reduction has already been achieved. Most EU member states must still reduce their emissions significantly, only Greece has already reached its goal. Lithuania, Malta, Poland, Latvia and Bulgaria had not reduced their emissions at all by 2023 compared to the base year.

Chart 2



Some EU countries, e.g. Austria, have implemented national carbon price systems to reach their ESR goals. These price systems either cover emissions which remain not affected by ETS-1 or provide a stronger incentive to reduce emissions in sectors already covered by ETS-1. Partly, these prices will be transferred into a second EU trading system (ETS-2) as of 2027, which will be managed in a market separate from ETS-1 (at least) until 2030. ETS-2 will cover GHG emissions from the building and road transport sectors as well as industrial production. Känzig and Konradt (2023) emphasize that sectors currently covered by ETS-1 are in a better position to pass on cost shocks because of market segmentation in the energy sector and the general dependence on energy.

[3] See Commission implementing decision (EU) 2023/1319 for more details.

2 Model simulations of carbon prices

To estimate the macroeconomic effects of the EU's carbon price policies, we employed the Global Economic Model by Oxford Economics (OE). OE has augmented its semistructural multicountry model with a climate module, which allows us not only to assess changes of macroeconomic variables under different carbon pricing scenarios, but also to estimate how much these price policies would contribute to reducing GHG emissions. Monetary policy follows a Taylor rule based on consumer prices and the output gap.

The model includes limited sectoral disaggregation. It simulates the demand for various energy sources, including gas, oil, coal and renewables, across different sectors such as households, firms and transport, but ultimately aggregates these demands at the macroeconomic level. The model assumes adaptive expectations and exhibits Keynesian characteristics in the short run, with sticky prices and output driven by aggregate demand. In the long run, the model aligns with neoclassical theory, where prices fully adjust and equilibrium is determined by supply-side factors such as productivity, labor and capital. Energy demand is modeled in detail, with functions for oil, natural gas, coal, and electricity depending on GDP, prices and energy efficiency for individual countries. These energy demand forecasts are then translated into carbon emissions. Hence, decarbonization efforts primarily focus on the energy sector level. The model also captures the impact of higher energy prices on total factor productivity, which in turn affects potential output and business investment. Additionally, the model adjusts post-tax fossil fuel prices that encourage a shift in consumption toward low-carbon alternatives to the extent of price increases dependent on the carbon content of fuels and energy efficiency. The data coverage in the OE model enables us to simulate only 13 of the 20 euro area economies (see table 1), but these countries together account for 98% of the euro area's output and 97% of its GHG emissions.

The ETS periodically distributes carbon allowances to firms, which allows them to determine the timing of their emissions within the limits of their allowances. Future reductions in carbon emissions are anticipated as the regulator progressively reduces the total number of allowances issued. This reduction in allowances is expected to drive up ETS prices as the market adjusts. Although the model does not explicitly incorporate a cap-and-trade system, it functions similarly to such a tax. The primary focus is on how the carbon tax impacts energy prices and consumption patterns, rather than on the allowances themselves.

The benchmark for our simulations is OE's baseline scenario, which reflects current policies as well as policy commitments that are backed up by measures and believed to be sufficiently detailed. Carbon prices are expected to increase moderately. Specifically, the OE baseline scenario forecasts a gradual increase in the ETS-1 price from EUR 78 per ton of CO2 in 2023 to EUR 88 per ton by 2030. Additionally, the scenario includes the introduction of emission pricing under ETS-2 starting in 2027, set initially at EUR 44 per ton of CO2. Even in the baseline scenario, we observe a GHG reduction by 44% in 2030 compared to 1990 while mean global warming is projected to reach 1.9 degrees Celsius above pre-industrial levels in 2050. While OE's original baseline scenario assumes the same carbon price for all countries in the euro area as an average ETS share coverage is assumed, we considered an individual price path for each member state in the euro area.

From a monetary policy perspective, it is interesting to note that the price changes that were implemented in the model do not require a significant monetary policy response to keep inflation at the target rate of 2%. Assuming a continuous increase in carbon prices over the whole period until 2030, the OE simulations yield an inflation rate and a monetary policy rate which are firmly anchored in the years after 2027.

2.1 GHG emissions under the Effort Sharing Regulation

In a first step, we assess the state of national efforts under the ESR, which target the emissions from sectors not covered by the current EU ETS. Table 1 compares the share of national GHG emissions covered by the ESR (column 1) with the share of GHG emissions covered by national carbon price schemes in total emissions (column 2). ESR shares vary significantly from country to country, depending on the sectoral composition of national production and the prevalent modes of energy generation. Countries where energy-intensive manufacturing sectors contribute more to GDP tend to have a higher share of emissions covered by the EU ETS. The more heating and transportation are fueled by renewable energy, the lower the emissions under the ESR. Not all member states have chosen to implement carbon prices as a policy instrument to reduce emissions. Only in Germany and Austria, more than half of the emissions covered by the ESR are subject to national carbon price schemes (note that emissions under ETS pricing are usually not taxed by national authorities, hence, all the emissions under national taxation fall under the ESR).

Based on the OE baseline scenario, we assume that countries that have not introduced legislation for national carbon taxes are assumed to continue without. Nevertheless, these assumptions result in an increase in carbon prices for most ESR sectors in 2030 because of the introduction of ETS-2. Given these carbon price increases, we find that 5 of the 13 euro area member states covered by the OE climate model fail to achieve their national effort sharing goals: Spain, Austria, France, Ireland and Germany. This may seem counterintuitive at first, since some of these countries have implemented comprehensive national carbon prices and other countries that meet their emission reduction targets according to our simulations have no national carbon price scheme (see column 2 in table 1). But whereas most national carbon price schemes were introduced in 2017 or later, some countries used to have much higher excise duties on fuels long before. According to OECD (2023), Italy and the Netherlands, for example, have not introduced a national carbon tax, but their fuel excise taxes result in higher effective carbon prices than in Austria or Germany.

Table 1

Effectiveness of national EU policies

Country	Share of emissions covered by ESR	Emissions under national CO2 prices	ESR emission reduction target by 2030	Estimated ESR emission reduction by 2030*
	%			
Finland	60	13	-50	-84
Netherlands	59	1	-48	-57
Italy	65	0	-44	-57
Belgium	64	0	-47	-57
Germany	**56**	**40**	**-50**	**-48**
France	**81**	**35**	**-48**	**-40**
Ireland	**70**	**0**	**-42**	**-40**
Portugal	75	36	-29	-37
Austria	**63**	**43**	**-48**	**-33**
Spain	**70**	**2**	**-38**	**-32**
Slovakia	57	0	-23	-31
Croatia	72	0	-16	-31
Greece	60	0	-23	-24

Source: European Commission, authors' calculations based on OE.

Note: Countries in bold will not manage to achieve their national effort sharing goals in 2030.

** According to OE baseline scenario.*

Countries which were hit hard by the economic crisis that started in 2008 recorded a severe reduction in economic activity, which in turn drastically lowered their GHG emissions. In Greece, real GDP shrank by 26.5% and GHG emissions sank by 33% between 2008 and 2013. None of the countries that were most severely affected by the great recession have recorded pre-crisis emission levels since. Hence, the decision to take 2005 GHG emissions as the reference value for ESR targets benefits these countries. In contrast, large countries, such as Germany or France, reached their highest GHG emission values in the early 1990s. Although Austria reached its GHG emission peak in 2005, the country is far off the 2030 relative target despite a comparatively high share of sectors covered by national carbon prices (which were introduced as late as 2022).

2.2 Fit-for-55 price scenario 2025 – 2030

In the next step, we assess what carbon prices are needed for the euro area countries to reach their Fit-for-55 targets. This is clearly a hypothetical exercise, since we know that the decarbonization of our economies will require a combination of different policy measures as indicated by Acemoglu et al. (2012) or IEA (2021). These measures include technology policies, mandatory energy efficiency standards, transport regulations or investments in infrastructure. But the results of our simulations may serve as a benchmark for the macroeconomic impact of these policies since some of them (e.g. energy efficiency standards) are rather difficult to simulate in macro models. In our simulations, we do not assume any additional investments in cleaner technologies or the expansion of renewable energy capacities, given that the simulation time frame is considered too brief to accommodate significant advancements in these areas. In the short run, economic effects of carbon prices are easier to model than other policies that might involve regulatory changes, subsidies or technological advancements. While other measures in the Fit-for-55 package (such as energy efficiency improvements, renewable energy targets, or transportation electrification) are crucial for long-term decarbonization, they often require more time for planning, investment and deployment, making them more suitable for medium- to long-term strategies.

Our simulations follow the line of Brand et al. (2023), who estimated the effects of higher carbon prices with a suite of different models, among them the OE model. They assume a carbon price increase from EUR 85/t of CO2 in 2021 to EUR 140/t of CO2 in 2030 for all countries in the euro area[4] and a milder carbon price path for the rest of the world. Comparing their results to a scenario assuming no carbon prices at all, they find a GDP loss of around 1% by 2030 and higher inflation by around 0.1 percentage points per year, while the reduction in CO2 emissions is around 5% and, hence, fails to reach the Fit-for-55 targets.

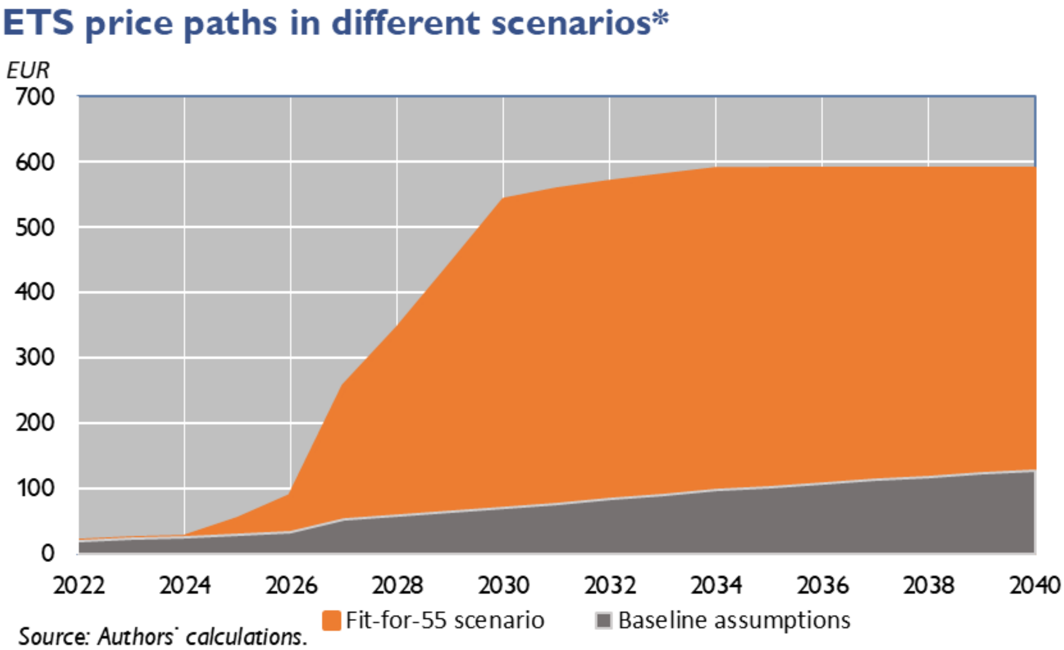
Based on our calculations of carbon prices needed to reach the targets, in our scenario, we assume an annual price increase of EUR 90 per t/CO2 for ETS-1 and ETS-2 starting in 2025. Hence, we assume that allowances under ETS-1 will have a price of EUR 180/t CO2 in 2025, which will rise by EUR 90/t CO2 each year until a final price of EUR 630/t CO2 is reached in 2030 (and is held constant after 2030). The price path for ETS-2 starts in 2027 with the same price as under ETS-1 in that year, namely, EUR 360/t CO2. In analogy, allowances under ETS-2 reach a final price of EUR 630/t CO2 in 2030. For each EU country i, the setup of the emission-weighted carbon prices p_i^{ETS} per t/CO2 under the integrated ETS system is as follows:

$$p_i^{ETS} = (p^{ETS-1} \times s_i^{ETS-1}) + (p^{ETS-2} \times s_i^{ETS-2})$$

with p^{ETS-1} and p^{ETS-2} representing the prices per t/CO2 for the sectors covered by the corresponding ETS system and the emission-weighted shares s_i^{ETS-1} and s_i^{ETS-2} are assumed according to the sectoral coverage of the ETS system, which differs for each EU country i. ETS prices are assumed to partially generate some government revenue (i.e., contributing to national budgets) and parts of the ETS revenues are assumed to go directly to EU modernization and innovation activities as well as to the EU's Social Climate Fund. The average government revenue from the current p^{ETS-1} is EUR 53/t CO2 in 2025 and, according to our simulation, this revenue will increase to EUR 541/t CO2 in 2030. In contrast to the baseline assumptions by Brand et al. (2023), we use the OE baseline scenario (as of Q4 2023) as a benchmark to measure the effects of higher carbon prices. This benchmark includes a mild increase in carbon prices over the projection horizon (see chart 3). We consider this a more realistic comparison than a scenario without any carbon price increases at all since several countries have already announced their intention to increase carbon prices over the coming years. According to the OE baseline scenario, the baseline for countries outside the EU also allows for increasing carbon prices if these have been announced or implemented sufficiently.

[4] The IEA World Energy Outlook (IEA, 2022) presents a "net zero emissions by 2050" scenario which assumes that advanced economies with net zero emissions pledges (like the EU) introduce a carbon price of 140 USD by 2030, which will be raised further to 205 USD in 2040 and 250 USD in 2050.

Chart 3



Source: Authors' calculations.
* ETS prices refer to the government-revenue generating share of carbon prices

In addition to p_i^{ETS}, each country may or may not introduce a national carbon price $p_i^{national}$. The total emission-weighted effective carbon price per t/CO2 for each country is calculated by:

$$p_i^{CO2} = \left(p_i^{national} \times s_i^{national}\right) + p_i^{ETS}$$

with $s_i^{national}$ representing the shares of emissions in country i covered by a national pricing mechanism (note that p_i^{ETS} has been calculated by using the shares of emissions under each ETS, therefore, no further weighting is required). We considered a price path for each member state in the euro area based on prices which are already in effect (starting in 2025).

Table 2 shows the evolution of the price required to meet the Fit-for-55 scenario, p_i^{CO2} for each country as well as the emission reduction compared to 1990 values. The average p^{CO2} for the euro area is EUR 668 in 2030, which results from a price increase of EUR 581 compared to the baseline scenario in 2030. We find a strong heterogeneity in emission reduction across euro area member states, with Finland leading by a considerable margin of -94% while Ireland shows the lowest reduction with only -14% in GHG emissions. According to the IEA (2023), Finland has already set one of the most ambitious energy targets, a legal obligation to reach carbon neutrality by 2035. The country is making progress toward this target and has one of the lowest levels of reliance on fossil fuels among IEA member countries. Ireland, by contrast, introduced a carbon tax as early as 2010, but still faces challenges in reducing its emissions. According to the IEA, natural gas will remain an element in Ireland's energy mix for the next decade, particularly to meet peak electricity demand. When looking at the aggregated results, the euro area would manage to reduce its emissions in line with its Fit-for-55 targets by 55% by 2030, which is an additional reduction of 11 percentage points compared to the baseline. Here, it should be noted that the euro area countries that we analyze already cut their GHG emissions on average by 34%

between 1990 and 2023, with Finland, Germany and Slovakia having recorded the strongest reductions, whereas in Ireland and Spain, total GHG emissions were growing over that period.

Table 2

Carbon prices and emission reduction in Fit-for-55 scenario in the euro area

Country	Carbon price		GHG emission changes compared to 1990*	
	2025	2030	2023	2030
	EUR		%	
Finland	101	736	-53	-94
Germany	123	759	-48	-67
Belgium	79	679	-17	-66
Slovakia	95	750	-46	-66
Netherlands	91	732	-32	-60
Italy	76	665	-44	-60
Croatia	61	601	-26	-50
France	70	518	-29	-42
Portugal	70	573	-15	-24
Austria	112	697	-15	-24
Spain	67	626	9	-22
Greece	88	721	-29	-15
Ireland	66	622	19	-14
Euro area	**84**	**668**	**-34**	**-55**

Source: Authors' calculations.

