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ORIGINAL PAPER

How do regional price levels affect income inequality? Household-level evidence from countries worldwide

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Abstract
Regional differences in price levels are substantial in many countries, but little is known about how they affect the measurement of income inequality and poverty. To bridge this gap, we construct a new regional price level database which combines indices published by official authorities, previous literature, and our original estimates. The database covers 23 countries including the world's seven biggest economies. The combination of these indices with household-level data from the Luxembourg Income Study allows us to assess changes in indicators of income inequality and relative poverty caused by the adjustment of income for within-country price level differences. Our findings point to the necessity of considering the properties of specific indicators while assessing the potential effects of regional price levels.

JEL classification R1 · E31 · I32 · D31

1 Introduction

Both researchers and policy-makers have devoted considerable effort and resources to accurately measuring income. Despite the significant attention they receive, a majority of currently used income inequality and poverty indicators suffer from a significant shortcoming as they rely on the assumption that price levels within countries are constant. However, this assumption has been rejected by both economic theory and available empirical evidence. Omitting spatial differences in price levels within countries can result in a considerable loss of efficiency as well as in erroneous inferences. Gibson et al. (2017) find that an adjustment for differences in regional

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price levels leads to a fall in the 2010 Vietnamese Gini coefficient from 0.427 to 0.404. According to the findings of Janský and Kolcunová (2017), 9% of EU regions have been misclassified in the framework of its cohesion policy due to a failure to adjust for price level differences. In this paper, we provide a significant contribution to existing literature by assessing the effects of within-country price level differences on income inequality and poverty indicators for 23 countries.

We study the extent to which the assumption of constant price levels within countries affects the precision of commonly used income inequality and poverty indicators. The direction of the change in the respective indicators is not easily predictable as it is determined by the joint distribution of income and price level differences within countries. Characteristics of applied regional indices further influence the resulting effect. Consequently, economic theory is unable to fully predict changes stemming from adjustment for within-country price level differences. Therefore, a comprehensive analysis of their effects on income inequality and poverty indicators is desirable. Nevertheless, no study has provided an assessment of the effects of within-country price level differences on income inequality and poverty indicators for multiple countries. Our objective is to fill this gap.

Since no central regional price level data repository is available, we collect all existing estimates of regional price levels to construct the largest currently available database of regional price levels. We combine these with household-level microdata provided by the Luxembourg Income Study (LIS) to produce Gini coefficients, decile ratios, and poverty headcount ratios. Using this approach, we cover a group of 13 countries and 34 country-year combinations, i.e., our core sample. The core sample includes the world's seven biggest economies as measured by gross domestic product: USA, China, Japan, Germany, India, UK, and Russia. Furthermore, we rely on available estimates to construct a prediction model and estimate regional price levels for an additional 10 countries for which sufficient data for prediction are available. These constitute our expanded sample.

Our results suggest that the influence of regional price levels on income inequality and poverty indicators is complex. We find that adjusting for differences in regional price levels leads to a change in both inequality and poverty indicators. Gini coefficients and all considered decile ratios are affected in a similar manner. Likewise, the size and direction of the adjustment are stable over time for countries for which we have regional indices for multiple years. On the other hand, the effect of regional price levels on the poverty headcount ratio is more heterogeneous. Unlike in the case of inequality measures, we observe countries for which the direction of the adjustment changes over time. Observed differences in changes caused by adjustments for differences in regional price levels stem from the characteristics of considered indicators.

We provide multiple contributions to the currently available literature. First, the evidence is constrained in scope and consists of country-specific studies. We significantly expand it by providing evidence for 23 countries. Second, certain studies are limited in the way they construct income inequality and poverty indicators. Brandt and Holz (2006) rely on an indicator of average regional income. We rely on household-level microdata which enable us to construct more reliable indicators. Third, certain studies are limited by applied regional indices. Mogstad et al. (2007) and

Jolliffe (2006) rely on indices based solely on housing prices. However, such indices fail to capture variation in the prices of other goods. Unfortunately, we are unable to fully control for the variation in characteristics of available regional indices. While this limits the comparability of our results between countries, we provide a thorough discussion of their properties and their possible influence on our findings.

The remainder of this paper is organised as follows. Section 2 discusses the possible changes in income inequality and poverty indicators stemming from adjustment for differences in regional price levels and reviews currently available empirical evidence. Section 3 describes all sources of regional price levels and their reliability. It also outlines the scope of our analysis and provides a brief description of the LIS database. Section 4 describes our methodological approach to measuring income inequality and poverty, while Sect. 5 presents our results. The final section concludes.

2 Modelling regional price levels and their effects

The variation in income inequality and poverty indicators caused by adjustments for within-country price level differences has received relatively little attention to date. Furthermore, a majority of currently available indicators makes no adjustment for spatial differences in price levels. However, economic theory refutes the assumption of constant price levels within a given country, as, for example, Suedekum (2006) shows that a core-periphery structure with higher price levels in the core can emerge. While economic theory can explain the emergence of price level differences within a country, their effects on income based economic indicators cannot be easily predicted. Nevertheless, the necessity to adjust for within-country differences in price levels is well recognised. Ferreira et al. (2016) discuss its importance for measuring global poverty while Attanasio and Pistaferri (2016) outline its potential implications for determining consumption inequality.

The joint distribution of income and within-country differences in price levels is the principal determinant of changes in the considered indicators. Consider a two-region economy in which all households have the mean income of their region. We further assume differences in mean nominal income and price levels between the two regions. Under this specification, the adjustment for regional price level differences will lead to a decrease in inequality if the price level is higher in the high-income region. Inequality will increase in the opposite case. However, the final effect is likely to be more complex due to considerable heterogeneity in nominal incomes within regions. Furthermore, the effect is unlikely to be uniform across countries due to differences in the geography of income distribution.

Quality of regional indices further influences the resulting change in income inequality and poverty indicators. We can identify three principal areas of variation related to our research question. First, the indices differ in the level of regional detail. Second, they are based on various data types. Third, there is significant variation in the methodologies used for their construction. We will consider these three criteria in the next section to evaluate the reliability of used regional indices. However, we provide a brief overview of available regional indices as well as of the evidence on their effects before doing so.

2.1 Regional price levels

Spatial price level differences can be measured by multiple approaches. Recently, Biggeri and Prasada Rao (2021) recognise the need for sub-national price level indices and discuss the data requirements and possible methodological approaches to their construction. Deaton and Heston (2010) provide an accessible overview of methodologies for measuring spatial price level differences, while Rao (2013) focuses specifically on the methodology adopted by the International Comparison Program. Balk (1995) and Diewert (1999) provide a technical discussion of the alternative index number approaches. Balk (1996) compares the alternative methods for measuring purchasing power parities.

Multiple factors hinder the application of available methodologies in the within-country context. The most significant limitation is the scarcity of suitable item-level price data. Ideally, these would provide sufficient detail to be both representative of prices in any given region as well as comparable between different regions. However, such data are seldom available as most price surveys are designed to measure temporal variation in price levels. As a result, these surveys track the prices of identical or at least similar items over time rather than assess the prices of comparable and representative items across regions. Nevertheless, regional price level indicators are available for multiple countries in spite of this constraint. Ray (2017) and Majumder and Ray (2020) provide a comprehensive review of methodologies used for their construction. While we do review currently available indices as well as frameworks used for their estimation, we would like to refer readers interested in the methodological details to these articles.

Only a limited number of statistical offices have ever provided official regional price level indicators. Available indices from official sources are usually based on data collected for the construction of temporal indices. These are sometimes complemented by data from additional sources. The joint project of the BEA and BLS constructs regional indices according to a methodology described by Aten (2017). Their approach consists of a combination of the Country–Product–Dummy methodology and the Geary–Khamis (GK) formula. Indices obtained using this methodology constitute the most reliable and representative indices regularly provided by any official authority. Alongside the joint project of the BEA & BLS, researchers and policy-makers may rely on indices provided by the Office for National Statistics (ONS) for the UK, TurkStat for Turkey, and the Statistics Bureau of Japan for Japan. However, these are either one-time estimates as in the case of Japan or are not provided annually as in the case of the UK and Turkey. Though it is possible to rely on regional consumer price index (CPI) to obtain indices for multiple years, as carried out by, for example, TurkStat, this approach may lead to imprecisions in the construction of the final indicator.

The limited availability of regional price levels from official sources motivated numerous researchers as well as institutions to construct their own regional price level indicators. A significant portion of these indices is based on item-level data. In Europe, regional indices were recently published for three countries. Cadil et al. (2014), Kocourek et al. (2016), and Kramulová et al. (2016) provide regional price levels for Czechia, Rokicki and Hewings (2019) for Poland, and Weinand and von Auer (2020) for Germany. While studies for Czechia and Poland rely on methodologies inspired by the methodology of the Eurostat–OECD programme, Weinand and von Auer (2020) rely on a variant of the weighted country-product-dummy method. Despite the methodological differences, all studies rely on comprehensive data sets and robust methodologies, thus providing reliable indices. In Asia, regional price levels for the Philippines are available thanks to a one-off exercise conducted by the Asian Development Bank. Dikhanov et al. (2011) discussed the methodological approach and provides the final indices. Multiple estimates of regional price levels are available for China. Brandt and Holz (2006) provide price levels for rural and urban parts of Chinese regions as well as a combined price level index for each region. Recently, Chen et al. (2020) rely on a more recent data set combined with a variety of methodologies to provide probably the most comprehensive and robust estimates of regional price levels in China. Furthermore, the authors provide a thorough review of other estimates of Chinese regional price levels such as those by Li et al. (2005) or Biggeri et al. (2017a).