** Compared to 1990 values according to the Fit-for-55 package.*

The macroeconomic effects of the required carbon price increase seem manageable at the aggregate euro area level. We see that in the Fit-for-55 scenario, GDP in the euro area drops by -2.2% until 2030 when compared to the baseline (see chart 4). The CPI in the euro area increases cumulatively by 6.4 percentage points by 2030 (see chart 5). The stronger rises in the CPI are due to the ETS-1 increase in 2025 and the ETS-2 introduction in 2027. The reduction in output depresses disposable personal income, but this income decline does not curb effective demand so much that it counterbalances the effects of the high carbon prices on the CPI. Inflation rates pick up only temporarily, returning to their anchored levels rather quickly; this is in line with the findings of Brand et al. (2023) and Coenen et al. (2024), who also report a transitory rise in inflation because of increasing carbon taxes. The simulations by Coenen et al. (2024) are most comparable to ours since they also estimate the effects of reducing carbon emissions by 25% from 2022 to 2030 and find that this would require increasing carbon taxes to EUR 375. In our Fit-for-55 scenario, the price of EUR 668 yields an emission reduction of 31% from 2022 to 2030.
Since the carbon tax is a cost-push shock to the economy, we would expect the price competitiveness of the affected countries to deteriorate, which consequently depresses the growth contribution of net trade. This effect is dampened by the fact that most euro area countries trade mostly with other euro area countries, and all of them are exposed to the same cost-push shock. For example, Austria conducts more than half of its international trade with the other 12 euro

area countries listed in table 2. Austria's trade balance is estimated at +1.8% of GDP in 2023 and would decline slowly in the baseline scenario but remain positive, whereas in the Fit-for-55 scenario, the trade balance turns negative in 2028 and the deficit increases continuously thereafter. Exports are projected to decline by 4% until 2030 in comparison, but imports would also be lower in the Fit-for-55 scenario – by about 2.5% – until 2030, with imports of fuels declining strongly for obvious reasons.

Chart 4

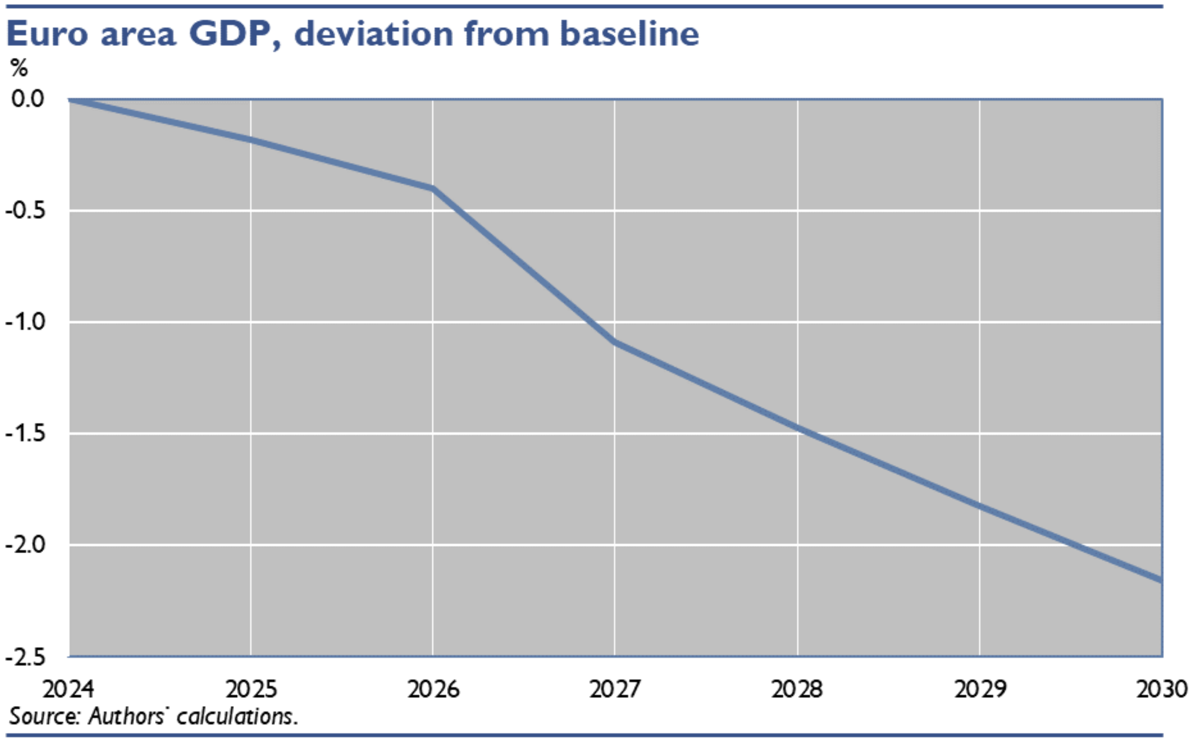
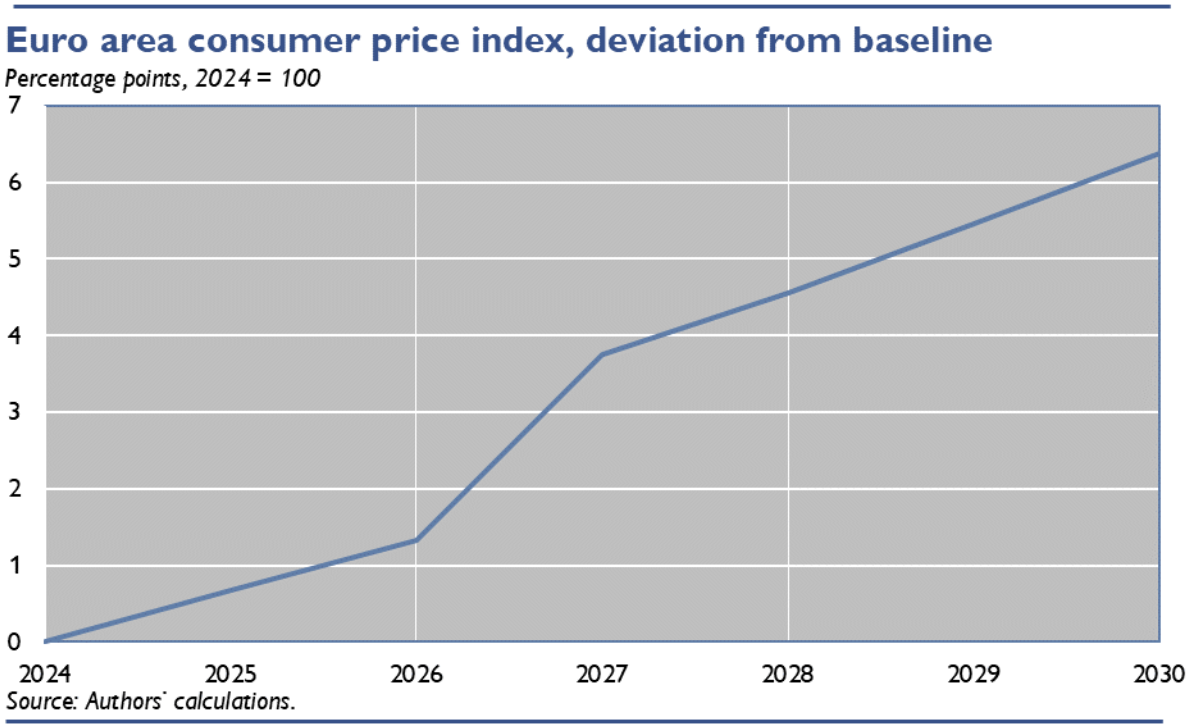


Chart 5



The varying impacts on GDP and CPI across EU countries reflects the fact that renewable energy adoption and reliance on fossil fuels varies among member states. Chart 6 shows a comparison of how big the simulated impact on GDP is on the national level. While for Ireland, we see a decline in GDP compared to the baseline which, at less than -1%, is significantly below the euro area average, for Slovakia, we see a GDP loss that is more than twice as high as the average, namely almost –5%. According to the IEA, the contribution of renewable energy sources to Slovakia's energy mix remains lower compared to some other euro area members as Slovakia still uses a significant amount of fossil fuels, especially natural gas and, to a lesser but still significant extent, coal (31% of total emissions in Slovakia come from fuel combustion). Moreover, Slovakia's economy relies heavily on carbon-intensive industries such as steel, cement, and chemicals (26% of total energy-related emissions come from manufacturing). It should be noted that our simulations do not incorporate an increase in the capacity for renewable energy production because this would warrant an explicit policy change and our aim was to isolate the price effects of a tax increase under ceteris paribus conditions. However, the share of renewable energy in electricity production does increase in Slovakia, but this is only due to the decrease in the fossil component of electricity production because of higher prices.

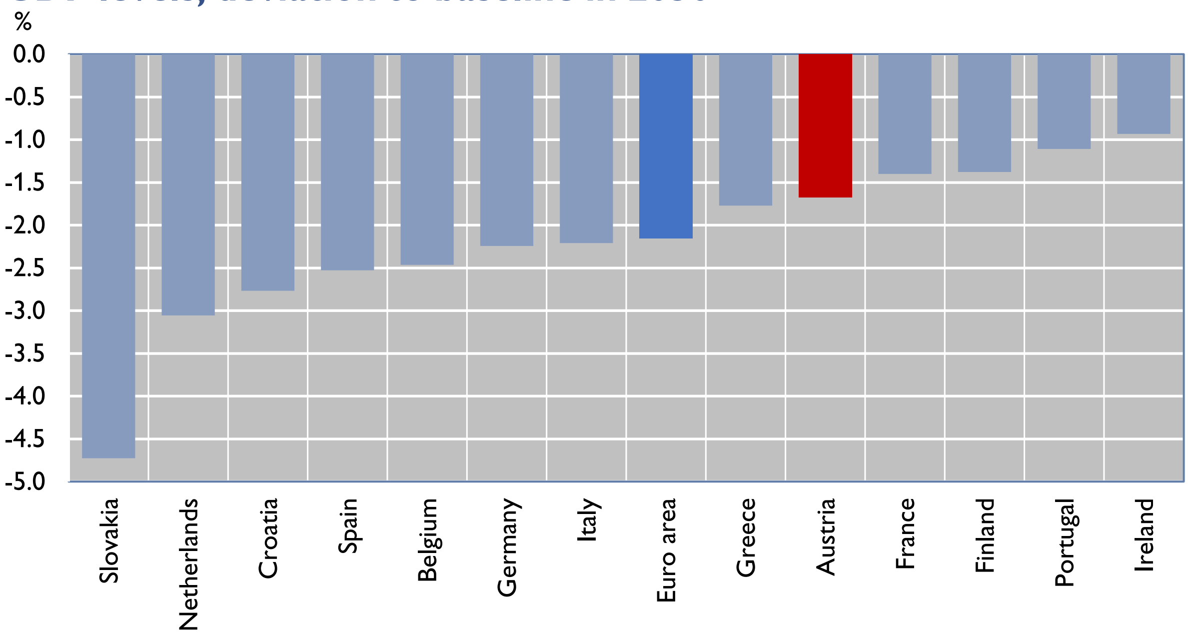
IEA data also highlights that Ireland has the lowest energy intensity per GDP by far (which is lower by 69% when comparing 2000 to 2020 values). Besides energy intensity, sources of energy also explain why some countries' GDP is affected less by higher carbon prices. While the primary source of energy is nuclear power in France, Portugal's domestic energy production is characterized by a diverse mix of renewable energy sources, particularly hydropower, wind and solar energy. Austria is below the euro area average when it comes to GDP impacts, as Austria's energy mix is characterized by a high share of renewable energy, particularly hydropower.

According to Eurostat, 33.8% of Austria' gross final energy consumption was generated by renewable sources in 2022 (compared to an EU average of 23%).

In chart 7, we see a comparison of the CPI effect at the national level. Here, again, Slovakia shows the highest effect by far, with a cumulative increase of consumer prices of 16.8% over the whole period compared to the baseline. The energy sector, and particularly the fuel component of energy, plays a significant role in Slovakia's consumer basket, while a very mild effect of around 4.3% to 4.6% can be observed for France, Finland and Portugal, where fuels do not have such a significant role in the consumer basket. This is in line with the findings of Känzig and Konradt (2023), who also find a stronger price response in countries with a more carbon-intensive energy mix.

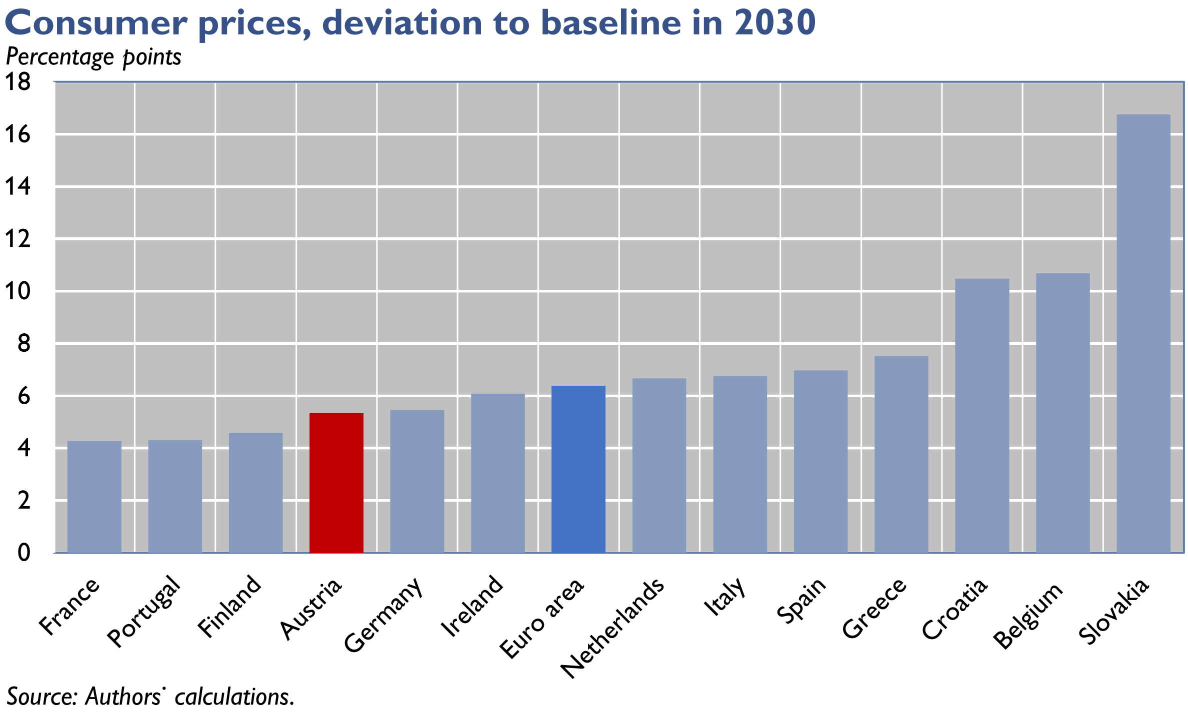
Chart 6

GDP levels, deviation to baseline in 2030



Source: Authors' calculations.

Chart 7



Revenues from carbon pricing are used by member states for national and EU-wide climate action measures. We examined how much in revenues relative to GDP member states could obtain from carbon prices in the Fit-for-55 scenario (see chart 8). At the aggregate level, the 13 euro area members included in our analysis would obtain EUR 2.62 trillion in revenues from 2025 to 2030, which corresponds to EUR 2.07 trillion in additional carbon tax revenues under the Fit-for-55 scenario compared to the baseline. National carbon tax revenues depend on the carbon intensity of the economies. n 2025, almost all national carbon tax revenues are below 1% of GDP, but by the end of the decade, Slovakia might generate revenues of more than 5% of GDP. For Austria, the expected tax revenues increase from 0.8% of GDP in 2025 to 2.7% in 2030. Other sources of tax revenues might decline temporarily due to the negative effects of carbon taxes on output, but these effects are rather modest in our simulations.

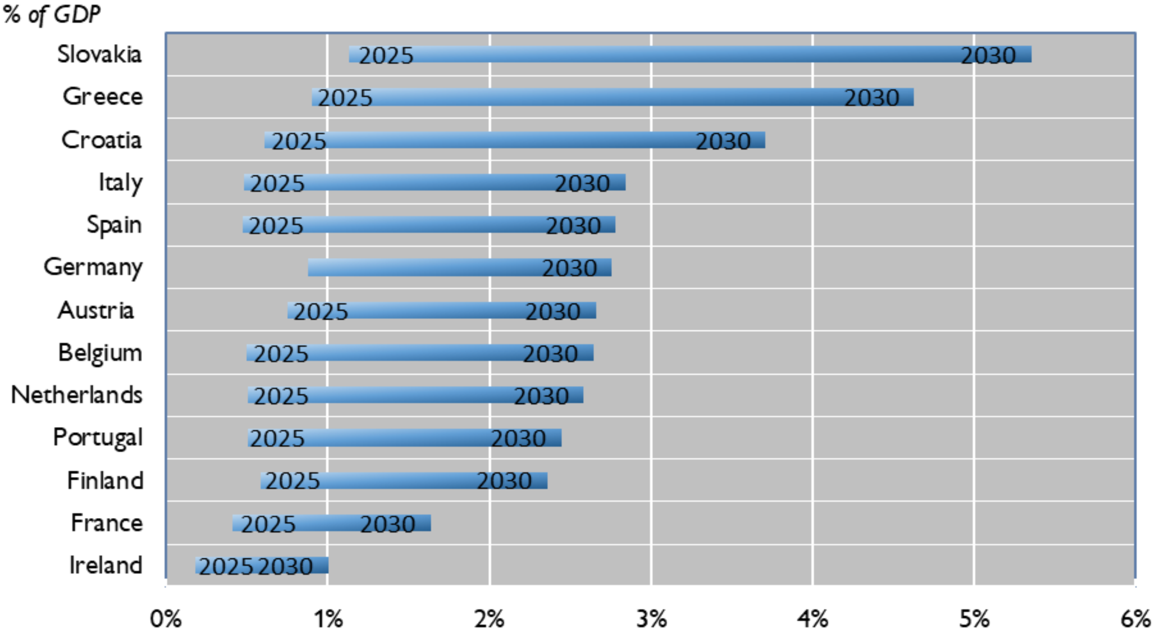
Since future revenues from carbon taxes will reach significant levels, governments will be faced with the political questions of what to do with these funds. The European Environment Agency estimates that the required investments in the sustainable transition amount to EUR 520 billion per year from 2021 to 2030 (EEA, 2023). The revenues from carbon taxes could cover almost half of these financing needs. In practice, however, it is probably necessary to recycle most of these revenues back to taxpayers to raise the social acceptability of carbon taxes. To assess the political economy constraints for carbon taxes, Muth (2023) compares 30 carbon pricing mechanisms at the national level and finds that a hybrid strategy of combining compensatory transfers to taxpayers with targeted spending on climate-related projects is most effective. For the simulations presented in this paper, we assume the national governments use the additional revenues from higher carbon taxes to reduce their sovereign debt levels, which does not induce any positive demand effects. Governments recycling their revenues back to households would strengthen demand, thereby pushing prices up; hence, our results can be seen as a conservative

estimate of the inflationary effects. But of course, the effect also depends on the behavioral response: if the recycled revenues are spent on less energy-intensive equipment (e.g., more efficient refrigerators), the long-term impact might be disinflationary. Känzig and Konradt (2023) also stress the importance of recycling channels for the macroeconomic effects of carbon prices.
According to the International Carbon Action Partnership, roughly 20% of ETS-1 revenues go to the EU's Modernisation Fund and its Innovation Fund. According to the European Commission, legislation provides for 25% of ETS-2 revenues going to the Social Climate Fund, which is also included in the Fit-for-55 package. Hence, out of the EUR 2.62 trillion which, according to our analysis, could be generated in total from national as well as ETS revenues, EUR 207 billion are intended to directly go to the aforementioned funds.

Chart 8

Carbon tax revenues 2025-2030 under the Fit-for-55 scenario

% of GDP



Source: Authors' calculations.

3 Conclusions

The results of our simulations show that a carbon price of EUR 668/t CO2 in 2030 would be required to reach the EU's Fit-for-55 targets for GHG emission reduction if the carbon price was the only policy instrument to trigger the necessary changes. Overall, the impacts that reaching the Fit-for-55 targets in 2030 has on GDP (a cumulative loss of 2.2%) and CPI (a cumulative increase of 6.4 percentage points) seem contained, but the economic repercussions are not uniformly distributed among the countries of the euro area. From a monetary policy perspective, it is important to note that inflation rates will pick up only temporarily.
Countries which have already made substantial investments in renewable energy and, hence, have a robust renewable framework will experience relatively mild economic impacts. More resilience can also be observed for countries which rely more on non-fossil energy sources like nuclear energy, such as France. Countries which have introduced effective carbon reduction policies in

the past overachieve the Fit-for-55 targets by far in our simulation. Conversely, countries with a heavy reliance on fossil fuels and carbon-intensive industries face stronger economic repercussions. Impacts on CPI are mainly driven by the energy component of consumption, and hence, low-wage countries face harsher outcomes. The projected GDP decline for Slovakia is more than twice as high as the euro area average, and the CPI is expected to rise cumulatively by 16.8 percentage points, also more than twice as high as the euro area average. This strong contrast underscores the challenges faced by countries with less diversified energy portfolios and a greater dependence on carbon-intensive industries, in particular, if incomes are low. While carbon pricing is a crucial tool for achieving the EU's climate goals, the great difference in economic impacts across member states highlights the need for coordinated support and targeted investment.

High carbon prices would generate substantial tax revenues. In our scenario, revenues of EUR 207 billion obtained over five years would be allocated, as intended, directly to the EU's Modernization Fund and its Innovation Fund as well as the Social Climate Fund, with the remaining revenues distributed among national governments. Political economy considerations about the use of these tax revenues are a valid concern but are outside the scope of our paper[5]. Key areas for national investment should be (a) increasing the share of renewables in the energy mix (the EU's Fit-for-55 goal is a minimum 40% share of renewables in the EU's overall energy mix by 2030), as well as (b) the mitigation of socioeconomic impacts of the transition on vulnerable households, micro-enterprises, and transport users, in particular, in countries where carbon taxes have high effects on consumer prices.

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The (de)globalization of migration: has the polycrisis period changed the patterns of global migration?

Jonathan Fitter, Anna Katharina Raggl, Paul Ramskogler[1]

Migration is a hotly discussed issue, and while the magnitude of migration is a frequent topic of debate, there is less discussion about its patterns (i.e. the diversity of migration). Yet, there is accumulating evidence that higher cultural heterogeneity among immigrants – a result of more globalized migrants – has positive impacts on productivity growth and innovation in destination countries and thus, ultimately, affects monetary policy. But is migration really becoming more globalized (i.e. more heterogenous), or is there evidence for recent (de)globalization trends, often attributed to flows of goods and capital? We address this question by composing an index of the globalization of migration that comprises three dimensions of global migration, following Czaika and de Haas (2015): the intensity – or relative magnitude – of migration, its diversity with respect to origin and destination countries, and the average distance of migration routes. These dimensions are combined to obtain an index of migration globalization that allows us to assess not only the degree of migration globalization, but also each country's integration in global migration processes. Using migration flow estimates for 1990–2020, we find that migration continued to become more globalized in the past three decades, but this upward trend started to flatten out after the period 2005–10. The intensity of global migration flows did not increase between 1990 and 2020. The spread of global emigrants across destination countries widened in these three decades, while the diversity of global immigrants with respect to their home countries changed little and remained at a high level. This constitutes a change in the trend seen in earlier decades, when migrants from increasingly different origin countries moved to a narrowing set of destination countries.

JEL classification: F22, F60, J11
Keywords: international migration, bilateral migration, (de)globalization, diversification of migrants

The second half of the 20th century was characterized by increasing global economic integration, which gained even more speed after the fall of the Iron Curtain. The global economic crisis in 2008–10 seemed to have put a first halt to this process: the ensuing recovery was uneven and shallow in many world regions. At the same time, many advanced economies started to question the benefits of globalization: The United Kingdom leaving the EU and the trade war between the USA and China can be seen as manifestations of this skepticism (Thompson, 2022). More recently, the COVID-19 pandemic and the Russian invasion of Ukraine highlighted the fragility of supply chains, imposing further challenges on globalization. Whether this leads to a permanent trend reversal or is merely a transitory development remains to be seen (see, for example, Goldberg and Reed, 2023, and a recent IMF staff discussion note, Aiyar et al., 2023, for an assessment of the risks associated with increasing policy-driven geo-economic fragmentation).

While global trade and capital flows are more closely monitored (see, for example, Abelianski et al., 2024), another dimension of bilateral flows receives less attention in the context of

[1] Vienna University of Economics and Business, jonathan.fitter@wu.ac.at, and Oesterreichische Nationalbank, International Economics Section, anna.raggl@oenb.at and paul.ramskogler@oenb.at. Opinions expressed by the authors of studies do not necessarily reflect the official viewpoint of the OeNB or the Eurosystem. The authors would like to thank Heider Kariem (WIFO) for excellent research assistance at the early stages of the project, the Editorial Board of the OeNB Bulletin, an anonymous referee and the GloMo project team for helpful comments and valuable suggestions. This publication is part of a larger project on (de)globalization, the (De)Globalization Monitor (GloMo), conducted at the OeNB's International Economics Section. The project comprises analyses of capital flows and cross-border investment (CapMo), trade (TradeMo) and migration (MigMo). All related publications, data and interactive charts will be published on a dedicated webpage, which will be the project's central hub. Current members of the project team are Ana Abeliansky, Christian Alexander Belabed, Julian Mayrhuber, Anna Katharina Raggl and Paul Ramskogler (all OeNB, International Economics Section).

(de)globalization: the bilateral flow of people. However, the composition of migration has important repercussions for trade channels, productivity, innovation and thus, ultimately, monetary policy. Conventional wisdom is that migration has been becoming increasingly global, more frequent and more diverse. Whether this is the case and/or whether migration flows are joining deglobalization trends often attributed to trade and capital flows has not been empirically assessed recently.

This study focuses on the question whether bilateral migration flows show signs of deglobalization, building on a concept developed by Czaika and de Haas (2015), who suggest measuring the degree of globalization along three dimensions: the intensity of migration, the spread/diversification of migration with respect to source and destination countries, and the average distance traveled by migrants. In this study, we apply the approach to estimates of global bilateral migration flows from Abel and Cohen (2019) in its most recent version (October 2022) and provided by Abel (2019) to address the following questions: First, looking at global migration *flows*, has migration continued to become more globalized since 1990? Has it become less globalized in the most recent past, in line with deglobalization tendencies often attributed to other cross-border flows (capital, trade)? Second, how do world regions differ with respect to the diversity of source countries of emigrants and destination countries of immigrants and their degree of migration globalization? Specifically, how does Europe differ from the rest of world? And how has this been changing over time?

These questions are not only intriguing in their own right but also integral to a comprehensive assessment of (de)globalization tendencies in global flows of capital, goods, services and people. Migration, in particular, has important implications for economic outcomes in both receiving and sending countries. In the euro area, the first and most direct impact is on the size of the working-age population. Especially against the background of shrinking working-age populations, immigration can counteract population decline at least in the short to medium run. Note, for instance, that the recent labor market boom in the USA can be largely explained by a surprise surge in immigration (Edelberg and Watson, 2024). In both the EU and the euro area, for example, the labor force would have shrunk between 2012 and 2022 without workers from foreign countries[2]. During the COVID-19 pandemic, on the other hand, weak net migration may have contributed to subdued labor force developments (ECB, 2022). Second, immigration does not only alter the size but also the age structure of a population. As immigrants tend to be relatively young, migration can counteract population aging in aging societies. It can contribute to lower old-age dependency ratios, which have been increasing strongly in most advanced economies (see, for example, Peri, 2020). The fact that immigrants tend to be young is also one of the reasons why several studies also find a positive fiscal impact of immigration (see, for example, OECD, 2021). Further, immigrants can contribute to a slowdown of population aging in advanced economies through, on average, higher fertility rates. Third, migration has been shown to foster productivity, thereby fueling economic growth. This effect is usually attributed to the complementarity of immigrants' skills to those of natives. With immigrants entering the labor market, natives move to different occupations that often require the performance of more complex tasks, linguistic and communication proficiency, etc. In other words, natives often upgrade their jobs as immigrants enter the labor market (see Foged and Peri, 2016.) Fourth,

[2] This result is calculated from Eurostat data (persons in the labor force, by country of birth). Between 2012 and 2022, the increase in the foreign-born labor force was larger than the increase in the total labor force (including foreign-born). This holds for both the EU and the euro area.

migration is related to other cross-country flows, such as trade and capital flows. Specifically, trade between home and host countries has been shown to increase as a result of migration (see, for example, Iranzo and Peri, 2009; Egger et al., 2012; Felbermayr et al., 2015; Bahar and Rappoport, 2018; OECD, 2022), just like FDI has been shown to increase with higher migration between two countries (see, for example, Buch et al., 2006; Javorcik et al., 2011; Kugler and Rapoport, 2007).

Thus, migration has an impact on economic variables, and in terms of growth and productivity, the impact is positive. But how does this relate to the globalization of migration? Does the globalization of migration have an effect on economic variables to an extent that it becomes relevant from a monetary policy perspective? In fact, there is accumulating evidence that higher cultural heterogeneity of migrants has positive impacts on productivity growth and innovation (see literature section below). As far as this is the case, migration affects the natural rate of interest. This is when it becomes relevant for monetary policy.

This study contributes to the literature in several ways. First, we address a topic that has received a lot of attention recently in the context of capital and trade flows and apply it to international migration dynamics. Second, we use a conceptual framework for assessing the globalization of migration developed by Czaika and de Haas (2015) and apply it to more recent data on migrant stocks. This allows us an assessment of (de)globalization trends of international migration up to the year 2020, an update compared to the existing results for 1960 to 2000. Third, we use estimates of global bilateral migration *flows* (Abel and Cohen, 2019). This way, the analysis is not diluted by previous migrants that show up in the stock figures although the actual year of migration might have been years or even decades ago. Migration flow estimates show current migration behavior and thus allow us to better study current trends. Fourth, we focus on the EU and assess how the intensity and diversification of migration has changed over time. This will feed into a follow-up study that will be dedicated to the assessment of possible implications for the size and age structure of the euro area population.

The remainder of this paper is structured as follows. In the next section, we will discuss the concept of measuring the degree of globalization of migration. After describing the data in section 2, we will present the results in chapter 3. Section 4 concludes.

1 The impact of migrant diversity on economic outcomes in the literature

The only paper that explicitly addresses the globalization of migration is that of Czaika and de Haas (2015). However, there is a body of literature that is concerned with the economic relevance of migration diversity. Migrants influence the economy in various ways: they impact demography, labor markets and productivity; migration has a fiscal dimension, and it also relates to trade and capital flows (see, for example, OECD, 2014; Koczan et al., 2019). An expansion of the workforce almost inevitably leads to an increase in a country's GDP. But there is also extensive research on the impact of migration on GDP per capita, and the majority of empirical studies find a growth-enhancing effect of immigration (see, for example, Brunow et al., 2015; Engler et al., 2023).

In the context of this study, however, the obvious question is whether the spread of migration, i.e. the heterogeneity of (im)migrants with respect to their origin, influences economic outcomes, and, if so, how. There is a limited but growing body of literature that addresses this question, and most analyses conclude that the diversity of immigrants with respect to their place of birth boosts economic performance in the recipient countries, regions, subregions or cities. The mechanism behind this positive impact is usually described as the complementarity in knowledge and skill sets that come with migrants that were raised and trained in different countries. Bahar et al. (2022) argue that this increase in the skill sets that countries can draw upon also enables a country to become active in a broader set of fields and to become more economically complex. They empirically explore this relationship and find cross-country evidence that countries with a birthplace-diverse population indeed exhibit higher economic complexity. This finding holds in particular for diversity among highly educated migrants and for countries with intermediate levels of economic complexity. They further provide evidence that the underlying mechanism of birthplace diversity boosting economic complexity is the increasing diversity in host countries' export baskets. Bove and Elia (2017) investigate whether cultural diversity brought about by immigration has an impact on economic growth and, if so, to what extent. They find a robust and positive relationship over long time periods. Similarly, Alesina et al. (2016) find that the diversity of immigrants relates positively to measures of economic prosperity. The results suggest that skill complementarities between immigrant and native workers are driving the effect. Trax et al. (2015) show at the firm level and for Germany that cultural heterogeneity in firms increases productivity levels (while the mere share of foreign workers in a firm does not). In addition, the cultural heterogeneity in the region where a firm is located, matters for plant-level productivity. Discussing evidence on the impact of migrant heterogeneity with respect to origin but also to skills, motives, culture, etc., Brunow et al. (2015) conclude that its impact is, on balance, positive on innovation and economic growth. Ortega and Peri (2014) explore the interrelationship between trade, migration and income per capita. They find that openness to immigration has a positive and robust long-run impact on income per capita, with the main impact of immigration operating through total factor productivity. The degree of diversity in migration flows has an additional positive impact on income: the set of skills in the labor force is better differentiated, and some evidence suggests that innovation activity is higher with more diversity among migrants.

These recent examples of studies investigating the impact of the diversity of migrants – instead of their numbers – on economic outcomes provide evidence of a positive impact of birthplace diversity. Underlying mechanisms are predominately related to (skill) complementarities between native and migrant workers and associated productivity improvements and innovation.

2 Measuring the degree of (de)globalization of migration

Along with the increase of trade and cross-border investment flows in the course of globalization, a common narrative is also that migration flows keep growing and are getting increasingly complex. At the same time, it is argued, albeit less commonly, that the share of people living outside their country of birth is actually rather small and did not change significantly over several decades, i.e. between the 1960s and 2000s, and after that only increased to a still moderate 3.6% in 2020 (UNDP, 2020). Czaika and de Haas (2015) challenged the common notion that global migration patterns have become increasingly complex over the past decades, with a formerly more clear-cut distinction between typical immigration and emigration countries becoming diluted over time and the initially few main corridors – often following colonial ties – becoming increasingly broad. They do so by investigating – in a structured way – the changes in the magnitude and the diversity of global migration during 1960 and 2000, using data on migrant stocks that measure the number of foreign-born individuals living in the reference countries at a given point in time.

It is not straightforward how to *measure* the degree of globalization of migration, and while there is literature that relates international migration *to* globalization, usually understood as openness to trade and foreign capital, research on (the measurement of) the globalization *of* migration is very scarce. Czaika and de Haas (2015) suggested a framework to quantitatively assess this question by considering three different dimensions: the intensity of global migration, the spread of migrants across origin and destination countries, and the average distance covered by global migrants.[3] The intensity of migration is measured by the share of migrants in the population. The spread of migration, i.e. the origin-country diversity of immigrants and the destination-country diversity of emigrants, is measured as unity minus the Herfindahl-Hirschman Index of concentration: the higher this spread measure, the more diverse the migrants. And the third dimension, the distance of migration, is measured as the average distance between migrants' origin and source country in a given year or period. Following Czaika and de Haas (2015), we combine these three dimensions to obtain an index of emigrant globalization and an index of immigrant globalization. The former summarizes how globalized emigrants are: how many emigrants are there, how diverse are their destinations, and how far away do they move. The latter index informs about the degree of globalization of immigrants: how many immigrants does a country have, how diverse are they, and from how far away are they? Finally, we combine these two subindices to obtain an index of migration globalization that measures the integration of a country into global migration processes, considering both emigrants from and immigrants to a country. Under this concept, migration becomes more globalized if the intensity of migration increases, migration is more diverse (with respect to origin and destination countries) and the distance becomes longer. Please refer to section A1 in the annex for a comprehensive explanation of the indicators constructed.