The limited availability of item-level price data instigated the development of alternative methods seeking to estimate regional price levels. One possible approach is to rely on unit values derived from consumption surveys instead of specially collected item-level price data. However, as unit values suffer from numerous limitations, they cannot serve as perfect substitutes for item-level data. According to Majumder et al. (2012), these include potential measurement errors, quality effects, and household composition effects on expenditure patterns. Coondoo et al. (2004) propose a hedonic regression framework for the estimation of within-country price level differences on the basis of unit values. Coondoo et al. (2011) propose an alternative solution to the constraint imposed by data availability based on an Engel curve analysis. Majumder et al. (2012) combine data on unit values with the Quadratic Almost Ideal Demand System (QAIDS) of Banks et al. (1997) and produce regional price levels for Indian states. Lasarte Navamuel et al. (2015) rely on a demand system to construct a cost of living index for food in Spain. As noted by Majumder et al. (2015), estimates based on demand systems might be considered preferable to conventional indices as they permit the incorporation of price-adjusted substitution.

Some authors sidestep the issue caused by limited item-level data availability by predicting regional price levels based on available indices. They either construct or collect available regional price levels and construct a model to explain them. They subsequently use this model to arrive at out-of-sample predictions of previously unavailable regional price levels. Roos (2006) uses this approach for German regions, while Janský and Kolcunová (2017) adopt it to estimate regional price levels for the NUTS 2 regions of the EU. However, Blien et al.

(2009) criticise this approach, asserting that the construction of an econometric model on the basis of estimated values with unknown standard errors leads to a bias in the estimated standard errors. Instead, the authors propose a multiple imputation framework as an alternate approach.

2.2 Effects of regional price levels

Despite the considerable attention devoted to the accurate measurement of regional price levels, evidence of changes to income inequality and poverty indicators resulting from their application is constrained. Furthermore, the number of studies quantifying this effect suffer from significant limitations. For example, Brandt and Holz (2006) show that an adjustment for spatial differences in price levels results in a decrease of 30% of the 1990 Chinese Gini coefficient. However, the authors base their calculation on average regional income instead of on representative microdata. Mogstad et al. (2007) conclude that region-specific poverty lines which take into account spatial differences in price levels affect both the geographical as well as the demographic distribution of poverty. However, as their regional price levels are based solely on housing prices, they fail to factor in variation in all other prices. Prado et al. (2021) rely on regional indices in their study of regional wage convergence in Sweden. Nevertheless, their indices only cover variation in food prices.

Evidence based on household-level survey data is scarce. Jolliffe (2006) provides a detailed assessment of the effects of regional price level differences on income distribution. The author finds that an adjustment for spatial differences in price levels causes a significant shift of poverty from US non-metropolitan to US metropolitan areas. Pittau et al. (2011) find that an adjustment for differences in regional price levels leads to a decrease in income inequality in Italy. According to Ayala et al. (2014), an adjustment of the national poverty line for differences in regional price levels causes a significant change in the ranking of Spanish regions according to their poverty rates. Gibson et al. (2017) find that an adjustment for differences in regional price levels leads to a fall in the 2010 Vietnamese Gini coefficient from 0.427 to 0.404.

3 Data

Our analysis stems from a combination of two types of data. First, we rely on indices measuring regional price level differences. We prefer indices based on item-level price data. However, as these are not widely available, we also consider those based on alternative data types. We obtain these indices from both official and academic sources reviewed in the previous section. Countries for which we find reliable existing regional price level estimates constitute the core sample. We also construct a prediction model based on the available indices which allows us to predict regional price levels for additional countries. Countries for which we rely on our predictions of regional price levels constitute the expanded sample. Second, we rely on household-level microdata provided by the LIS. These allow us to accurately measure income distribution. The availability of both data types determines the final scope of our analysis. Though the primary restriction stems from the availability of regional price levels, additional restrictions are also posed by the LIS. Consequently, the core sample consists of 13 countries and 34 country-year combinations while the expanded sample includes 10 additional countries.

In this section, we describe the data used in our analysis. We present the composition of our core sample and all regional price level sources which we have adopted. However, as we rely on indices based on a variety of data and methodologies, we also discuss how these differences might affect our results. Furthermore, we present our methodology used for estimating the regional price levels of countries included in the expanded sample. Finally, we provide a brief description of the household-level microdata provided by the LIS and their coverage.

3.1 Core sample

The core sample consists of 13 countries and 34 country-year combinations. In constructing the sample, we consider all available regional price level estimates. We prefer indices from official authorities and those available in published articles. In case such indices are not available, we rely on those published in working papers. All indices must fulfil the following two conditions in order to be included in the core sample. First, they must provide regional price levels relative to the price level of the whole country. Second, they must facilitate combination with LIS data. As a result of the first condition, we cannot rely on indices provided, for example, by Li et al. (2005) and Biggeri et al. (2017a) for China, whereas the second condition prevents us from using, for example, indices provided by Glewwe (1985) for Ivory Coast. In case multiple indices are available for a given country-year combination, we consider all potential sources. If the LIS database does not contain data for a given year we rely on data from the closest year to that for which the price levels were constructed. Table 1 presents the composition of the core sample, all considered country-year combinations, regional level on which the indices are provided, and the source of the respective price levels. Table A.1 includes the actual price levels for all considered country-year combinations as well as a brief description of all considered sources. Table B.1 contains a list of all available regional price level estimates which did not meet our criteria. We believe that this list of all existing regional price level estimates may serve as a useful reference for all researchers interested in the topic.

The fact that we rely on regional price levels obtained from multiple alternative sources requires additional attention. Differences in the methodologies used for their construction may have different implications for their expected effects on the considered indicators. Three areas of variation are of crucial interest to us. We can observe variation in the representativeness of the data on which the indices are based. Furthermore, as indicated in Table 1, the indices differ in the level of regional detail on which they are provided. Finally, there is significant variation in the methodologies used for their construction. As stated in the previous section, we use these three

Table 1 Core sample

Country	Year LIS	Price levels: year, source	Territorial level[a]
Australia	2010	2009/2010, Mishra and Ray (2014)	States and the Northern Territory
Austria	2007	2008, Matzka and Nachbagauer (2009)	NUTS 2
China	2002	2002, Brandt and Holz (2006)	Provinces
	2013	2013, Brandt and Holz (2006)	Provinces
Czechia	2007	2007, Cadil et al. (2014)	NUTS 3
	2013	2012, Kramulová et al. (2016)	NUTS 3
	2013	2011–2013, Kocourek et al. (2016)	NUTS 3
Germany	1994	1993, Roos (2006)	NUTS 1
	2016	2016, Weinand and von Auer (2020)	NUTS 1
India	2004	2004/2005, Chakrabarty et al. (2018)	States
	2011	2011/2012, Chakrabarty et al. (2018)	States
Italy	2004	2006, Pittau et al. (2011)	NUTS 2
	2008	2006, Pittau et al. (2011)	NUTS 2
Japan	2008	2007, SBJ (2016)	Regions
Poland	2004	2004, Rokicki and Hewings (2019)	NUTS 2
	2007	2007, Rokicki and Hewings (2019)	NUTS 2
	2010	2010, Rokicki and Hewings (2019)	NUTS 2
Russia	2000	1998, Gluschenko (2006)	Economic regions
Slovakia	2010	2009, Radvansky et al. (2012)	NUTS 3
UK	1999	2000, Baran and O'Donoghue (2002)	NUTS 1
	2004	2003, Ball and Fenwick (2004)	NUTS 1
	2004	2004, Wingfield et al. (2005)	NUTS 1
	2010	2010, ONS (2010)	NUTS 1
	2016	2016, ONS (2016)	NUTS 1
USA	2008 to 2017	2008 to 2017, Bureau of Economic Analysis (2019)	All States and the District of Columbia

The table specifies the composition of the core sample. [a]Where applicable, the Eurostat NUTS classification is used

criteria, i.e. price data scope, regional detail level, and methodological approach to assess the reliability of individual indices.

The characteristics of the underlying price data are one of the major determinants with respect to the representativeness of regional price levels. Comprehensive item-level data representative of the price dynamics in each of the considered regions constitute ideal inputs. Nevertheless, these are usually unavailable. Therefore, the usual sources of item-level data on prices are those collected for the construction of temporal price indices such as the CPI. For example, Cadil et al. (2014) and Kocourek et al. (2016) rely on this type of data. The main limitation of this type of data is that it does not guarantee sufficient coverage of all regions by comparable products, as the surveys are designed to follow the price of a given product over time rather than facilitate the comparison of prices between different regions. Multiple authors have devised numerous robust aggregation methods to overcome this limitation. Furthermore, e.g. Bureau of Economic Analysis (2019) or ONS (2016) combines these data with additional data on prices. Consequently, we believe that indices based on these data provide the most reliable measures of differences in regional price levels. However, some authors had to rely on alternative data sources. Chief among those are unit values based on data from consumption surveys. For example, Chakrabarty et al. (2018) base their analysis on unit values. We have already discussed the limitations of these data in the previous section.

The underlying price data should cover the complete consumption basket of households living in a given region. However, the coverage varies between the sources included in our core sample. Most notably, the price levels differ in terms of whether they incorporate variations in housing costs between regions. Chakrabarty et al. (2018), ONS (2010), ONS (2016), Roos (2006), and SBJ (2016) do not cover variations in housing costs. Moreover, Gluschenko (2006), and Radvansky et al. (2012) do not provide sufficient information to distinguish whether their price levels cover housing costs. Therefore, the remaining price levels included in our final sample are likely more representative.