We use this approach to address the question of (de)globalization of migration, using recent data on global migration flow estimates in addition to migration stock data. We also use the most recent data on migration stocks, currently available for 1990 to 2020, to directly compare and update the results by Czaika and de Haas (2015). In all dimensions, it is crucial to look beyond the global average that might hide important regional heterogeneities. Geographically, our particular emphasis is on the EU.

3 Data

The core data we use in this analysis are estimates of international migration stocks and estimates of international migration flows. For a comprehensive overview of currently available data on international migration, see Buettner (2022).

3.1 Global bilateral migrant stocks

The UN's International Migrant Stock 2020 dataset (UNDP, 2020) is currently the most complete global database for bilateral stocks of migrants. It contains estimates of the total number of international migrants by age, sex and origin for the mid-point (July 1) of every fifth year between 1990 and 2020. The data are available for 232 countries and areas[4] of the world and are based on official statistics of the foreign-born population. Most of the estimates rely on population censuses but also use information from population registers and nationally representative surveys. Generally, international migrants are equated with the foreign-born population, which is possible

[3] This framework has more recently also been applied to global refugee migration (Fransen and de Haas, 2022) and in parts also to the global mobility of scientists (Czaika and Orazbayev, 2018).

[4] In the UN migration data, the term country does not solely refer to states but also to overseas territories/unincorporated territories, such as Bermuda, the British Virgin Islands or Gibraltar.

for most countries. Whenever the necessary information on the country of birth is not available, and that is the case for approximately 20% of the countries/areas, the country of citizenship is used instead. See section A6 in the annex for further information.

3.2 Global bilateral migrant flows

Migrant *stocks* also reflect to a large extent past migration patterns. Because we are mostly interested in current trends and developments, estimates of international migration *flows* are more interesting for us: they are not "diluted" by previous migration behavior and reflect concurrent migration dynamics. Migration flow data have additional important advantages over stock data. First, they are more appropriate for policy analysis, as flows can show direct reactions to policy changes and do not include migration movements that happened years or even decades ago independent of current policies. Second, migration flow estimates take into account *return migration*: a movement from A to B and back to A would be reflected and counted as two movements while it would not show up in migrant stock data once the return migration is completed. Third, flow data also better reflect *onward migration*: a movement from A to B to C would be counted as two movements while in migrant stock data, it would be interpreted as one movement from A to C once the onward migration is completed.

However, a global dataset on migration flows is not available, as in many countries migration flow data are not collected. In addition, even if the data are available for certain countries, it is difficult to compare the data for different countries, as underlying definitions often differ. We thus rely on estimates in our analysis. In particular, we make use of the bilateral international migration estimates provided by Abel (2019) and Abel and Cohen (2019), who – motivated by the lack of migration flow data – estimate global bilateral migration flows drawing on UN international migrant stock data. For this analysis, we use the most recent update of the database (Abel, 2019, version 6, October 28, 2022). This update has been prepared to incorporate current UN migrant stock estimates (UNDP, 2020) and current UN population statistics updates (UNDP, 2022). Following the periodicity of the UN migration data, the dataset provides estimates of migration flows between country pairs over five-year periods from 1990–1995 to 2015–2020 (in each case from July 1 onward). The estimates cover 225 countries for the periods 1990–1995 to 2000–2005, 226 countries for 2005–2010, and 229 from the period 2010–2015 onward. Abel and Cohen (2019) provide six different estimates of global bilateral migration flows and show validation exercises that help to choose the estimates according to the intended use. We use migration flows estimated by the closed demographic accounting method (pseudo-bayesian), as these estimates exhibit the best performance in validation exercises, in particular when the bilateral dimension of the data is of importance, as in this application.

3.3 Further data sources

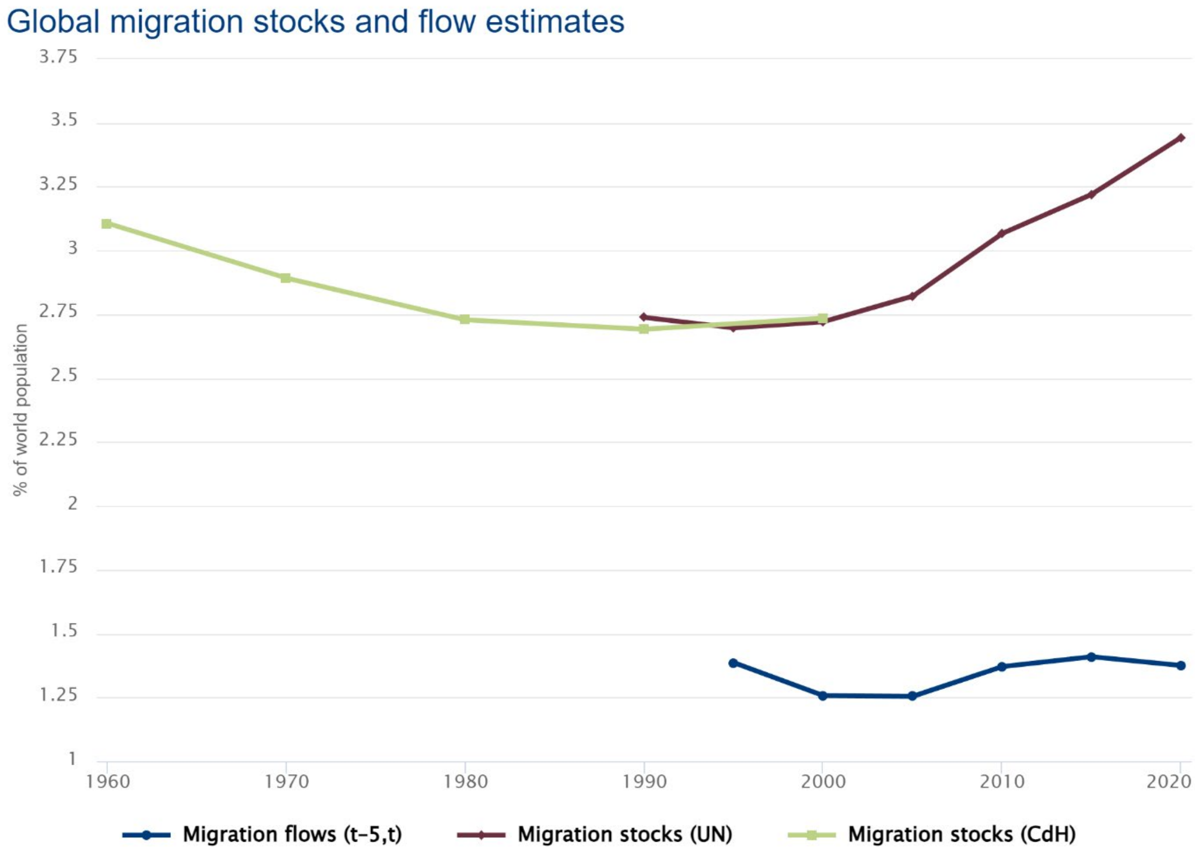
In addition, we use data on the total population from the UN (UNDP, 2022) and the distance between countries, measured by the geographical distance between their largest cities from the CEPII Gravity Database (Conte et al., 2022).

4 Empirical findings

4.1 Intensity of global migration flows

The number of international migrants continuously increased in the past decades. In 1960, an estimated 77 million people lived outside the country they had been born in (United Nations, 2009). By the year 2000, this number had grown to 173 million and increased further to 281 million by 2020.[5] Considering the simultaneous growth in the global population, relative numbers provide a more insightful perspective and show a rather different picture: The global share of migrants, i.e. the number of people living outside their birth country relative to the total global population, remained fairly constant at or below 3% from the 1960s to 2005, before it moderately increased in the past 15 years, to reach 3.5% in 2020 (see chart 1[6] and table 1 in section 4.4, which summarizes trend changes in all the indicators discussed). Currently, the stock of migrants – in absolute and relative terms – is at an all-time high. Political instability, geopolitics, inequality, and climate change are part of the story behind this recent increase (see, for example, IOM, 2024). Nevertheless, migrants still constitute a small share of the global population.

Chart 1



Source: Authors' calculations based on the UN International Migrant Stock (2020) database and migration flow estimates (Abel, 2019, version 9); Czaika and De Haas (2015) (CdH).

When looking at the estimates of global migration *flows*, i.e. the number of people that move from one country to another in a five-year period, we see that in relative terms, they remained fairly constant: In the period 1990–95, around 1.4% of the global population migrated, and in the period 2015–20, this share was approximately the same. This implies that the absolute values

[5] The UN does no longer publish data on the global bilateral migrant stock between 1960 and 1985, but several publications (e.g. IOM, 2024) and the methodological note on the 2008 revision of the data refer to the numbers.

[6] In this chart, and in the remaining analysis, our migrant stock data do not include migrants of unknown origin. For this reason, the global stock of migrants amounts to currently approximately 3.5% of the population in our data, while the UN's estimate is 3.6% (including migrants of unknown origins).

grew at rates comparable to overall population growth[7] and migration did not become more frequent between 1990 and 2020. Positive relative migration flows –even constant ones – mean that the relative *stock* of migrants can still increase, and so it did.

At this point, it is important to keep in mind that UN migration stock data are based on the country-of-birth-concept, whereas the flow estimates aim at counting each act of migration. So the flow estimates do not merely reflect changes in the stocks of migrants. They aim at counting each "regular" *outward* migration, where a person leaves their country of birth, but also each *return* and *transit* migration (i.e. onward migration). Each outward migration increases the global stock of migrants, whereas each return migration reduces it. Transit migration does not change the overall global migrant stock. The relative importance of these three types of migration in the overall flow estimates thus determines how stocks react to flows. Azose and Raftery (2019) show that return and transit migration constitute considerable parts of global migration. They provide estimates of migration flows by the type of movement between 1990 and 2015 and find that approximately 10% of global migration flows can be attributed to transit migration and around 30% to return migration, with the remaining 60% being typical emigration.[8]

What we thus observe in terms of global migration intensity is that while *migration* did not become more frequent in relative terms between 1990 and 2020 (i.e. constant relative migration flows), the presence of migrants did increase (i.e. rising relative migrant stocks).

Czaika and de Haas (2015) find considerable heterogeneities in migration intensities across world regions. Their analysis concentrates on the period from 1960 to 2000 and finds that emigrant intensity, measured by migrant stocks, decreased somewhat for Europe, which had the highest emigration rate, and also for Africa. Emigration rates from other regions, namely the Americas and Oceania, increased between 1960 and 2000. Immigration rates, on the other hand, increased for Europe (and the Americas), with Europe changing from a region predominantly sending migrants to a receiving region.

Looking at more recent years and using migration flow estimates (see charts A1 and A2[9] in the annex), we find notable variations in migration intensities and their trends across regions. Globally, however, this yields fairly constant migration rates between 1990 and 2020, but an increasing stock of migrants relative to the population. This first dimension does not contribute to an increase in the globalization of migration (flows) between 1990 and 2000, at least not globally. Regionally, we see mixed evidence: While in the EU, both emigration and immigration intensities increased (which would result in a higher globalization index), in other world regions, we observe little changes in both emigration and immigration rates (Asia) or significant changes in only one of the two (non-EU Europe, Latin America, Oceania). North America saw increases in emigration rates, with immigration rates dropping. So migration intensities will feed rather differently into regional migration globalization indices (see table 1 for an overview).

4.2 Spread of migration flows

The *global spread of migrants*, i.e. the dispersion of migrants across all possible (bilateral) corridors (country-pairs), see equation 4 in section A1 in the annex, has been increasing since the 1960s, but the increase slowed down considerably in the past two decades. The green line in chart 2

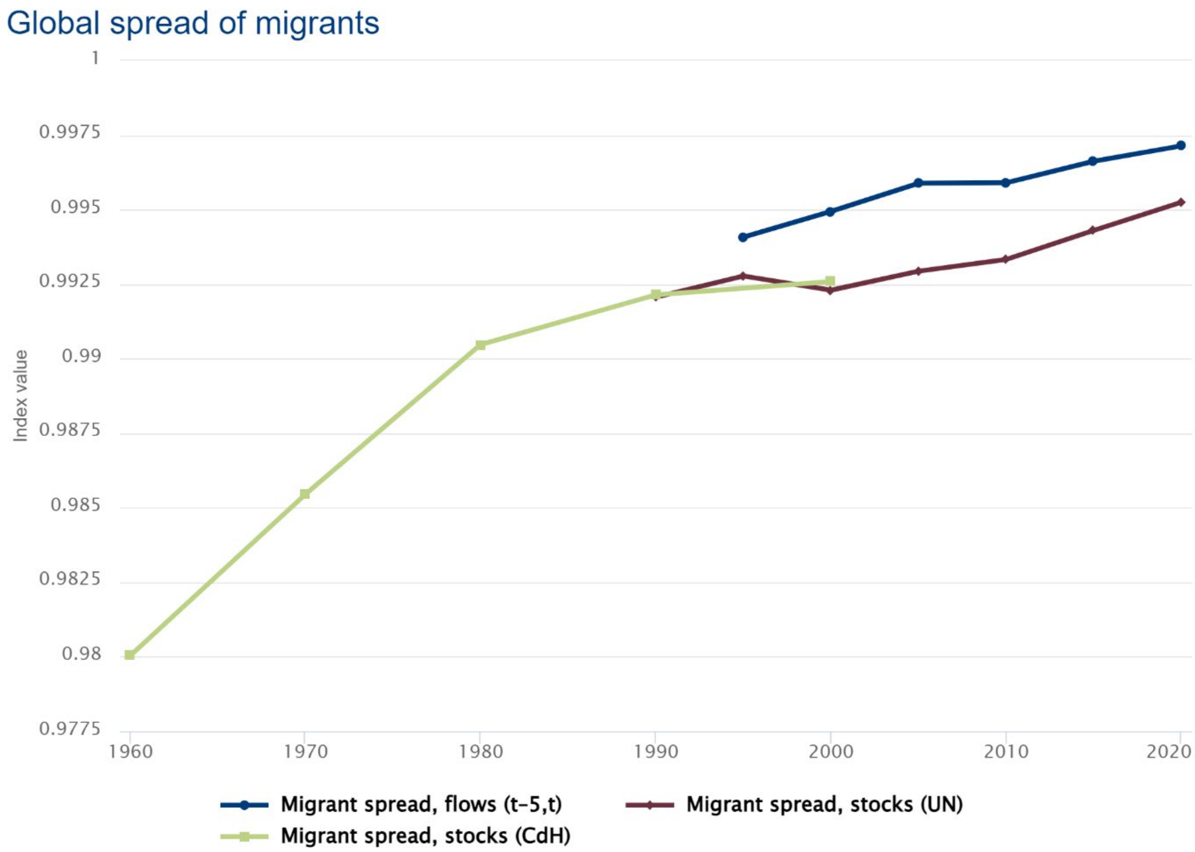
[7] The growth rate of the global population declined from 1.7% in 1990 to 0.9% in 2020 (UN World Population Prospects).

[8] See also migration flow estimates by type of move, Abel and Cohen (2022), available at https://figshare.com/articles/dataset/12845726.

[9] Emigration and immigration intensities displayed in these two charts include within-continent migration. Rates are estimated by dividing the sum of all emigrants (immigrants) of countries belonging to the continents by the continents' population.

shows the results found by Czaika and de Haas (2015) using data on the stock of migrants: Between 1960 and 2000, global migration was becoming increasingly dispersed across all possible migration corridors: the spread of global migration increased. The chart displays index values (based on equation 4 in section A1 in the annex) and for its application, index values are very close to one. The underlying reason is that well over 40,000 bilateral corridors are involved in its estimate and a large number of already very small shares are squared, added up and subtracted from one. The index may be interpreted as the probability that two randomly drawn migrants travel *different* corridors (see, for example, Alesina et al., 2003). Given the high number of possible corridors, this probability – and thus the index value – is very high (and that changes in the applications below, where the index is calculated for just above 200 countries). What is interesting for us here, however, is how the index develops over time.

Chart 2



Source: Authors' calculations based on the UN International Migrant Stock (2020) database and migration flow estimates (Abel, 2019, version 9); Czaika and De Haas (2015) (CdH).

The red line in chart 2 shows how the global spread of migrants has developed since 2000 on the basis of data on migrant stocks. We see that it has continued to increase, but at a slower pace. In other words, the bilateral routes migrants use have continued to get broader and more diverse, but only moderately compared to the increases observed between the 1960 and the 1980s. The blue line shows the spread of global migrants on the basis of estimates of migration flows and reveal a similar pattern: between 1990 and 2020, migrants spread more widely across different migration corridors, but the pace of increase slowed down.[10] This is also confirmed by a look at the share of "filled" corridors in the migration flow estimates: While in the period 1990–1995, 63% of all possible routes (origin-destination country pairs) were "filled" (non-zero), in the period 2015–2020, 67% were filled. Corridors that opened up between 1990 and 2020 are, for example, Iran to Brazil, Nigeria to Estonia and Sri Lanka to Romania, all of which recorded positive and increasing estimated flows in 1995–2000 or later while showing zero flows in 1990–95. When counting only corridors with a flow of 50 or more, approximately 85 opened up after 1990–95.