During the course of interpreting our results, we must also consider the level of regional detail at which we are operating in a given country. The regional level is determined by both the properties of the available regional price levels and the LIS database. The majority of available indices is provided at administrative region level. Though such regions constitute a convenient division of a given country, there is no support for the hypothesis that differences in price levels should follow differences in administratively defined regions. Furthermore, the level of regional detail at which we can operate differs between countries. This variation may induce differences in the magnitude of changes induced by the adjustment for regional price level differences. We believe that indices provided at more detailed levels such as those by Kocourek et al. (2016) or Radvansky et al. (2012) provide a better measure of regional price level differences. Consequently, their application might lead to more significant changes in the considered indicators. On the other hand, indices provided at aggregate regional levels, such as for US or Indian states, are likely to miss some of the underlying price level heterogeneity, thus leading to less precise adjustments.

The properties and interpretation of regional price levels depend on the methodology used for their construction. Most regional price levels included in our core sample are based on the application of superlative price indices. For example, Cadil et al. (2014) or Kocourek et al. (2016) rely on approaches derived from the methodology used by the Eurostat–OECD PPP programme. These are based on the application of the Gini-Éltető-Köves-Szulc (GEKS) formula. As described by Aten (2017) the regional price levels for the USA are based on the Geary–Khamis formula, whereas the indices provided by SBJ (2016) and Matzka and Nachbagauer (2009) are based on the Fisher price index. Other methods include the construction of the EASI demand system by Mishra and Ray (2014) or the estimation of the Dynamic Household Regional Product Dummy Model by Chakrabarty et al. (2018). Despite differences in methodologies used for their construction, we believe that all considered indices provide reliable indicators of regional price level differences. Nevertheless, we wish to emphasise that our results should be interpreted as a set of individual case studies, i.e., the methodological differences used for the construction of regional price levels between countries must be kept in mind. We also wish to point out that currently available indices facilitate the assessment of the effects of regional price levels on income inequality and poverty indicators only at national level. Consequently, the issue of their effects on global inequality, raised, for example, by Ravallion (2018), is yet to be quantified as our database does not allow us to study this issue in appropriate fashion.

The above described criteria allow us to identify countries where we can expect the most representative estimates of the effects of regional price levels on income inequality and poverty indicators. These are countries whose regional price levels achieve the best balance between the three considered criteria. First, they are based on a sufficiently comprehensive set of prices. Second, they are provided on a sufficiently detailed regional level. Third, they are constructed using a sufficiently robust methodology. Indices for Czechia, Italy, and Poland will likely result in the most precise adjustments. Results for the USA, UK, and Germany will likely suffer from the fact that the indices cover an aggregate regional level, i.e. NUTS 1 regions in the case of the UK and Germany and the level of states in the case of the USA. Consequently, these indices will likely miss some of the underlying price level heterogeneity. Indices for China, India, Japan, and Australia suffer from a similar shortcoming. In the case of Germany (Roos 2006), UK (ONS 2010, 2016), India (Chakrabarty et al. 2018), and Japan (SBJ 2016), this issue is aggravated by the fact that these indices do not cover housing costs. Results obtained based on the indices for Austria, Russia, and Slovakia ought to be interpreted most carefully as the authors provided only limited insights into their construction.

Combination of regional indices and household-level microdata from different years may further affect our results. For a share of covered country-year combinations, we rely on regional indices and household-level microdata from different years. While determined by data availability, this mismatch can affect the robustness of our results. To combine indices and survey data from different years, we assume no variation in the joint distribution of income and price level differences within countries. We prefer this solution to adjustment by regional CPI as spatial and temporal regional indices are unlikely to be compatible. China is the only exception to this rule. This is caused by the considerable difference between years for which indices and survey data are available as well as by the fact that authors of original indices, i.e. Brandt and Holz (2006), regularly provide updated versions of their original estimates. Overall, results based on indices and survey data from identical year should be considered as more representative.

3.2 Expanded sample

The expanded sample consists of 10 countries for which we construct original regional price level estimates. The prediction of regional price levels allows us to broaden our analysis, as a study based solely on already available regional price levels would leave a considerable portion of the LIS database unexplored. Due to the limited availability of item-level price data, we rely on an alternative approach. We first construct an econometric model based on available regional price level estimates. We than use it to perform an out-of-sample prediction of new indices. We are naturally well aware that the prediction of regional price levels for a set of countries based on existing indices is burdened by several limitations. First, the mechanisms for determining within-country price level variation likely differ between countries. For example, Aten (2017) finds that differences in housing prices are one of the most significant determinants of regional price levels in the USA, while according to Rokicki and Hewings (2019) they have only limited influence in the case of Poland. Second, as discussed in the previous section, currently available indices were obtained using a variety of different approaches. Consequently, relying on pooled indices which differ in their characteristics might result in biased estimates. Third, these indices are provided on different levels of regional detail.

We rely on two alternative approaches to modelling regional price level differences. Appendix C contains a detailed description of both methodologies, results from all considered specifications as well as a more detailed discussion. The first approach is similar to that adopted by Roos (2006) and Janský and Kolcunová (2017). It relies on a set of assumptions under which differences in regional price levels are determined solely by differences in regional supply and demand. Based on these assumptions and an iterative estimation procedure we identify the most suitable model for modelling regional price levels. We will refer to this approach as to the demand–supply framework. The second approach was recently proposed by Costa et al. (2019) and is based on the Balassa-Samuelson hypothesis. We will refer to this approach as to the Balassa-Samuelson framework. Relying on the two approaches, we construct a total of 26 models. Of these we select the one most suitable for predicting the regional price levels of countries in the expanded sample. Equation 1 presents the final model.

$$price\ level_i = 0.204 * income_i + 0.035 * regional\ GDP_i + 0.207 * population_i + 74.807 \tag{1}$$

The final model is based on the Demand–Supply framework. In our view, it is the most suitable model for predicting regional price levels of countries included in the expanded sample. The sign of all variables included in the model follows economic intuition. Nevertheless, the goodness of fit of the model is limited. Consequently, as noted previously, when discussing the effects of regional price levels on income inequality and poverty indicators we focus primarily on countries in the core sample. These are likely to provide better insight into the studied relationship.

3.3 Household-level microdata

We rely on the LIS database to construct income inequality and poverty indicators. The LIS database provides access to harmonised microdata covering over 50 countries. These come from various surveys harmonised into a common template by the LIS, as it does not field its own surveys. The harmonised surveys are always cross-sectional, which makes longitudinal analysis infeasible. While the raw microfiles are unavailable directly, researchers can work with them through a remote submission interface. Consequently, we base our inequality and poverty indicators on household-level observations instead of relying on aggregate measures such as mean regional income. Ravallion (2015) and Gornick et al. (2015) provide more detail on the LIS database. We have concluded our research in November 2020. We thus base our calculations on the modernised version of the LIS database following its 2019 update.

We construct the considered inequality and poverty indicators based on total household disposable income. Following the LIS template, household income is composed of factor and transfer income. The former can be further decomposed into labour and capital income, while the latter consists of pensions, private transfers, and public transfers. Subtracting income taxes and social security contributions yields total household disposable income. Alongside household disposable income, we rely on the variables indicating the region and size of the household. The latter enables us to convert total income into per capita, and equalised terms. Finally, all indicators use household weights provided by the LIS to ensure representativeness. Though the LIS provides more information on the socio-demographic characteristics of household members, including their education, health, citizenship, and labour market activity, these are not required to complete our objective.

Countries in our final sample fulfil the following three conditions. First, the regional variable is available in the LIS database. Otherwise, it is impossible to adjust income for differences in regional price levels. Second, price levels for the respective country are either available or can be estimated. Third, it is possible to combine the available regional price levels with the microdata in the LIS database. Consequently, the regional level must be either identical in both data sets, or it can be transferred to the same level.

4 Methodology

We quantify imprecisions caused by the omission to adjust for within-country differences in price levels for a variety of indicators. We consider two indicators of inequality, i.e., the Gini coefficient and the decile ratio. Furthermore, we consider the poverty headcount ratio as an indicator of poverty. First, we estimate all considered indicators based on household income as recorded in the LIS database. Second, we adjust all reported incomes for differences in price levels and re-estimate all considered indicators. Using this approach we obtain indices both adjusted and unadjusted for price level differences. This allows us to quantify the change caused by adjustment for differences in price levels.

We rely on three equivalence scales to measure income. First, we simply consider total household income as recorded in the LIS database. However, as this specification of income does not make any adjustment for the number of household members, we also consider total household income expressed in per capita terms. We obtain this measure by dividing the total household income by the number of household members. Shortcomings of the per capita measure, especially the fact that it does not take into account economies of scale within households, lead us to consider a third equivalence scale. We refer to household income measured using this scale as equalised income. We obtain equalised income by dividing the total household income by the square root of the number of household members. Though multiple alternatives to this scale exist, we choose this specification as it is used by the LIS for the construction of income inequality and poverty indicators. We calculate the decile ratio and the poverty headcount ratio based on equalised income, whereas our estimates of the Gini coefficient are based on all types equivalence scales. All measures of income are bottom-coded at zero and top-coded at ten times the median income.

We quantify the effect of adjustment for differences in regional price levels for the Gini coefficient and for multiple decile ratios. We choose these two indicators because they are most frequently used in both policy and academic works. While the Gini coefficient measures the distribution of income within an entire population, the decile ratio is defined as the income of a person at the i^{th} percentile of income distribution over the income of a person at the j^{th} percentile of income distribution. We consider three specifications of decile ratios, specifically the 90/10, 90/50, and 80/20 decile ratios.

The poverty headcount ratio serves as our indicator of poverty. Similarly to considered inequality measures, we choose to rely on the headcount ratio as it is likely the most frequently used indicator of poverty by both policy-makers and academic researchers. It is defined as the proportion of the population living below a considered poverty line. It belongs to the class of poverty indicators defined by Foster et al. (1984). However, it does not satisfy the transfer and monotonicity axioms outlined by Sen (1976) or Zheng (1993). Consequently, we quantify the effect of adjustment for differences in price levels on poverty incidence rather than depth. We consider poverty lines set at 40%, 50%, and 60% of median income.

We calculate all considered indicators based on income as reported by the LIS database as well as on income adjusted for differences in regional price levels. To obtain income Y_i^{adj} adjusted for within-country differences in price levels, we divide household-level incomes in region i, Y_i^{unadj}, by the relevant regional price levels.

$$Y_i^{\text{adj}} = \frac{Y_i^{\text{unadj}}}{\text{regional price level}_i} \tag{2}$$

We rely on a bootstrap procedure to test the statistical significance of changes in all considered indicators. Unfortunately, the limited computational capacity of the LIS interface does not allow execution of computationally intensive calculations. Consequently, we rely on a simple percentile bootstrap with 1,000 replications to construct 95% confidence intervals for all indicators. We consider a change in an indicator to be statistically significant in case the adjusted indicator is outside of the respective 95% confidence interval.

5 Results

By combining our database of regional price levels with the LIS database, we are able to assess the effect of regional price levels on income inequality and poverty indicators for 23 countries. The scope of our analysis allows us to study the robustness of all considered indicators and to identify countries where the omission of adjustments for regional price level differences leads to the biggest imprecisions in the measurement of inequality and poverty. Table D.1 and Table D.2 present our complete results for all income inequality indicators, i.e., the Gini coefficient and decile ratios. Table D.3 presents our complete results for all considered specifications of the poverty headcount ratio. Adjustments for differences in regional price levels has a similar effect on all considered measures of inequality. For a majority of countries, it results in a decrease of inequality. On the other hand, changes in the poverty headcount ratio are more heterogeneous.

We focus on two aspects of the relationship between regional price levels and income inequality and poverty indicators. First, we assess the extent of the imprecision in the considered indicators stemming from the omission of the adjustment for regional price level differences. When approaching the analysis from this vantage point, we concentrate especially on identifying countries where the adjustment for regional price level differences leads to the most pronounced changes in the considered indicators. We believe that this part of our analysis is relevant especially to practitioners and policy-makers. However, as the considered indicators play a prominent role in numerous empirical analyses, results stemming from this approach should also be of interest for academic researchers. Second, we focus on the extent to which the characteristics of regional price levels affect the results. The most relevant aspects are the level of regional detail on which the respective price levels are provided and the characteristics of the underlying data set from which the price levels were constructed. These insights should be of relevance to anyone wishing to rely on regional price level indicators. Due to the limitations of the expanded sample, we focus primarily on the core sample when interpreting our results.

5.1 Inequality and poverty indicators

All considered income inequality indicators react similarly to the adjustment of income for differences in regional price levels. The adjustment results in a decrease of measured income inequality for the majority of countries and country-year combinations. Furthermore, the direction of the adjustment is identical for the majority of countries regardless of the specific indicator. Figures 1 and 2 provide a graphical representation of adjustments for all considered specifications of the Gini coefficient and decile ratios. Adjustments are expressed in terms of shares of unadjusted indicators. Our results indicate that the omission of the adjustment for regional price level differences leads to the largest overestimation of inequality in case of Italy and the largest underestimation in case of Australia. As both Italy and Australia belong to the core sample, we consider the range bounded by these two countries as indicative of the possible effects of regional price levels on income inequality indicators. The direction of the correction is homogeneous for countries with multiple country-year combinations available, as indicated, for example, by the case of the USA and the UK. Our calculations indicate that the adjustment for regional price level differences has only limited impact on inequality in China and India. This result might seem

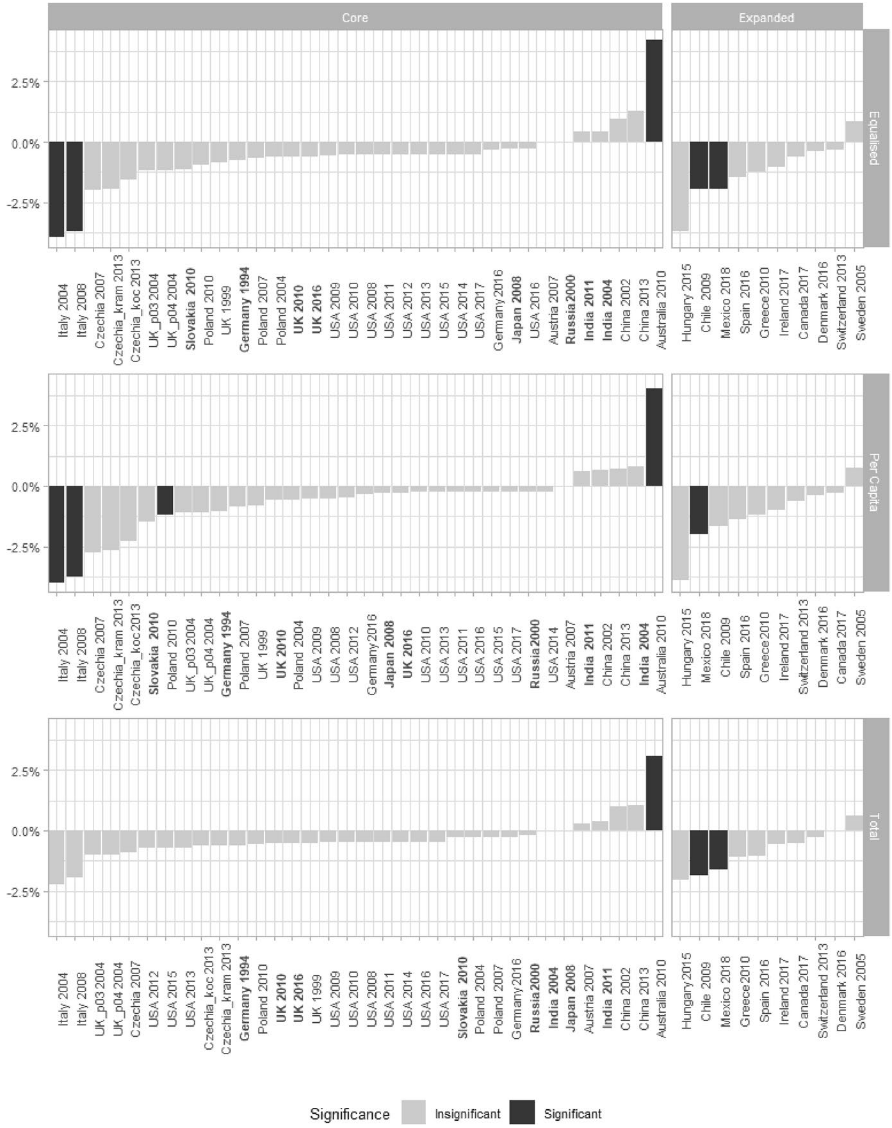

Fig. 1 Gini coefficient. *Source:* Authors. *Note:* The figure displays the changes in the Gini coefficient caused by the adjustment of income for regional price level differences. The changes are expressed as the share of the original unadjusted value. Price levels of countries in bold either do not cover housing costs (DE 1994, IN, JP, UK 2010, UK 2016) or we cannot identify whether these are covered (RU, SK)

counter-intuitive due to the considerable differences in regional price levels within these countries and we will discuss it later in this section.

The impact of the adjustment for regional price level differences on the poverty headcount ratio is more heterogeneous. In contrast to indicators of income