When distinguishing between global *emigrant spreads* (equation 5 in section A1 in the annex) – how dispersed are (e)migrants in terms of the destination countries – and global *immigrant spreads* (equation 6 in section A1 in the annex) – how diversified are (im)migrants in terms of their origins – Czaika and de Haas (2015) find for the period between 1960 and 2000 that emigrant spreads declined while immigrant spreads increased (see solid and dashed green lines in chart 3). In other words, migrants from more and more diverse origin countries were increasingly concentrated in fewer and fewer different destination countries.

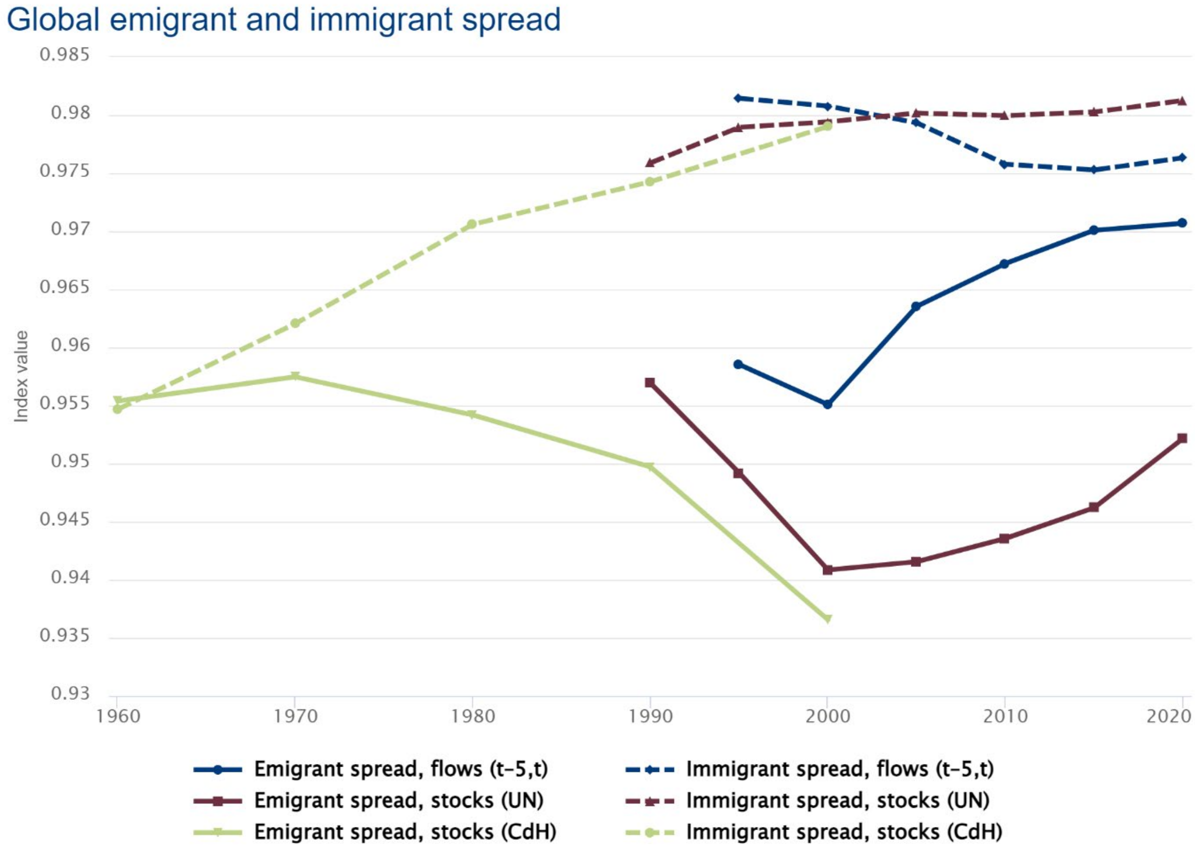
When applying the same method to more recent data on migrant stocks, we find that this diverging trend has been reversed: global migrants were moving to an increasingly diverse set of destinations between 2000 and 2020, and the trend of an ever-narrower set of destinations found for the decades between 1960 and 2000 reversed (see solid and dashed red lines in chart 3). We find the same trend reversal when the indicators are calculated on the basis of estimated migration flows (instead of stocks; solid and dashed blue line in chart 3). This is an important finding: the results show that while immigrants come from a (still) diverse set of origin countries, they are no longer concentrated in an increasingly narrow set of destinations but spread out more across different destinations.

This global aggregate again hides regional heterogeneities (charts A3 and A4 in the annex and table 1).[11] Latin America, for instance, exhibits both the lowest emigrant spread and the lowest immigrant spread among all world regions, but also the strongest increase over time. Immigrant spreads, on the other hand, dropped significantly between 1990 and 2020, from already low levels. Immigrants to African countries are not particularly diverse in terms of their origin countries while emigrant spreads of Asian countries have been increasing since 1990, but a recent flattening is observable. Immigrants to Asian countries do not have highly diversified origins. In North America, emigrant spreads are comparably low and stagnant, while immigrant spreads – which are not particularly high in comparison either – increased over time, especially after 2010.

[10] We also see the level of global migrant spreads being higher for flow data. This is consistent with the fact that stock data also reflect past migration patterns, where spreads were lower. This "inertia" of stock data is a key reason for our preference for flow data estimates in our analysis.

[11] It should be noted that for spreads, continent-specific and global values could appear to contradict each other. They do not add up, and it could be the case, for example, that continent-level spreads increase while the global spread remains unchanged: if immigration diversity increases for all continents, but the origin countries increasingly *overlap*, this can result in a constant global spread. Vice versa, if origin country sets of continents become more different (i.e. they overlap less), this could result in changing global spreads even when the number of origin countries does not change. Thus, the degree of overlap of the origin/destination country sets also matters in the relationship between global and continent-level spreads.

Chart 3

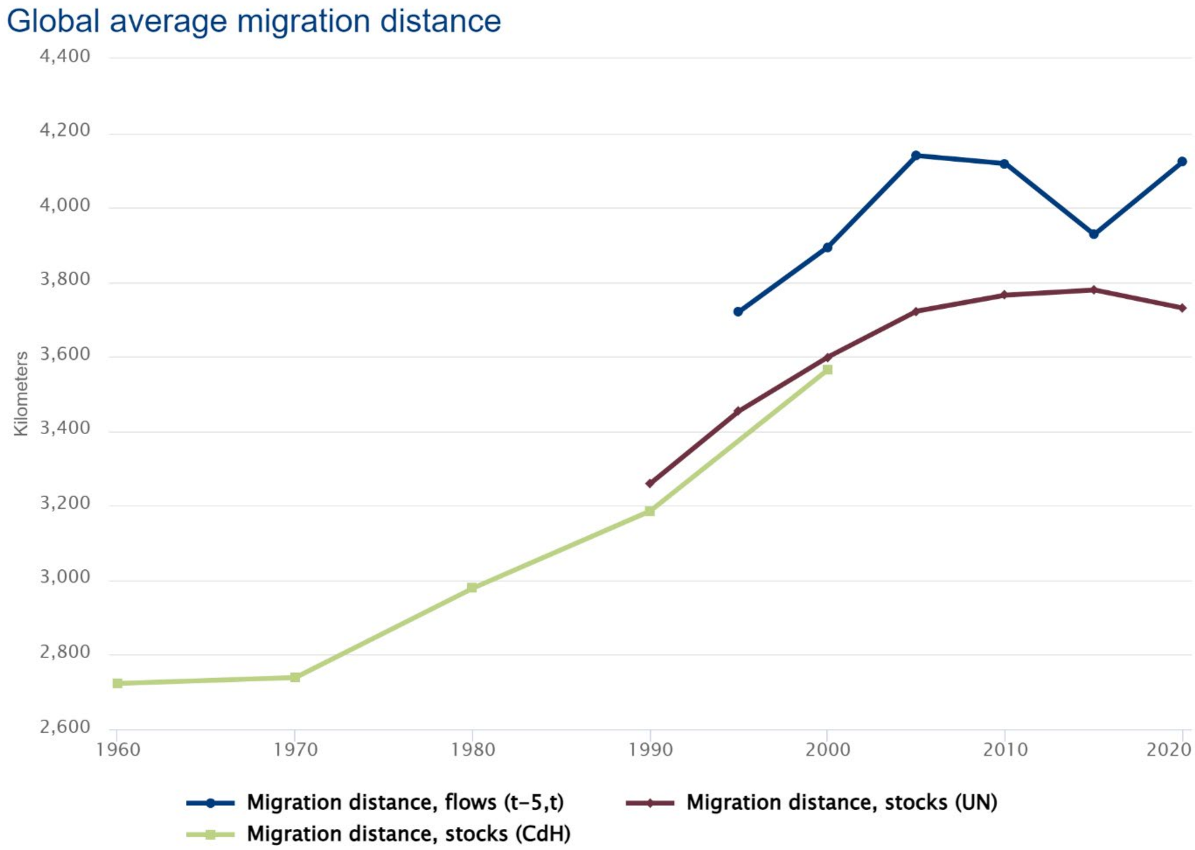


Source: Authors' calculations based on the UN International Migrant Stock (2020) database and migration flow estimates (Abel, 2019, version 9); Czaika and De Haas (2015) (CdH).

Turning to the EU, we find that both emigrant and immigrant spreads are high in a global comparison. In the most recent periods, emigrant spreads decreased significantly, the diversity of origins of EU immigrants on the other hand remained consistently high, ranking highest among world regions. In non-EU Europe, the emigrant spread has seen a moderate increase, while the immigrant spread has grown more markedly. The latter development has been particularly driven by an underlying increasing diversity of origins from Asia and Africa, as well as a balancing across existing corridors. Generally, European migration is comparatively diverse in terms of both origin and destination.

4.3 Distances covered by migrants

Chart 4



Source: Authors' calculations based on the UN International Migrant Stock (2020) database, migration flow estimates (Abel, 2019, version 9) and the CEPII Gravity Database (Conte et al., 2022); Czaika and De Haas (2015) (CdH).

Czaika and de Haas (2015) find that the geographical distance between origin and destination countries increased considerably between 1960 and 2000. Using more recent data on migration stocks, we find an overall increase between 1990 and 2020. This is mostly due to the 1990s and early 2000s, however. As of the period 2000–05, we do not find a further increase in the average distance covered by global migrants.[12]

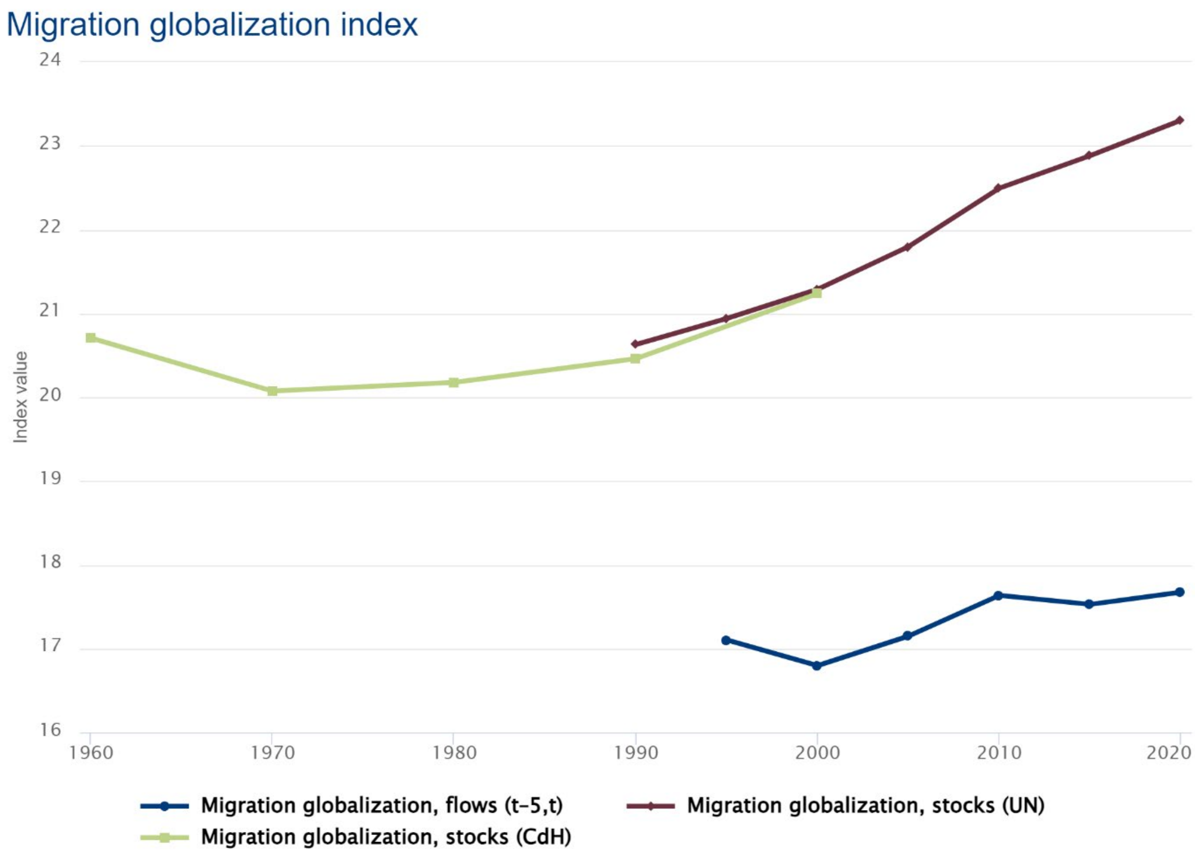
Variations at the regional level are strongly related to the remoteness of countries, with migrants from Oceania having covered by far the largest average distance among regions. Immigrants to and emigrants from North America travel on average 7,000km to 8,000km. The global average migration distance is around 4,000km. The lowest emigration distances are observed for Europe and Africa. Immigration distances are again lowest for Africa, which is related to the high share of within-continent and neighboring-country migration, as well as for Asia. The dynamics over time are limited, and the mild upward trend observed globally can mostly be attributed to increasing distances between source and destination for North American emigrants and immigrants, and African and Asian immigrants.

[12] It is not surprising that the average distance measured by migration flows is somewhat higher than that measured by stocks, as the stocks reflect also past migration patterns, which have been found to be of shorter distance.

4.4 An index of the globalization of migration

The index of the globalization of migration combines the three dimensions discussed above to form an overall measure (equation 14 in section A1 in the annex). Looking at global values and the stock of migrants, we see that from the 1970s, migration started to become globalized (see chart 5). This trend gained speed in the 1990s, and the globalization of migration is currently at its highest level. This increase in the index of approximately 12% results from an increase in the intensity of migration when measured by stocks, an increase in the spread of migrants as well as the distances covered by migrants.

Chart 5



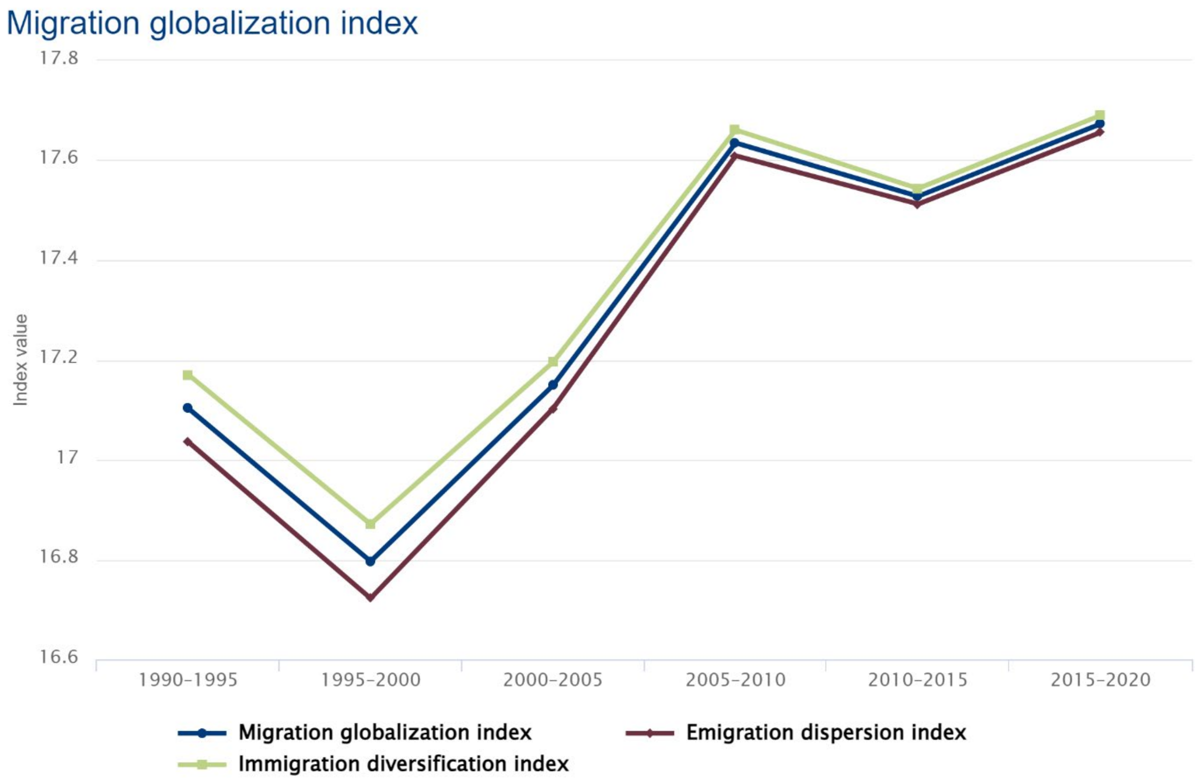
Source: Authors' calculations based on the UN International Migrant Stock (2020) database, migration flow estimates (Abel, 2019, version 9) and the CEPII Gravity Database (Conte et al., 2022); Czaika and De Haas (2015) (CdH).