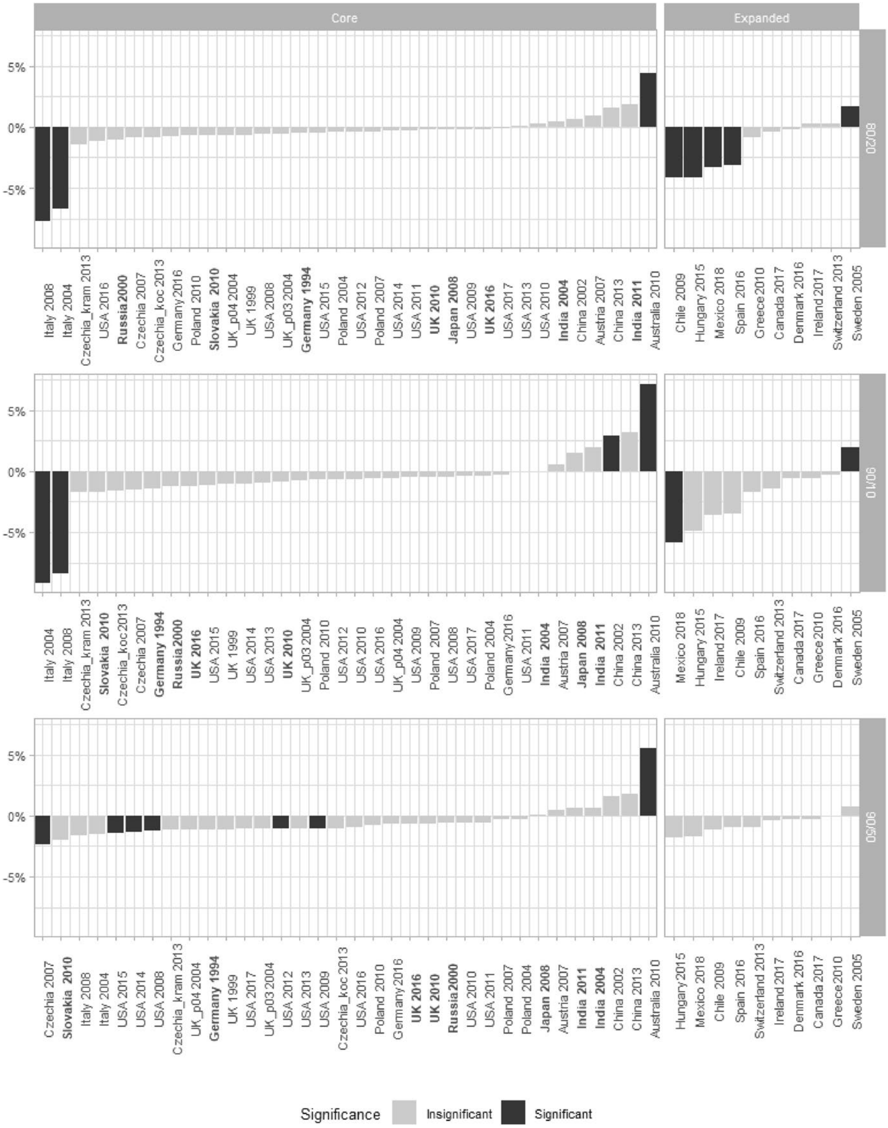

Fig. 2 Decile ratio. *Source:* Authors. *Note:* The figure displays the changes in all considered decile ratios caused by the adjustment of income for regional price level differences. The changes are expressed as the share of the original unadjusted value. Price levels of countries in bold either do not cover housing costs (DE 1994, IN, JP, UK 2010, UK 2016) or we cannot identify whether these are covered (RU, SK)

inequality, we observe that the direction of change in the poverty headcount ratio varies between years for countries with price levels available for multiple years. This is visible, for example, in the case of Czechia where the adjustment for the year

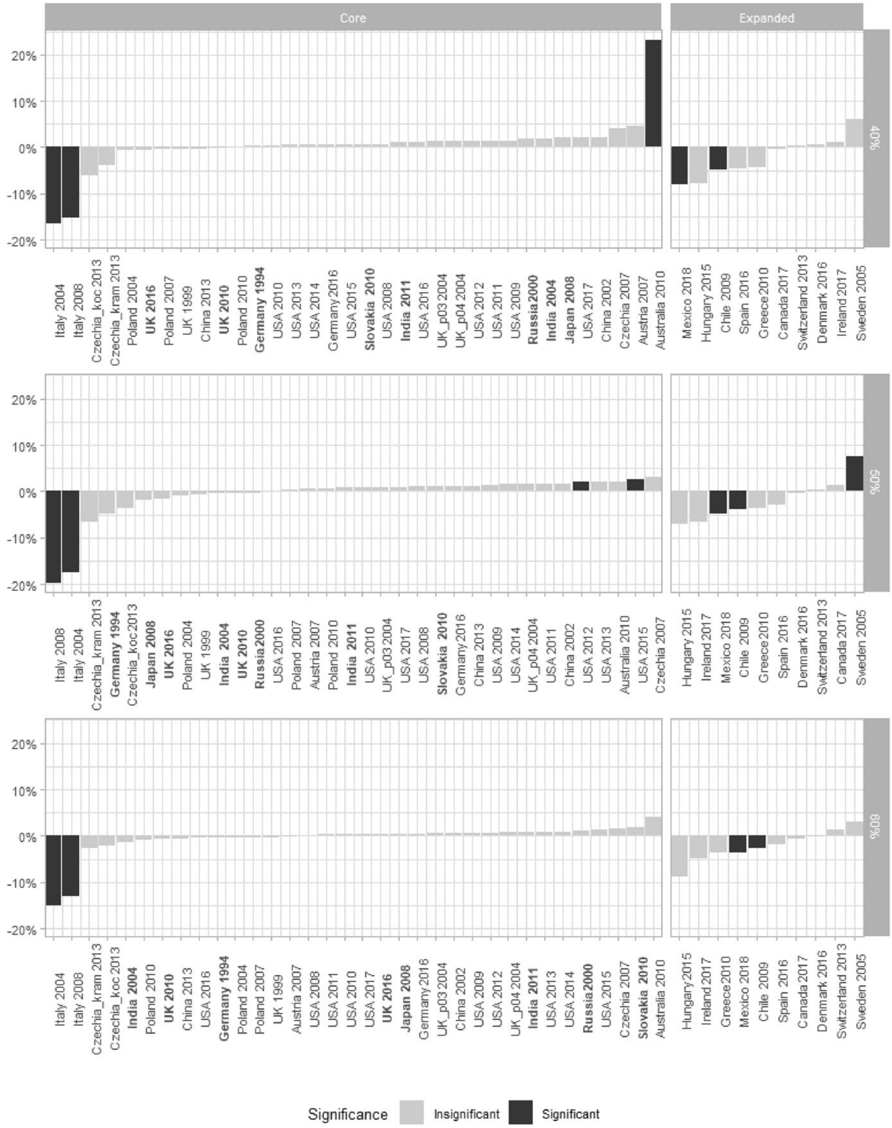

Fig. 3 Poverty headcount ratio. *Source:* Authors. *Note:* The figure displays the changes in all considered poverty headcount ratios caused by the adjustment of income for regional price level differences. The changes are expressed as the share of the original unadjusted value. Price levels of countries in bold either do not cover housing costs (DE 1994, IN, JP, UK 2010, UK 2016) or we cannot identify whether these are covered (RU, SK)

2007 results in an increase of the poverty headcount ratio, while it has the opposite effect for the year 2013 regardless of the source of regional price levels. Figure 3 provides a graphical representation of the result. Similarly to Figs. 1 and 2, the size of the adjustment is expressed as a share of the unadjusted indicator. We consistently observe the most pronounced downward correction of the poverty headcount ratio in the case of Italy. On the other hand, in the case of Australia the adjustment for differences in regional price levels results in the biggest increase in measured poverty. Again, we observe only a limited impact of the adjustment for differences in regional price levels for China and India.

Differences in the properties of considered indicators explain the variation in their reaction to the adjustment of income for regional price level differences. We observe only limited variation in the Gini coefficient. As the Gini coefficient is an indicator of the distribution of income over the whole population, this seeming lack of impact might conceal underlying shifts in the distribution. In graphical terms, the adjustment for regional price level differences may alter the shape of the Lorenz curve in ways not captured by the Gini coefficient. The fact that observed changes in decile ratios are larger corroborates this hypothesis. Furthermore, the poverty headcount ratio seems to be the most sensible measure to adjustments for regional price level differences. This result is to some extent intuitive as the poverty headcount ratio is based on a specific income distribution threshold. Therefore, if a significant share of poor persons is located in a region with a low price level, the adjustment for differences in price levels may shift them over the threshold, thus causing a considerable shift in the poverty headcount ratio. This effect is even stronger in case the income of the poor persons is close to the poverty line as in such a case only a limited variation in price levels is sufficient to cause a shift in the poverty headcount ratio.

The statistical significance of changes corresponds to their size. We observe that changes tend to be significant for Australia, Italy, Mexico, and Chile. In all these countries we observe considerable differences in regional price levels. The proportion of country-year combinations for which the adjustment for regional price level differences leads to a statistically significant shift is not constant across all considered indicator types. Our results indicate that changes in decile ratios and poverty headcount ratios tend to be of greater statistical significance.

An interesting finding featured in our results is the limited impact of the adjustment for regional price level differences on inequality and poverty in India and China. However, the lack of change in aggregate indicators does not imply an absence of this effect. It is possible that the adjustment leads to significant changes in the within-country geography of poverty and distribution of income. In case the changes are proportional, there might be no identifiable change in the aggregate indicator of inequality or poverty. Consider an example of two regions, region A with a low price level whose residents are close to, yet below, the poverty line, and region B with a high price level whose residents are close to, but above, the poverty line. Under this specification, an adjustment for differences in price levels might result in a significant shift in the geography of poverty, i.e. from region A to region

B, but no significant shift in the poverty headcount ratio, especially if the groups of ex ante and ex post poor persons in region A and B are similar in size. Nevertheless, it is possible that differences in the sizes of adjustments are driven by differences in the characteristics of regional price levels.

5.2 Effect of regional price-level characteristics

The level of regional detail on which the indices are available is a major determinant of their effect on the considered indicators. If the level of regional disaggregation is a good proxy for differences in regional price levels, the application of the individual indices can lead to more pronounced changes in the considered indicators. For example, the indices we use for Italy and USA are provided on the same level of regional disaggregation, i.e. Territorial level 2 according to the OECD regional classification. However, they are likely to be a better measure of regional price level differences in the case of Italy as regional indices for the USA are provided on the level of states. As we may expect considerable differences in price levels within individual states, the capacity of these indices to accurately measure differences in price levels is limited. The question of regional detail is especially salient in the case of large countries such as the USA, India, and China. The application of regional price levels based on administrative regions might be problematic as within-country variation in price levels may follow differences between the rural and urban parts of a given country rather than between administrative regions.

The second significant determinant of the change in inequality and poverty indicators is the representativeness of price level data. These determine the reliability of the resulting indices. As a result, indices based on more comprehensive baskets of goods might be more representative of the underlying price level differences. For example, indices for Czechia and Poland represent such a case. On the other hand, indices based on constrained data sets such as those used for China, or unit values, such as those used for India, should be interpreted more cautiously. Their limited representativeness might affect their impact on the considered indicators. Therefore, we believe that more research and especially higher-quality item-level price data are required for a more robust assessment of the influence of regional price levels on the distribution of income and poverty.

6 Conclusion

We have studied imprecisions in income inequality and poverty indicators caused by the omission to adjust for differences in regional price levels. This issue has received only limited attention in spite of the fact that the existence of within-country price level differences has previously been established in both theoretical and empirical literature. As existing studies only provide country-specific assessments and given the relevance of the subject to academic researchers and policymakers, we provide novel evidence for a group of countries. In order to do so, we construct a new regional price level database, which compiles indices provided by previous research and covers 13 countries and 34 country-year combinations. We also estimate regional price levels for an additional 10 countries. We then combine these indices with household-level data from the LIS database. By combining these resources, we are thus able to study changes in income inequality and poverty indicators. We consider three types of indicators, specifically two measures of income inequality and a measure of poverty: the Gini coefficient, the decile ratio, and the poverty headcount ratio.

Our research leads us to multiple conclusions. The adjustment of income for regional price level differences affects all considered indicators of income inequality similarly. Our results indicate that both the size and direction of this adjustment tend to be stable over time for countries with regional indices for multiple years. On the other hand, the reaction of the poverty headcount ratio to the adjustment is more heterogeneous. We observe that both the direction and size of the adjustment in the poverty headcount ratio varies between years for individual countries. We believe that the characteristics of considered indicators determine to a significant extent the significance of the adjustments. It is therefore crucial to consider them when interpreting the induced changes. Furthermore, it is important to consider the characteristics of the regional price levels as these can also considerably influence the significance of the adjustment. Our results indicate that the effect of the adjustment of income for regional price level differences on income inequality and poverty indicators is not universal. Instead, it is important to consider each country as a separate case and focus on the representativeness of the utilised indices, the level of regional disaggregation, and the properties of the considered indicator.

Multiple issues raised in this study constitute suitable future research targets. We believe that our work, and especially the constructed database, can serve as a useful starting point for all researchers interested in regional price levels. Future research should address the issue of the appropriate level of regional disaggregation on which price levels ought to be constructed. While a variety of indices are currently available, more indices should be constructed; we would thus welcome the better availability of item-level data on prices from official authorities. This would facilitate the construction of robust indicators of regional price levels and a direct comparison of the performance of different methodologies used to measure within-country price level differences. Finally, alternative modelling approaches to regional price level prediction based on available indices should be assessed.

Appendices

A Regional price levels

See Table A.1.

Table A.1 Regional price levels

Country	Regions	Regional price level	
Australia	AU1: New South Wales		102.9
	AU2: Victoria		99
	AU3: Queensland		125
	AU4: South Australia		92
	AU5: Western Australia		190.5
	AU6: Tasmania		79
	AU7: Northern Territory		72.8
Year			2009/2010
Source	Mishra and Ray (2014)		
Description	True cost of living index constructed using the Exact Affine Stone Index Demand System. Estimation based on the Household Expenditure Survey conducted in 2009 and 2010		
Austria	AT11: Burgenland (AT)		96.6
	AT12: Lower Austria		97.5
	AT13: Vienna		103.8
	AT21: Carinthia		97.2
	AT22: Styria		98.1
	AT31: Upper Austria		98.4
	AT32: Salzburg		104.1
	AT33: Tyrol		102.1
	AT34: Vorarlberg		103.6
Year			2008
Source	Matzka and Nachbagauer (2009)		
Description	Fisher price index based on item-level data obtained from multiple sources		
China	Beijing	157	145
	Tianjin	123	119
	Hebei	92	94

Table A.1 (continued)

Country	Regions	Regional price level	
	Shanxi	108	111
	Neimenggu	101	103
	Liaoning	103	102
	Jilin	100	100
	Heilongjiang	102	104
	Shanghai	152	143
	Jiangsu	109	109
	Zhejiang	108	106
	Anhui	97	98
	Fujian	107	104
	Jiangxi	101	100
	Shandong	102	99
	Henan	91	95
	Hubei	102	106
	Hunan	110	114
	Guangdong	132	127
	Guangxi	103	106
	Hainan	128	132
	Chongqing	89	89
	Sichuan	97	100
	Guizhou	110	112
	Yunnan	114	118
	Xizang	119	117
	Shaanxi	111	115

Table A.1 (continued)

Country	Regions	Regional price level		
	Gansu		107	112
	Qinghai		110	123
	Ningxia		103	111
	Xinjiang		108	112
Year			2002	2013
Source	Brandt and Holz (2006)			
Description	Regional price levels constructed for 1990 due to price data availability; price levels subsequently shifted using official regional CPIs to 2002 and 2013			
Czechia	CZ010: Prague	120.8	117.1	122.3
	CZ020: Central Bohemia	102.6	104.8	106.3
	CZ031: South Bohemia	97.5	99.7	99
	CZ032: Plzeň	97.1	100.1	100
	CZ041: Karlovy Vary	101.3	97.7	99.9
	CZ042: Ústí nad Labem	94.1	97.4	96.7
	CZ051: Liberec	100.2	101.4	100.5
	CZ052: Hradec Kràlové	96.2	101.2	96.7
	CZ053: Pardubice	98.9	100.1	96.2
	CZ063: Vysočina	95.1	97.7	93.1
	CZ064: South Moravia	104.6	103	100.6
	CZ071: Olomouc	96.6	99.2	96.9
	CZ072: Zlín	100.8	101.5	97.5
	CZ080: Moravia-Silesia	96.9	98.9	97.2
Year		2007	2011–2013	2012
Source	Cadil et al. (2014), Kocourek et al. (2016), Kramulová et al. (2016)			

Table A.1 (continued)

Country	Regions	Regional price level	
Description	All indices are based on item-level data collected for the construction of CPI. Kocourek et al. (2016) relied on data collected across multiple years. All authors rely on methodologies based on the Eurostat–OECD approach. Limited differences in methodological approaches may occur		
Germany	DE1: Baden-Württemberg	98.3	101.9
	DE2: Bavaria	98.1	100.3
	DE3: Berlin	100.2	102.6
	DE4: Brandenburg	92.4	98.3
	DE5: Bremen	99	100.7
	DE6: Hamburg	99.9	106.7
	DE7: Hesse	98.7	103.3
	DE8: Mecklenburg-Vorpommern	92.5	96.8
	DE9: Lower Saxony	97.5	98
	DEA: North Rhine-Westphalia	98.4	100.6
	DEB: Rhineland-Palatinate	97.7	98
	DEC: Saarland	97.6	99.4
	DED: Saxony	92.5	96.3
	DEE: Saxony-Anhalt	92.3	96.1
	DEF: Schleswig-Holstein	97.6	100.5
	DEG: Thuringia	92.3	94.8
Year		1993	2016
Source	Roos (2006), Weinand and von Auer (2020)		
Description	Price levels constructed using a two-step methodology. In the first step, indices for 50 German cities were obtained based on item-level data. In the second step, regional price levels were obtained by extrapolation. Weinand and von Auer (2020) provide regional price levels on a more detailed regional level than the regional level available in LIS. Final indices were constructed as averages of the underlying regions' price levels weighted by the regional population shares		
India	Andhra Pradesh	93.5	98.7

Table A.1 (continued)

Country	Regions	Regional price level		
	Assam		116.5	108.2
	Bihar		96.5	93.5
	Gujarat		109.3	101.6
	Haryana		117.2	114.3
	Karnataka		84.2	86.9
	Kerala		86.1	83.9
	Madhya Pradesh		93.5	97.4
	Maharashtra		94.5	104.4
	Orissa		94	90.5
	Punjab		115.8	117.6
	Rajasthan		112.8	105.5
	Tamil Nadu		85.8	89.8
	Uttar Pradesh		103.4	101.6
	West Bengal		106.3	104.3
Year			2004/ 2005	2011/ 2012
Source	Chakrabarty et al. (2018)			
Description	Indices obtained using the Dynamic Household Regional Product model and based on unit values reported during the 61st (July, 2004–June, 2005) and 68th (July, 2011–June, 2012) waves of India's National Sample Survey			
Italy	ITC1: Piedmont			105.1
	ITC2: Aosta Valley			106.4
	ITC3: Liguria			112.9
	ITC4: Lombardy			114.1
	ITF1: Abruzzo			92.6
	ITF2: Molise			85.1

Table A.1 (continued)

Country	Regions	Regional price level
	ITF3: Campania	91.5
	ITF4: Apulia	91.9
	ITF5: Basilicata	85.1
	ITF6: Calabria	85.2
	ITG1: Sicily	92.8
	ITG2: Sardinia	90.7
	ITH2: Province of Trento	112.3
	ITH3: Veneto	101
	ITH4: Friuli-Venezia Giulia	106.9
	ITH5: Emilia-Romagna	108.9
	ITI1: Tuscany	111.8
	ITI2: Umbria	106.5
	ITI3: Marche	96.9
	ITI4: Lazio	112.4
Year		2006
Source	Pittau et al. (2011)	
Description	Indices constructed by the Union of Italian Chambers of Commerce and the Bank of Italy	
Japan	JPA: Hokkaido	99.7
	JPB: Tohoku	97.4
	Kanto	102.3
	Chubu	98.4
	JPG: Kinki	100.9
	JPH: Chugoku	98.6
	JPI: Shikoku	96.2