When looking at migration flows, which reflect solely *current* but not historical migration dynamics (see blue line in chart 5, and in more detail in chart 6, as well as the overview table 1), we observe an increase in the globalization of migration between 1990 and 2010, followed by a flattening. At the time of the global financial crisis, the trend toward increasing globalization of migration came to a halt and globalization remained stagnant until the most recent period (2015–20). The underlying developments here are a stagnant intensity of migration, a shift from increasing to flattening, even decreasing, immigrant spreads, and only minimal changes in the average distance covered by migrants in this time span.

Chart 6 further shows the difference between the two components of the globalization index: emigrant dispersion – the globalization of emigration (equation 12 in section A1 in the annex) –

and immigrant diversification – the globalization of immigration (equation 13 in section A1 in the annex). Over time, these two components converged, as the globalization of emigration increased faster than the globalization of immigration. Since the intensity of migration flows did not increase, and the average distance lengthened merely in the 1990s, the overall increase is mostly related to the previous finding that emigrants spread more over different destination countries and the diversity of immigrants exhibited a sideways movement in the past three decades.
How does this compare to the flows of goods or capital? Generally speaking, the observation that a steep increase in globalization starting from the mid-1990s was followed by a mere lateral movement at a higher level since the late-2000s also applies to other measures of international economic connectedness such as trade or capital flows or to other measures of globalization such as the KOF Index of Globalization (Gygli et al. 2019; see chart 7).

Chart 6



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9) and the CEPII Gravity Database (Conte et al., 2022).

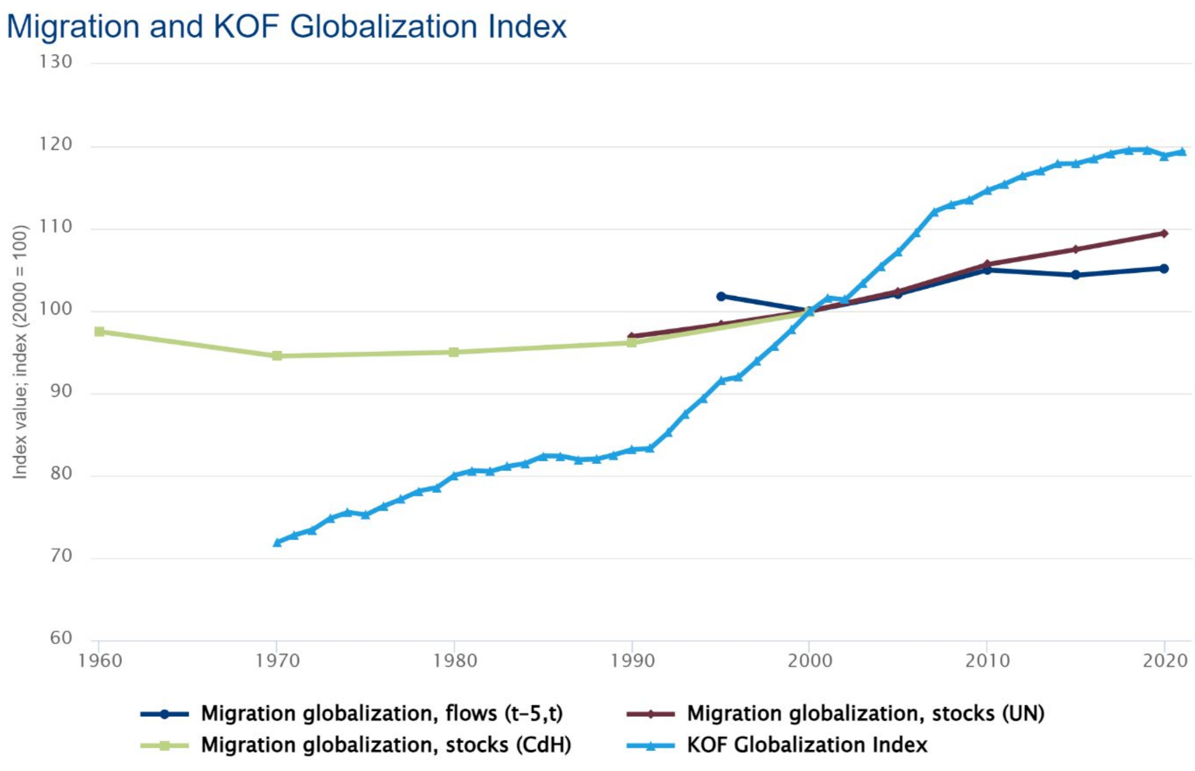
Table 1

Changes in migration intensity, spread, distance and in the globalization of migration between 1990–1995 and 2015–2020

	Global	EU	Non-EU Europe	Africa	Asia	Latin America and the Caribbean	North America	Oceania
Migration intensity	–							
Emigration intensity		↑	–	↓	–	–	↑	–
Immigration intensity		↑	↑	↓	–	↑	↓	↑
Spread of migrants	↑							
Emigrant spread	↑	–	▲	↑	↑	↑	–	↑
Immigrant spread	↓	–	↑	–	–	–	–	↑
Distance	▲							
Emigrants		–	↑	–	–	–	↑	–
Immigrants		–	▲	↑	↑	↓	↑	–
Globalization	↑	↑	↑	↓	↑	↑	↑	↑
Emigrant globalization	↑	↑	–	↓	↑	–	↑	–
Immigrant globalization	↑	–	↑	–	↑	↑	–	↑

Note: Upward (downward) arrows indicate increases (decreases) between 1990–1995 and 2015–2020, based on OLS estimations of the respective measure on a variable indicating the time period and an intercept. Large (small) arrows indicate a statistical significance level of 10% (15%); "–" indicates no statistically significant change. Values in empty cells have not been computed, either because the global values equal the values for emigration and immigration (intensity, distance) or because values are not uniquely defined without specifying either an emigrant or immigrant perspective (continent-level values).

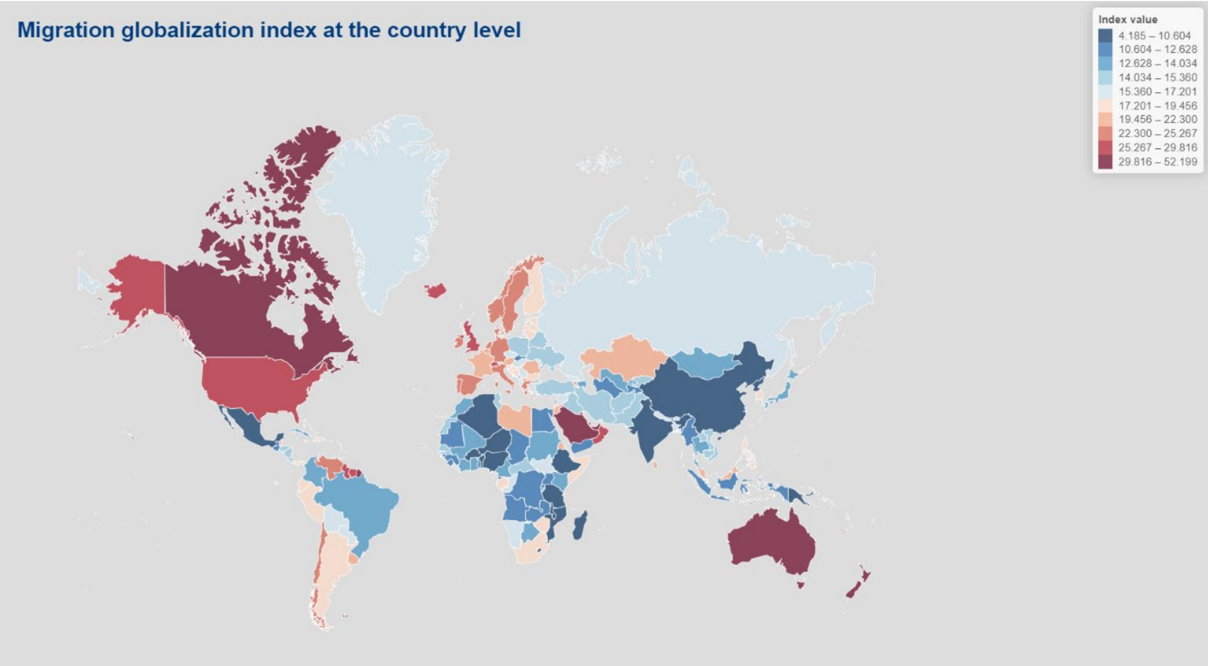
Chart 7



Source: Authors' calculations based on the UN International Migrant Stock (2020) database, migration flow estimates (Abel, 2019, version 9) and the CEPII Gravity Database (Conte et al., 2022); Czaika and De Haas (2015) (CdH); KOF Globalization Index (Gygli et al., 2019).

At the country-level, the results are highly heterogeneous across countries (see figure 1). Many small (island) states exhibit the highest degrees of migration globalization. After excluding countries with a population of less than half a million, Australia, the United Arab Emirates, New Zealand, Canada and Kuwait are the countries with the highest degrees of globalization in 2015–20. Many of those high-ranking countries have been typical immigration countries for decades or longer or are resource-rich countries with small populations and large numbers of immigrant workers. European countries exhibit high – but not the highest – degrees of migration globalization. Table 1 shows the direction and statistical significance of changes in the globalization index and the underlying subcomponents.

Figure 1



Source: Own calculations based on Abel and Cohen (2019) migration flow estimates.

Overall, we find a high degree of migration globalization especially in countries that have a long-standing migration history (and thus large diasporas and networks) and resource-rich countries with a high demand for foreign labor (like the Gulf region).[13] When relating the globalization of emigration to the GDP per capita in origin countries, and the globalization of immigration to the GDP per capita in destination countries, we find a positive correlation in both cases: the richer a country, the more globalized its emigrants and immigrants. The former is likely related to affordability, with emigrants from poor countries either not being able to emigrate at all or merely to a small set of neighboring (or close) countries. This reduces emigration intensities, spreads and distances and thereby the index. The latter might be generally related to the broad attractiveness of advanced economies for migrants from very different source countries, and the corresponding willingness to move far away from home.

[13] This is in addition to several small-island states that typically have very high emigration rates that feed into our index.

5 Conclusions

Our research on changing trends in the globalization of migration is motivated by the observation that the discussion of (de)globalization focuses predominantly on trade and capital flows, while another important cross-border flow – the flow of people – is often neglected. However, the degree of heterogeneity of migration has important economic implications on destination countries through its effects on productivity and innovation but also through its potential to mitigate challenges associated with aging societies. These effects are likely to influence the optimal course of monetary policy. Against this backdrop, we attempt to systematically address the question of a possible slowdown of the globalization of migration in the recent period of multiple crises.

We follow the seminal work by Czaika and de Haas (2015) and use more recent data on migrant stocks as well as – for the first time – estimates of global bilateral migration flows by Abel and Cohen (2019; most recent update from October 2022) to identify changing trends in the degree of globalization of migration, often attributed to trade or capital flows. We construct an index based on three dimensions: The first dimension, the intensity of global migration, did not increase between 1990 and 2020; the relative magnitude of global flows amounted to roughly 1.4% in the period 1990–95 as well as in our last period of observation, 2015–20. The second dimension reveals that migrants continued to spread more across all possible migration corridors between 1990 and 2020, but at a considerably slower pace than pre-1990. Between 1990 and 2020, we also observe an important change in emigration and immigration spreads: while Czaika and de Haas (2015) found that migrants come from an increasingly diverse set of origin countries and settle in narrowing destination countries, we find the opposite for the periods after 1990: Immigrants still come from diverse (albeit slightly less diverse) origin countries, but the variety of destination countries has increased (again). Thus, we find no evidence that there is an increasing concentration of migrants in fewer destination countries. In fact, quite the opposite is true: after 2000, the dispersion of emigrants over destinations increased considerably. The third dimension shows that the distance between source and destination country for an average migrant did not continue its upward trend that was observed before 2000.

What do these dimensions tell us about a possible deglobalization of migration? We combine them to obtain an index of the degree of migration globalization and find that – on a global scale – the globalization of migration, which was increasing constantly between 1960 and 2000, slowed down from 2005–10 onward. Between 2010 and 2020, a period characterized by multiple crises, migration did not become more globalized. When distinguishing between emigrant dispersion and immigrant diversification, our finding suggests that both did not further increase during this crisis period. Of course, there might be level effects at work here (globalization cannot increase indefinitely), yet it appears that the overall development could also reflect a changing momentum of globalization. To what extent this is the case remains to be seen in future research.

As argued above (section 1), an increase in the diversity of the immigrant population as such contains the potential to generate economic benefits (e.g. via increases in productivity, trade links, etc.). However, this will only be the case if integration into the labor market succeeds. Importantly, the fact that immigrants come from a still highly diverse set of countries underlines the need for flexibility and creativity in active labor market policies. It will be increasingly necessary to implement measures aimed at minimizing potential brain waste, i.e. an underutilization of the human capital of migrants on the labor market. Further, even if the pace of globalization is diminishing, it is still high and hence underlines the necessity for international cooperation. As shown above, there is an increasing number of destination countries and thus cooperative efforts are ever more important. These efforts should be directed toward ensuring timely information about migration trends (again, informing labor market policy) but also to harmonizing migration processes across countries.

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Annex

A.1 Measuring the degree of (de)globalization of migration: technical chapter

A.1.1 Intensity of global migration

Following Czaika and de Haas (2025), we consider the intensity of migration as a first dimension. Here, it is important to distinguish between absolute and relative magnitudes of global migration, i.e. between the absolute number of migrants and the share of migrants in the population both at the global and country level. Only relative magnitudes can inform about an increasing intensity of migration – or an acceleration of migration rates. We define the global migration intensity I_G as

$$I_G = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{m_{ij}}{N} = \frac{M}{N} \tag{1}$$

where m_{ij} are migration flows between origin i and destination j, N is the total global population, and M is the total number of migrants.[14]

Regional- or country-level intensity may reveal interesting heterogeneities which would be invisible at the global level. We define emigration intensity of country i, EI_i, as

$$EI_i = \frac{m_{i\cdot}}{N_i} \tag{2}$$

with $m_{i\cdot}$ denoting all emigrants from and N_i total population of country i, and immigration intensity of country j, II_j, as

$$II_j = \frac{m_{\cdot j}}{N_j} \tag{3}$$

where $m_{\cdot j}$ refers to all immigrants to country j.

A.1.2 Spread of global migration

Apart from the number of global migrants, we are interested in the diversity of origin countries and the dispersion across destination countries. The second dimension thus covers the heterogeneity of source and destination countries in global migration.

Global spread of migrants across all possible (bilateral) routes

Following Czaika and de Haas (2015), we use a measure that is based on the Herfindahl-Hirschman Index to quantify the spread of global migrants over all possible migration corridors, i.e. over all possible origin-destination country pairs[15]. As the Herfindahl-Hirschman Index is a measure of concentration, it is subtracted from unity to obtain a measure of spread/diversity[16].

[14] The migration intensity and all measures below are calculated for different points in time (stocks) or time periods (flows). The time index is omitted from all formulas for the sake of brevity.

[15] Koech and Wynne (2017) use the Herfindahl-Hirschman index to measure the diversity of US states' exports, immigrants and financial links with respect to countries. For an application of the Herfindahl-Hirschman index to measure the concentration of remittances, see Hosny (2020).