Table A.1 (continued)

Country	Regions	Regional price level		
	JPJ: Kyushu, Okinawa			96.9
Year				2007
Source	SBJ (2016)			
Description	Indices obtained using the Fisher index			
Poland	PL11: Lodzkie	98.73	99.01	100.37
	PL12: Mazovia	106.3	105.74	106.23
	PL21: Lesser Poland	101.35	100.28	100.34
	PL22: Silesia	102.64	101.54	101.08
	PL31: Lublin Province	99.86	98.25	97.62
	PL32: Podkarpacia	95.49	95.68	95.7
	PL33: Swietokrzyskie	95.91	96.81	96.97
	PL34: Podlasie	98.9	98.51	96.61
	PL41: Greater Poland	98.18	97.69	97.53
	PL42: West Pomerania	102.76	102.69	101.22
	PL43: Lubusz	102.64	102.19	103.29
	PL51: Lower Silesia	100.61	102.01	103.49
	PL52: Opole region	99.64	100.47	100.63
	PL61: Kuyavian-Pomerania	93.75	95.32	96.39
	PL62: Warmian-Masuria	99.82	100.16	98.98
	PL63: Pomerania	104.25	104.3	104.29
Year		2004	2007	2010
Source	Rokicki and Hewings (2019)			
Description	Price levels based on item-level data. Indices obtained by an approach based on the OECD–Eurostat methodology. Regional indices available for the period 2000–2012			

Table A.1 (continued)

Country	Regions	Regional price level				
Russia	Metropolitan areas: Moscow and St.Petersurg					95.6
	Northern and North Western					102.2
	Central and Central Black-Earth					93.2
	Volga-Vaytski and Volga Basin					95
	North Caucasian					95
	Ural					102
	Western Siberian					103
	Eastern Siberian and Far Eastern					122.4
Year						1998
Source	Gluschenko (2006)					
Description	Gluschenko (2006) provides regional price levels on a more detailed regional level than the regional level available in LIS. Final indices were constructed as averages of the underlying regions' price levels weighted by the regional population shares					
Slovakia	SK010: Bratislava					117
	SK021: Trnava					98
	SK022: Trenčín					100
	SK023: Nitra					99
	SK031: Žilina					100
	SK032: Banská Bystrica					93
	SK041: Prešov					93
	SK042: Košice					103
Year						2009
Source	Radvansky et al. (2012)					
Description	Indices constructed on the base of unit values from consumption expenditure survey					
UK	UKC: North East England	95.3	91.5	94.2	98.2	98.8

Table A.1 (continued)

Country	Regions	Regional price level									
	UKD: North West England						97.8	97.9	96.9	98.2	98.8
	UKE: Yorkshire and The Humber						96.6	94.6	94.2	97	97.7
	UKF: East Midlands						98.3	98	97.4	99.4	99.6
	UKG: West Midlands						98.8	98.6	97.8	100.6	98.5
	UKH: East of England						101.5	100.9	101.1	101.2	99.8
	UKI: Greater London						106.8	107.6	109.7	107.9	107.2
	UKJ: South East England						103.1	106.3	105.3	102.3	101.5
	UKK: South West England						99.3	100.4	101.3	99.5	102.4
	UKL: Wales						96.2	93.7	93.1	98.4	98.1
	UKM: Scotland						99.1	95.7	94.5	99.7	100.4
	UKN: Northern Ireland						NA	95.7	95.8	98.1	97.6
Year							2000	2003	2004	2010	2016
Source	Baran and O'Donoghue (2002), Ball and Fenwick (2004), Wingfield et al. (2005), ONS (2010), ONS (2016)										
Description	Official indices provided by the Office for National Statistics. Estimation based on the Eurostat–OECD methodology. Indices based on data collected for the construction of CPI as well as data obtained using specialised surveys										
USA	US01: Alabama	87.6	87.5	87.9	87.7	88.1	87.8	87.1	86.8	86.7	86.7
	US02: Alaska	106.9	106.9	105.5	105.1	105.4	104.9	106.3	105.5	105.1	104.4
	US04: Arizona	100.6	100.1	98.6	97.9	97.1	96.5	96	96.1	96.1	96.4
	US05: Arkansas	86.9	86.6	87.7	87.6	87.8	87.8	86.9	87.4	87	86.5
	US06: California	113.1	112.9	113.6	113.4	112.9	113.1	113.7	113.8	114.5	114.8
	US08: Colorado	100.4	101.1	100.9	101.4	101.1	102.1	102	102.3	102.7	103.2
	US09: Connecticut	110.7	110.4	109.4	109	109.2	108.5	108.6	108.5	108.4	108
	US10: Delaware	102	103.2	102.8	101.8	101.2	100.6	101.1	100	100.1	100.1
	US11: District of Columbia	115.6	116.4	118.2	117.8	117.7	117	118.2	116.8	115.4	116.9

Table A.1 (continued)

Country	Regions	Regional price level									
	US12: Florida	100.8	100	99.1	99.2	99.1	99.2	99.4	99.5	99.8	99.9
	US13: Georgia	93.5	93.1	92.3	91.9	92.2	92.3	92	92.8	92.4	92.5
	US15: Hawaii	118.1	117.1	117.2	116.9	117.8	118.3	118.4	119.2	118.5	118.5
	US16: Idaho	95.2	94.8	93.5	93.3	93.4	93.2	93.6	93.3	92.9	93
	US17: Illinois	100.2	100.9	100.9	101.1	100.7	99.7	99.3	99	98.7	98.5
	US18: Indiana	91.2	91.4	91.4	91.7	91.4	91.3	90.8	90.1	89.8	89.8
	US19: Iowa	88.6	89	89.2	90	90.2	90.6	90.3	89.9	89.8	89.8
	US20: Kansas	89.3	89.6	89.9	90.7	90.6	91.3	90.9	90.2	90.1	90
	US21: Kentucky	88.9	88.7	88.6	88.6	88.8	89.3	88.3	88.7	87.9	87.9
	US22: Louisiana	90.7	91.4	91.2	91	91.4	91.2	90.9	90.5	90.4	90.1
	US23: Maine	98	98.1	96.8	97.4	98.4	98.5	98	99.1	98.8	98.4
	US24: Maryland	110.3	111.3	111	110.9	110.1	109.9	110.2	109.6	109.4	109.4
	US25: Massachusetts	108.3	108	108	107.8	106.6	106.7	107.3	107.6	108.1	107.9
	US26: Michigan	95.4	95.2	94.7	94.6	94.5	94.3	93.6	93	93	93
	US27: Minnesota	97.4	97.7	97.1	97.2	97.6	97.5	97.5	97.2	97.3	97.5
	US28: Mississippi	86.4	85.8	86.7	86.8	86.5	87.2	86.2	86.2	86.5	85.7
	US29: Missouri	87.8	87.9	88.3	89.1	89.3	89.9	89.8	89.6	89.5	89.5
	US30: Montana (US)	95.3	94.5	93.9	93.8	93.5	94.6	94.7	95.1	94.1	94.6
	US31: Nebraska	89.7	89.6	90.3	90.3	90.6	90.7	90.5	90.2	90	89.6
	US32: Nevada	100.8	100.7	99.9	99.8	98.7	98.7	97.5	97.3	97.1	97.6
	US33: New Hampshire	107.2	106.4	106.5	105.3	105.6	105.4	105.7	105.7	106.1	105.8
	US34: New Jersey	112.9	113.3	114.1	114.6	114.4	113.4	113.8	113.4	113.3	112.9
	US35: New Mexico	94.4	94.4	94.6	95.3	95	95.3	94.7	93.8	93.3	93.3
	US36: New York	115.1	115.3	115.2	115.2	115.3	115.2	115.7	115.8	116.1	115.8

Table A.1 (continued)

Country	Regions	Regional price level									
	US37: North Carolina	92	92.1	91.3	91.5	91.7	91.8	91.4	91.2	91	91.3
	US38: North Dakota	88.5	89	89.2	89.7	91	91.7	91.6	92	91.1	90.1
	US39: Ohio	90	89.3	89.8	89.7	89.4	89.5	89.4	89.2	89.1	88.9
	US40: Oklahoma	88.9	89.5	89.6	89.6	89.9	90	89.5	89.8	89.1	89
	US41: Oregon	98.3	98.9	98.5	98.5	98.7	98.9	98.8	98.5	99.4	99.5
	US42: Pennsylvania	98.2	98.2	98.5	98.4	98.4	98.6	98.1	98.2	98.5	97.9
	US44: Rhode Island	100.2	100	99.1	99.4	98.8	98.8	99.8	99.9	100	98.6
	US45: South Carolina	91.1	91.5	90.4	90.8	90.8	90.5	90	90.3	90.4	90.4
	US46: South Dakota	86.9	85.8	86.9	87.3	88.9	88	88	88	88	88.2
	US47: Tennessee	90.5	90.5	90.2	90.3	90.8	90.7	89.8	89.9	90.3	90.4
	US48: Texas	96.5	96.4	96.3	96.2	96.2	96.3	96.5	96.7	96.8	97
	US49: Utah	96.8	97.8	96.9	97.2	97.1	97.7	96.8	96.4	97.1	97
	US50: Vermont	100.4	100.6	99.5	99.9	100.8	100.9	102.5	102.7	102	102.5
	US51: Virginia	102.8	103.5	103.1	103	103	102.8	102.7	102.6	102.2	102.1
	US53: Washington	103.2	103.7	103	102.9	103.5	104.2	104.9	105.2	105.8	106.4
	US54: West Virginia	87	87.5	88.4	88.5	88.6	88.6	88.2	88.7	87.6	87
	US55: Wisconsin	93	92.9	92.8	93.3	93.5	93.2	93.3	93	92.5	92.4
	US56: Wyoming	96.1	96.1	95.9	96.7	95.8	96	96.8	96.4	96.7	95.2
Year		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Source	Bureau of Economic Analysis (2019)										
Description	Official indices constructed by the joint project of the Bureau of Economic Analysis and the Bureau of Labour Statistics. Aten (2017) provides a detailed description of the methodology										

B Unused regional price levels

See Table B.1.