[16] This index is also used in the trade literature to measure import/export diversification with respect to sectors (see for example UNCTAD 2024, Chapter 1). A Hirschman-based index is also often employed when measuring the diversity of a population with respect to different groups. A well-known index is the ethnolinguistic fractionalization index (see Alesina et al., 2003). It ranges between zero (perfectly homogeneous population) and one (maximally fractionalized population) and identifies the probability that two randomly chosen individuals in a population belong to a different group.

$$S_G = 1 - \sum_{i=1}^{N}\sum_{j=1}^{N} \left(\frac{m_{ij}}{M}\right)^2 \quad (4)$$

S_G denotes the index for the global spread of migrants, i and j are the indexes for the origin and destination countries. m_{ij} are migration flows between origin i and destination j, and M is the overall number of global migrants, i.e. $M = \sum_{i=1}^{N} m_{i.} = \sum_{j=1}^{N} m_{.j}$. The index ranges from 0 to $\left(1 - \frac{1}{N^2}\right)$. A value of 0 indicates that all flows occur on one migration corridor (i.e. only between one origin and one destination country), and a value of $\left(1 - \frac{1}{N^2}\right)$ indicates that flows are equally distributed across all possible migration corridors. As the shares that enter the sum are squared, bilateral corridors that exhibit relatively small flows receive a small weight in the index, whereas corridors that are characterized by relatively high flows receive a high weight. The index is a continuous function of the shares per corridor, i.e. small changes in the shares lead to small changes in the index value (no jumps). The order of the shares that enter the sum is irrelevant. The index is furthermore zero-indifferent, i.e. adding or removing possible migration corridors that are not used (and exhibit a share of zero) do not change the index value. If one *new* bilateral corridor is used and a new small share enters the sum, the sum of squared shares will be lower and the index will increase slightly, indicating a moderately higher diversification.[17]

Global *emigrant* and global *immigrant* spread

While the global spread of migrants informs at a very aggregate level how diversified migrants' movements along all possible migration corridors are, distinguishing between emigrant and immigrant spread can shed light on potentially different degrees of diversification from an origin and destination country perspective. We calculate the **global emigrant spread, ES_G,** which informs about the dispersion of global migrants over destination countries. Also using a Herfindahl-Hirschman-based index, we compute it as unity minus the sum of squared shares of incoming migrants per destination country.

$$\mathrm{ES}_G = 1 - \sum_{j=1}^{N} \left(\frac{m_{.j}}{M}\right)^2 \quad (5)$$

An index value of 0 indicates that all migrants are moving to the same destination country, whereas an index value of $\left(1 - \frac{1}{N}\right)$, the maximum value of the index, indicates that global emigrants are equally spread over destination countries. The **global immigrant spread, IS_G,** measures the diversification of global migrants with respect to their origin countries, and is calculated as unity minus the sum of squared shares of emigrants per origin country:

$$IS_G = 1 - \sum_{i=1}^{N} \left(\frac{m_{i.}}{M}\right)^2 \quad (6)$$

Emigrant and immigrant spread by countries or country groups

In order to address regional heterogeneities, we also calculate emigrant and immigrant spreads at regional or individual country levels. The **emigrant spread of (source) country (or**

[17] See for example Kvalseth (2022) for a detailed discussion of the index properties.

country group/region) $\boldsymbol{i}$**,** $\boldsymbol{ES_i}$**,** is a measure for the diversity of destinations of emigrants from country (or country group/region) i.

$$ES_i = 1 - \sum_{j=1}^{N} \left(\frac{m_{ij}}{m_{i.}}\right)^2 \tag{7}$$

Accordingly, the **immigrant spread of (destination) country (or country group/region)** $\boldsymbol{j}$ **,** $\boldsymbol{IS_j}$**,** informs about the origin country diversity of all immigrants to country/region j.

$$IS_j = 1 - \sum_{i=1}^{N} \left(\frac{m_{ij}}{m_{.j}}\right)^2 \tag{8}$$

A.1.3 Distance covered by migrants

The third dimension considered is the average geographical distance covered by a migrant in a given period. This global average migration distance D_G is calculated as the geographical distance between the largest cities in the origin and destination countries, weighted by the relative share of migrations between them. It is measured in kilometers and can be interpreted as the distance traveled by an average migrant in a certain time period.

$$D_G = \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \frac{m_{ij}}{M} \tag{9}$$

d_{ij} denotes the geographical distance between countries i and j. On the regional or country level, the emigration distance of country/region i, ED_i, is defined as

$$ED_i = \sum_{j=1}^{N} d_{ij} \frac{m_{ij}}{m_{i.}} \tag{10}$$

and the immigration distance of country/region j, ID_j, as

$$ID_j = \sum_{i=1}^{N} d_{ij} \frac{m_{ij}}{m_{.j}} \tag{11}$$

Under this concept, migration becomes more globalized if the distances between origin and destination countries increase. Of course, one could also think of alternative measure of distance, for example cultural distance or the similarity in spoken languages. We stick to the original concept and apply a geographical distance measure.

A.1.4 An index of the globalization of migration

The three measures on intensity, spread and distance of migration can be combined to calculate an index of globalization. We use a geometric mean, following Czaika and de Haas (2015), which is scale-invariant and allows us to combine the three dimensions, which are all measured at a different scale, with equal weights on the subdimensions. At the country level, we can therefore calculate an emigrant dispersion – or emigrant globalization – index

$$EGI_{it} = [EI_{it}\, ES_{it}\, ED_{it}]^{\frac{1}{3}} \tag{12}$$

and an immigrant diversification – or immigrant globalization – index

$$IGI_{it} = [II_{it}\, IS_{it}\, ID_{it}]^{\frac{1}{3}} \tag{13}$$

The former looks at a country's emigrants: how many leave, how distributed are the destination countries, and how far do they go? The latter focuses on immigrants, their relative numbers, the diversity of their origin countries and the average distance between origin and destination. When combined, again using a geometric mean with equal weights, the resulting index subsumes the degree of globalization of a country's emigrants and immigrants and can be interpreted as a country's overall migration globalization:

$$GI_{it} = [EGI_{it}\, IGI_{it}]^{\frac{1}{2}} \quad (14)$$

It shows how deeply integrated countries are in global migration processes. High emigration or immigration rates, diverse immigrants and dispersed emigrants increase the degree of a country's migration globalization, so does a larger distance to the source and destination countries of migrants.

A.2 Summary statistics

Table A1

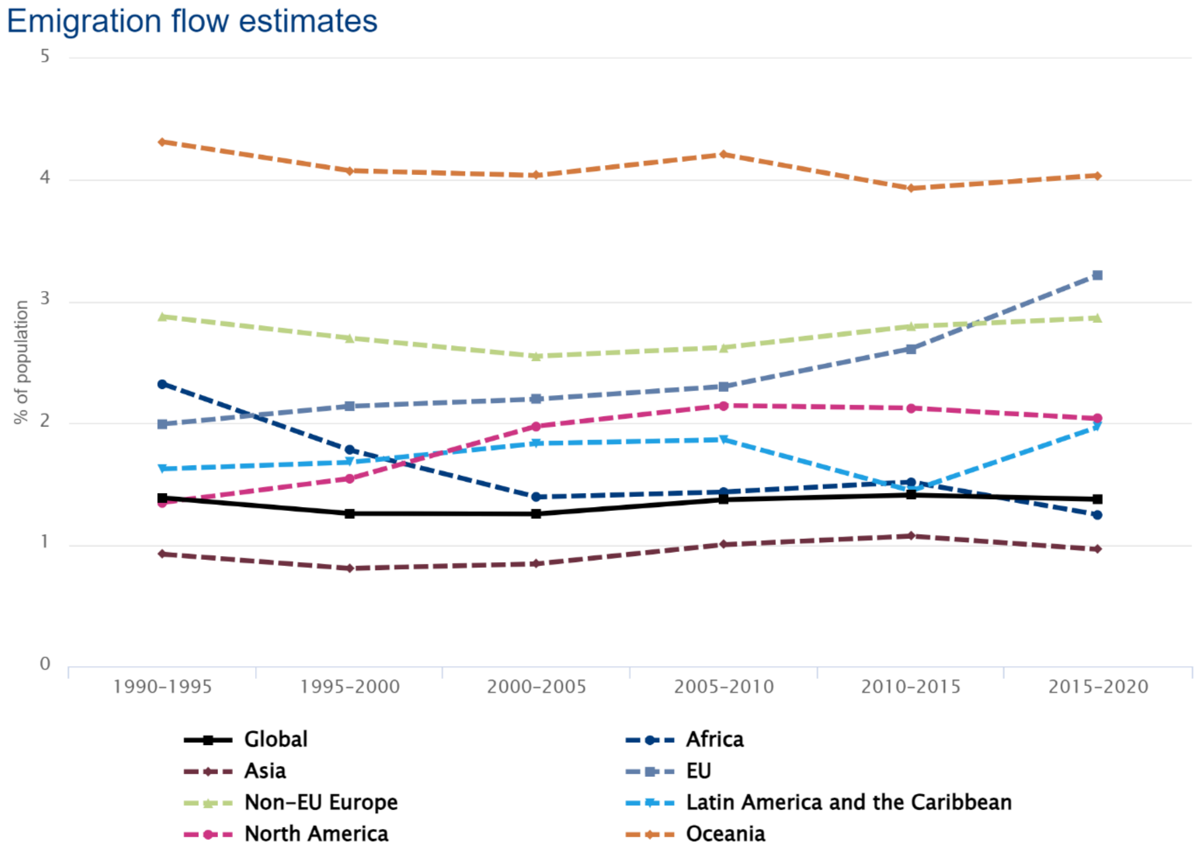
Summary statistics

Period	Continent	Emigration			Immigration			Globalization		
		Intensity (% of population)	Spread (index)	Distance (km)	Intensity (% of population)	Spread (index)	Distance (km)	Emigration (index)	Immigration (index)	Globalization of migration (index)
1990–1995	Global	1.4	1.0	3,721	1.4	1.0	3,721	17.0	17.2	17.1
1995–2000	Global	1.3	1.0	3,894	1.3	1.0	3,894	16.7	16.9	16.8
2000–2005	Global	1.3	1.0	4,140	1.3	1.0	4,140	17.1	17.2	17.1
2005–2010	Global	1.4	1.0	4,118	1.4	1.0	4,118	17.6	17.7	17.6
2010–2015	Global	1.4	1.0	3,928	1.4	1.0	3,928	17.5	17.5	17.5
2015–2020	Global	1.4	1.0	4,123	1.4	1.0	4,123	17.7	17.7	17.7
1990–1995	Africa	2.3	1.0	2,638	1.8	0.9	1,430	18.0	13.3	15.5
1995–2000	Africa	1.8	1.0	2,994	1.3	0.9	1,481	17.2	12.2	14.5
2000–2005	Africa	1.4	1.0	2,933	1.1	1.0	1,615	15.8	11.8	13.7
2005–2010	Africa	1.4	1.0	3,015	1.0	1.0	1,834	16.1	12.2	14.0
2010–2015	Africa	1.5	1.0	2,829	1.1	1.0	1,769	16.1	12.5	14.2
2015–2020	Africa	1.2	1.0	3,034	0.9	1.0	1,786	15.4	11.7	13.4
1990–1995	Asia	0.9	0.9	4,055	0.7	0.9	2,780	15.2	12.3	13.6
1995–2000	Asia	0.8	0.9	4,204	0.6	0.9	3,010	14.7	12.0	13.3
2000–2005	Asia	0.8	1.0	4,543	0.6	0.9	2,988	15.4	12.2	13.7
2005–2010	Asia	1.0	1.0	4,298	0.8	0.9	3,049	16.0	13.2	14.5
2010–2015	Asia	1.1	1.0	3,939	0.9	0.9	2,903	15.9	13.4	14.6
2015–2020	Asia	1.0	1.0	4,599	0.7	0.9	3,221	16.2	12.9	14.4
1990–1995	EU	2.0	1.0	3,158	2.8	1.0	3,224	18.2	20.6	19.3
1995–2000	EU	2.1	1.0	3,063	2.7	1.0	3,257	18.5	20.5	19.4
2000–2005	EU	2.2	1.0	2,652	3.5	1.0	4,042	17.8	24.0	20.7
2005–2010	EU	2.3	1.0	2,702	3.7	1.0	4,080	18.2	24.5	21.1
2010–2015	EU	2.6	1.0	3,061	3.3	1.0	3,360	19.8	22.1	20.9
2015–2020	EU	3.2	1.0	2,838	4.3	1.0	3,307	20.6	24.0	22.2
1990–1995	Non-EU Europe	2.9	0.9	2,637	3.3	0.9	2,819	19.2	20.7	19.9
1995–2000	Non-EU Europe	2.7	0.9	2,842	3.4	0.9	2,918	19.3	21.1	20.2
2000–2005	Non-EU Europe	2.6	0.9	2,636	3.2	1.0	3,371	18.5	21.7	20.0
2005–2010	Non-EU Europe	2.6	0.9	2,757	3.5	1.0	3,620	19.0	23.1	20.9
2010–2015	Non-EU Europe	2.8	0.9	3,034	3.7	1.0	3,266	20.0	22.7	21.3
2015–2020	Non-EU Europe	2.9	0.9	2,962	3.8	1.0	3,370	20.0	23.1	21.5
1990–1995	Latin America and the Caribbean	1.6	0.6	4,078	0.8	0.9	4,227	15.4	14.1	14.7
1995–2000	Latin America and the Caribbean	1.7	0.5	3,983	0.8	0.8	3,965	15.1	13.6	14.3
2000–2005	Latin America and the Caribbean	1.8	0.6	4,563	0.9	0.8	3,790	17.6	13.6	15.5
2005–2010	Latin America and the Caribbean	1.9	0.7	4,692	1.0	0.8	3,734	18.2	14.0	16.0
2010–2015	Latin America and the Caribbean	1.4	0.7	4,192	1.0	0.8	3,956	15.9	14.6	15.3
2015–2020	Latin America and the Caribbean	2.0	0.8	3,602	1.7	0.8	3,624	18.1	17.0	17.5
1990–1995	North America	1.3	0.9	6,326	4.7	0.9	7,468	20.1	32.1	25.4
1995–2000	North America	1.5	0.9	6,273	4.7	0.9	7,216	20.9	31.8	25.8
2000–2005	North America	2.0	0.9	6,470	4.3	0.9	7,688	22.9	31.2	26.8
2005–2010	North America	2.1	0.9	6,592	4.1	0.9	7,626	23.7	30.8	27.0
2010–2015	North America	2.1	0.9	7,035	4.3	1.0	8,042	24.1	32.1	27.9
2015–2020	North America	2.0	0.9	6,829	4.2	1.0	8,276	23.6	32.2	27.6
1990–1995	Oceania	4.3	0.9	10,769	5.9	0.9	10,945	35.2	39.2	37.2
1995–2000	Oceania	4.1	0.9	10,331	6.1	0.9	10,622	34.0	39.2	36.5
2000–2005	Oceania	4.0	0.9	10,630	6.5	1.0	10,037	34.3	39.7	36.9
2005–2010	Oceania	4.2	0.9	10,304	7.9	0.9	9,941	34.4	42.0	38.0
2010–2015	Oceania	3.9	0.9	10,347	7.1	0.9	10,763	33.7	41.7	37.5
2015–2020	Oceania	4.0	0.9	10,741	7.6	0.9	10,871	34.5	42.7	38.4

Source: Authors' calculations based on migration flow estimates (Abel, 2019) and the CEPII Gravity Databse (Conte et al., 2022).

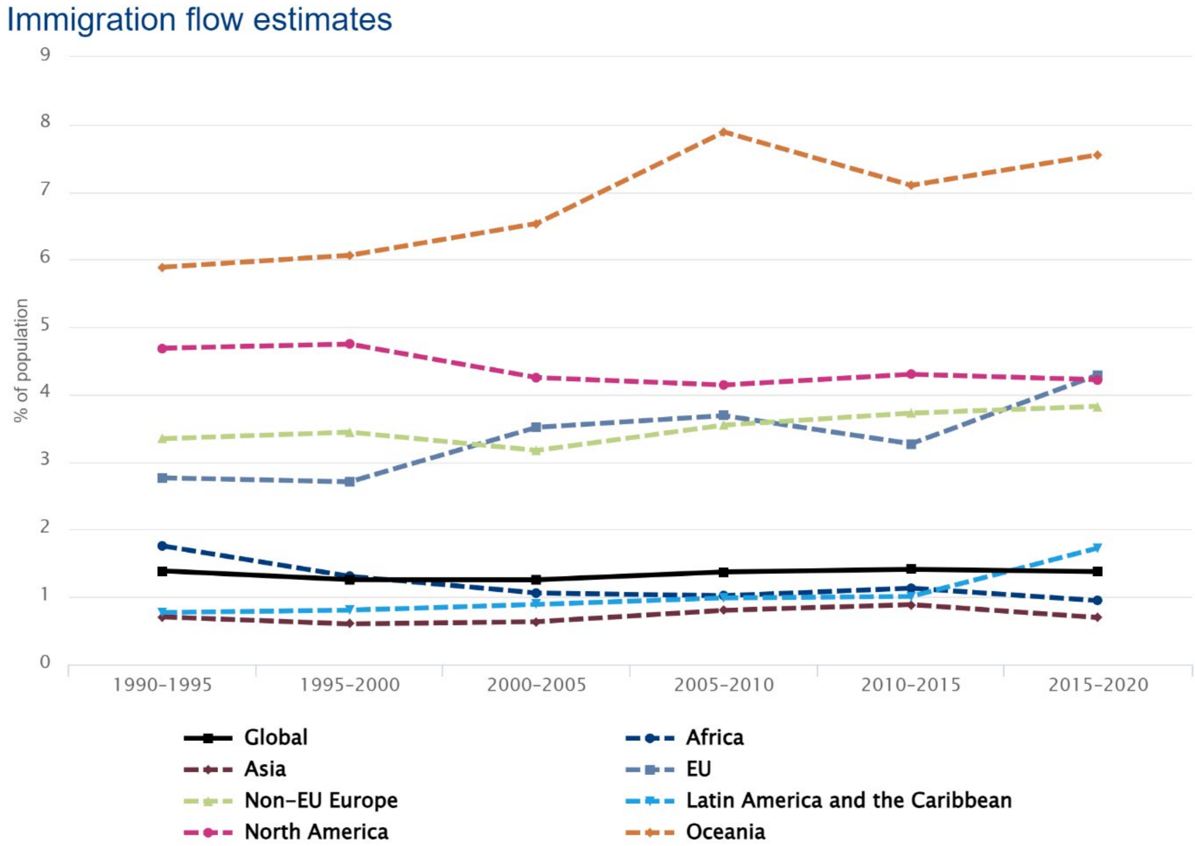
A.3 Emigrant and immigrant intensities by region

Chart A1



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9).

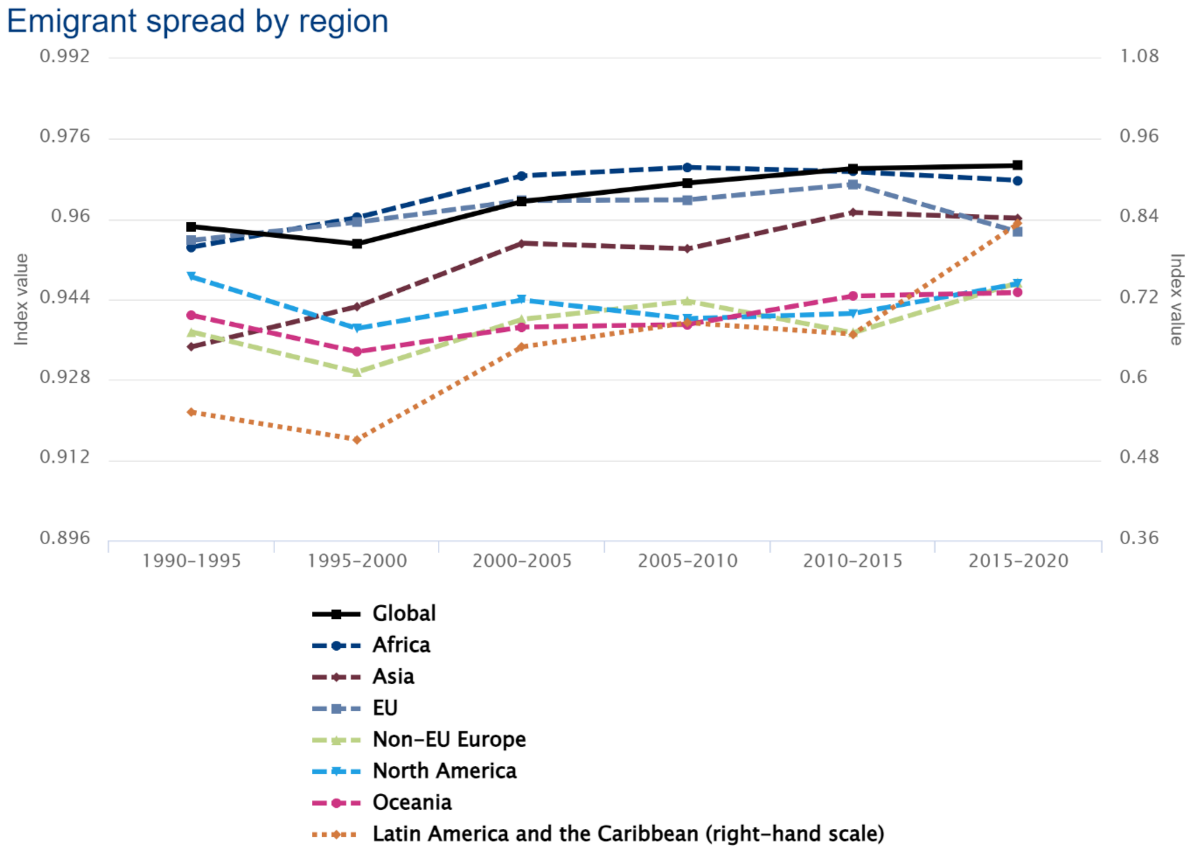
Chart A2



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9).

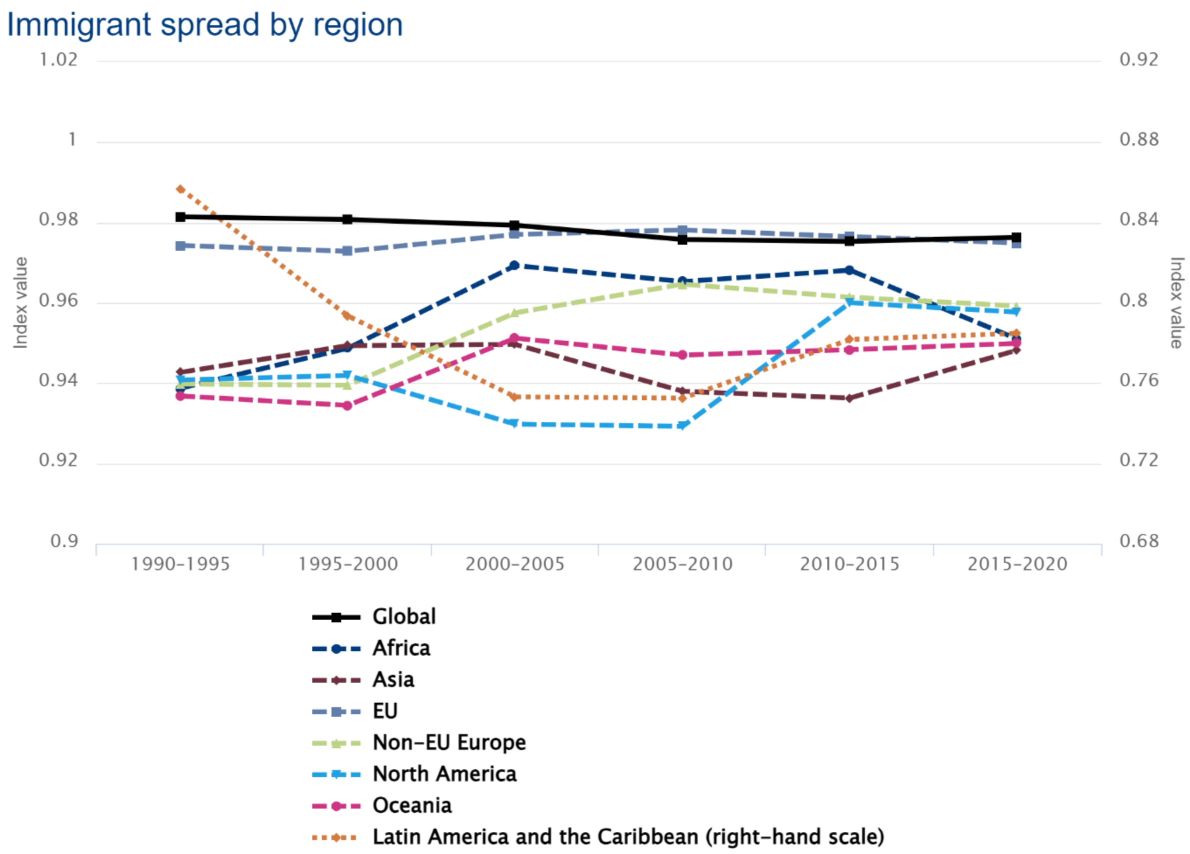
A.4 Emigrant and immigrant spreads by region

Chart A3



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9).

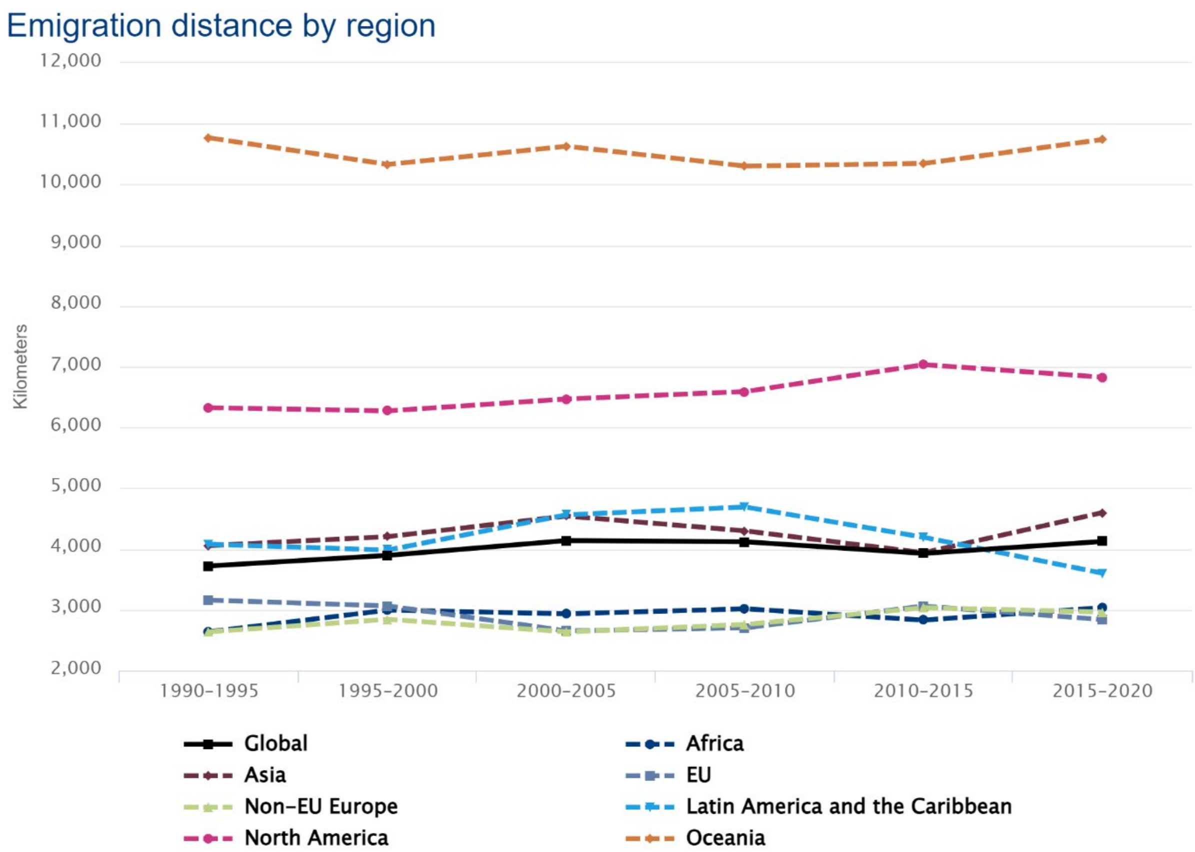
Chart A4



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9).

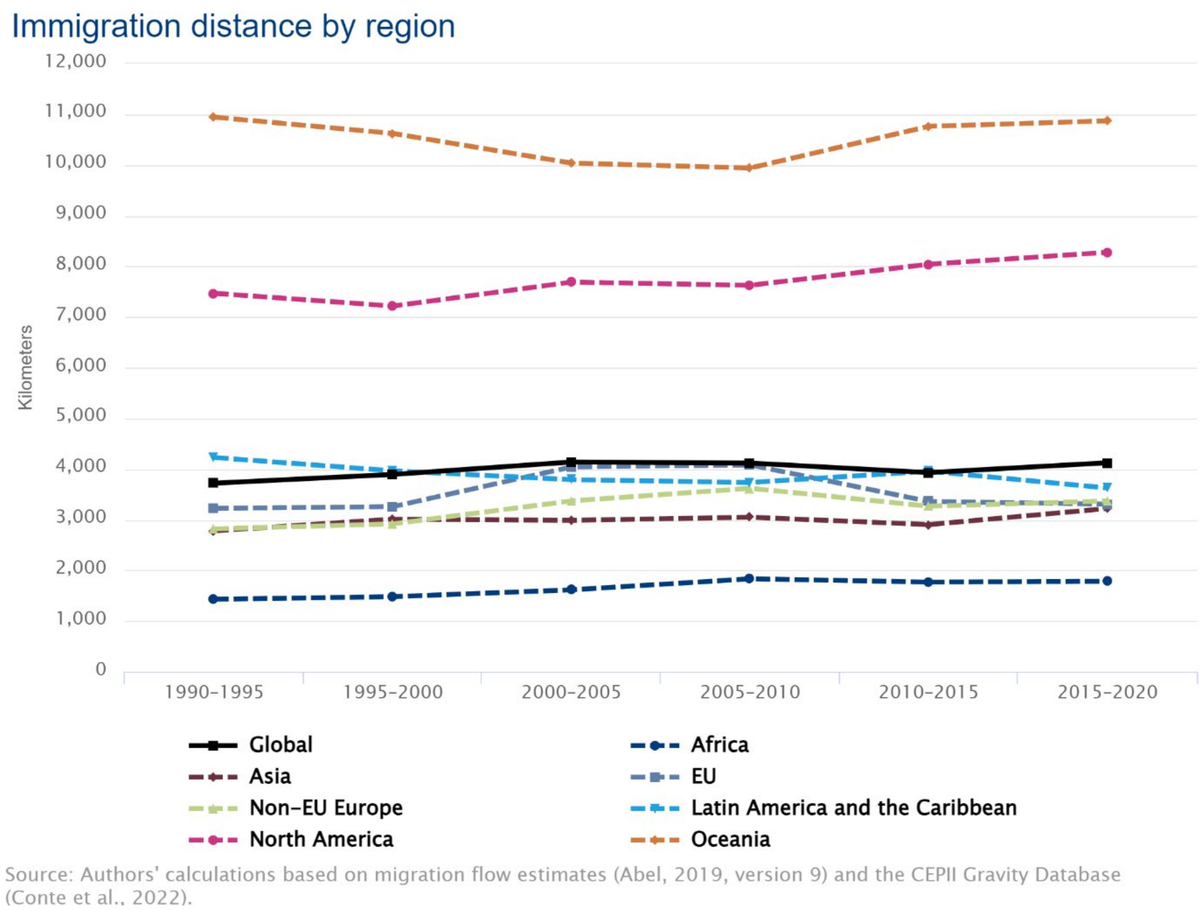
A.5 Average distance covered by region

Chart A5



Source: Authors' calculations based on migration flow estimates (Abel, 2019, version 9) and the CEPII Gravity Database (Conte et al., 2022).

Chart A6



A.6 Technical notes

Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index is a concentration index that is also used in the trade literature to measure import/export diversification with respect to sectors (see for example UNCTAD, 2024, Chapter 1). A Hirschman-based index also often employed when measuring the diversity of a population with respect to different groups. These groups can be defined based on nationality, country of birth, ethnic group, etc., and a well-known index is the ethnolinguistic fractionalization index (see Alesina et al., 2003). These indices range between zero (perfectly homogeneous population) and one (maximally fractionalized population, i.e. each person belongs to a different group) and identify the probability that two randomly chosen individuals in a population belong to a different group. Koech and Wynne (2017) use the Herfindahl index to measure the diversity of US states' exports, immigrants and financial links with respect to countries. For an application of the Herfindahl index to measure the concentration of remittances, see Hosny (2020).

Migrant stock data

Whenever possible, international migrants are equated with the **foreign-born population** in this data. If the necessary information on the country of birth is not available, and that is the case for approximately 20% of the countries/areas, the country of citizenship is used instead. Note that when the migrant population is equated with the foreign-citizenship population instead of the foreign-born population. This has important shortcomings: in countries where the citizenship of children depends on the citizenship of their parents (jus sanguinis) and not on the country of birth (jus soli), people might be included in the international migrant stock even though they never lived abroad. People who were naturalized in their country of residence, on the other hand, might not be included in the migrant stock, even though they immigrated from another country. (In addition, the legal framework for conferring citizenships – jus sanguinis vs. jus solis – has also consequences for the estimated age distribution of migrants, as under the former system, more children are attributed to the group of international migrants.) Estimates based on the country of citizenship instead of the country of birth are nevertheless included in the dataset in order to obtain a comprehensive bilateral database.

The migrant stock estimates also include **international refugees**. In countries where refugees hold an asylum status, they are usually included in the population census and no further adjustments are made by the UN. In countries where refugees mainly reside in restricted areas/refugee camps, they are typically not included in the census, and neither can they be included in a census if a refugee inflow occurred recently or rapidly. In these cases, estimates of the number of refugees, taken from international agencies such as the UNHCR, are added. For further details on the estimate of the migrant stock data, please refer to the documentation (UNDP, 2020).

The 2020 version of the estimates are adjusted to the restrictions that took place in the context of the **global COVID-19 pandemic**. Whenever there is no empirical data on the impact of the pandemic on international migrants available, it is assumed for the mid-year 2020 estimates that there were no changes in international migration between March 1 and July 1, 2020. This approach might be revised in the future, if and when more information on the impact of the pandemic becomes available.

Migrant flow data

There are efforts, mainly by international institutions, to collect flow data from statistical agencies and governments (e.g. the OECD for the foreign-born population in OECD countries, or Eurostat for immigration to and emigration from EU and selected non-EU countries). But even in countries with established and efficient statistics agencies (European countries, the USA, Canada, Australia, or New Zealand, for example), inconsistencies in the data can be found. In particular, data on immigration are usually better than data on emigration (see Buettner, 2022).

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