Table B.1 Regional price levels—not used

Country	Source	Grounds for exclusion
China	Li et al. (2005)	Regional price levels expressed relative to the price level of the region of Shanghai instead of the required form, i.e. relative to the price level of the whole country
	Biggeri et al. (2017a)	Regional price levels expressed relative to the price level of the region of Beijing instead of the required form, i.e. relative to the price level of the whole country
	Chen et al. (2020)	Regional price levels expressed relative to the price level of the region of Beijing instead of the required form, i.e. relative to the price level of the whole country
Germany	Deckers et al. (2016)	Regional price levels expressed relative to the price level of the region of Bonn instead of the required form, i.e. relative to the price level of the whole country. Furthermore, provided regional price levels do not match the regional level used by the Luxembourg Income Study database
Italy	Biggeri et al. (2017b)	Provided regional price levels do not match the regional level used by the Luxembourg Income Study database
	Montero et al. (2020)	Authors provide regional price levels for regional capitals relative to the price level of Rome instead of the required form, i.e. relative to the price level of the whole country
India	Coondoo et al. (2004)	Regional price levels expressed relative to the price level of the region of Northern India instead of the required form, i.e. relative to the price level of the whole country
	Coondoo et al. (2011)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database
	Majumder et al. (2012)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database
	Majumder et al. (2015)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database
	Chakrabarty et al. (2015)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database

Table B.1 (continued)

Country	Source	Grounds for exclusion
	Majumder and Ray (2017)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database
Ivory Coast	Glewwe (1985)	Provided regional price levels do not match the regional level used by the Luxembourg Income Study database
Philippines	Dikhanov et al. (2011)	Luxembourg Income Study database does not contain data for the Philippines
Spain	Lorente (1992) used in Ayala et al. (2014)	We were unable to locate the original article
	Lasarte Navamuel et al. (2015)	Authors express regional price levels either relative to the price level of Madrid instead of the required form, i.e. relative to the price level of the whole country
Turkey	The Turkish Statistical Institute (TurkStat) provides a series of regional price levels.	Luxembourg Income Study database does not contain data for Turkey
Vietnam	Gibson et al. (2017)	Authors provide separate indices for rural and urban parts of regions, thereby precluding their combination with data from the Luxembourg Income Study database

C Expanded sample: modelling

C.1 Methodology

We use two methodological approaches to estimate regional price levels for included countries in the expanded sample. Both methodologies are similar in that they rely on existing regional price level estimates. Both use available indices to construct an econometric model to explain differences in regional price levels. They subsequently use the estimated model for the out-of-sample prediction of regional price levels for countries for which these were not previously available. However, the two methodologies differ in their theoretical foundations. The first methodology, adopted, for example, by Roos (2006) and Janský and Kolcunová (2017), relies on a set of assumptions where regional price level differences are determined solely by differences in regional supply and demand. Consequently, we refer to it as the Demand–Supply (DS) approach. The second methodology, proposed recently by Costa et al. (2019), is based on the Balassa–Samuelson hypothesis. We refer to is as to the Balassa–Samuelson (BS) approach.

The DS approach relies on a number of assumptions. These include the spatial segmentation of regional markets, which makes any strategic price setting or spatial arbitrage impossible; the short term immobility of consumers and firms; and the trading of intermediate inputs between regions at no transportation cost and at the same price in each of the regions. Under these assumptions, regional price level differences are determined solely by differences in regional supply and demand. We consider a set of variables to model these differences. These include regional disposable income, population, population density, area, GDP per capita, employment rate, unemployment rate, participation rate, and a dummy variable indicating the presence of the capital city within the region. We adopt the following algorithm to construct the prediction model:

1. We regress available regional price level estimates on all explanatory variables one by one and identify the statistically most significant one.
2. We keep the statistically most significant variable in the model and successively add all remaining explanatory variables. We identify the most statistically significant variable among those added to the model and keep it in the model.
3. We repeat the second step until none of the remaining variables are statistically significant at least on the 10% significance level when added to the model.

The BS approach is based on economic theory. It stems from the Balassa–Samuelson hypothesis which implies that countries with higher incomes tend to have higher price levels. The method was proposed by Costa et al. (2019). We would like to refer readers interested in the derivation of the methodology to their work. In this framework, the logarithm of regional price level is explained by the logarithm of disposable income and by the logs of shares of industry and services in total gross value added relative to the GDP of the respective region. Industry covers codes B, C, E, and F from the ISIC Rev. 4 classification, while services cover codes G and I from the ISIC Rev. 4 classification.

C.2 Data

Both methodologies are based on existing regional price level estimates. The first four columns of Table C.1 present all sources of regional price levels used for modelling. They specify the country, territorial level, and years for which the indices are available. With the exception of Turkey, which was not included in the core sample as the LIS does not provide household-level microdata for it, and Russia and Germany (2016) for which the price levels had to be aggregated from more detailed regional classifications, the scope of the data set is similar to that of our core sample. However, due to the limitations imposed by the availability of control variables, the considered approaches cannot be deployed on identical sets of countries.

The availability of control variables determines the composition of data sets which we can use for deploying each of the considered methodologies. Column (5) of Table C.1 indicates which regional price levels were used for the DS framework. Columns (6) to (13) list sources of all control variables considered for the DS framework. All control variables were primarily sourced from the OECD regional database. However, in certain cases it either did not include the data at the desired regional level or failed to cover individual countries entirely. In such cases we therefore turned to additional sources: Eurostat and the National Bureau of Statistics of China. However, reliance on multiple sources raises potential issues with the comparability of variables. This concern is especially salient in the case of Chinese labour marker statistics. We take these into consideration when specifying the sample of countries used for the estimation of our model. Furthermore, for this reason we do not rely on regional indices provided by Dikhanov et al. (2011) for the Philippines as the Philippines are not covered by the OECD regional database and as variables sourced from the Philippines Statistical Yearbook might thus not be directly comparable with data from the main sources used in our analysis. Column (14) of Table C.1 indicates which regional price levels were used for the BS framework. Similarly to Costa et al. (2019), we have obtained all control variables for the BS framework from the OECD regional database.

We deploy both methodologies on multiple data sets. Data set composition may affect the resulting estimates through two main channels. First, as discussed in the second section of this paper, available empirical evidence indicates that determinants of regional price levels likely vary between countries. Second, in the case of the DS framework we rely on variables obtained from alternative sources. This may raise issues in terms of comparability, especially for labour market indicators obtained from the National Bureau of Statistics of China. For these reasons we consider a variety of data sets for both the DS and BS methodology. We deploy the DS methodology on all countries for which we have the relevant data as indicated in column (5) of Table C.1. Furthermore, we consider a data set which includes all available

Table C.1 Regional price levels

				Demand–supply									Balassa-Samu-elson	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Country	Price levels	Year	Territorial level	Included	Income	GDP	Empl	Unempl	Part. rate	Pop	Pop. density	Area	Included	GVA
Australia	Mishra and Ray (2014)	2009	States	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
Austria	Matzka and Nachbagauer (2009)	2008	NUTS2	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
China	Brandt and Holz (2006)	2013	Provinces	Yes	OECD	OECD		NBS		OECD	OECD	OECD	No	
Czechia	Kocourek et al. (2016)	2013	NUTS3	Yes	OECD	Eurostat	OECD	OECD	OECD	OECD	Eurostat	Eurostat	Yes	OECD
Germany	Roos (2006)	2002	NUTS1	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
Italy	Pittau et al. (2011)	2006	NUTS2	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
Poland	Rokicki and Hewings (2019)	2000 to 2012	NUTS2	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
Slovakia	Radvansky et al. (2012)	2009	NUTS3	Yes	OECD	Eurostat	OECD	OECD	OECD	OECD	OECD	Eurostat	No	
Turkey		2014		Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	No	
UK	ONS (2016)	2016	NUTS1	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD
USA	Bureau of Economic Analysis (2019)	2008 to 2016	States, DoC	Yes	OECD	OECD	OECD	OECD	OECD	OECD	OECD	OECD	Yes	OECD

countries with the exception of China due to potential comparability issues. For the BS framework we first emulate the approach of Costa et al. (2019) and base our estimates on a panel of US regional price levels for the 2008–2016 period. In addition, we consider models based on a panel of Polish regional price levels for the 2000–2012 period. In order to test how the BS approach performs compared to the DS framework, we also rely on a data set of all countries with relevant data available as indicated in column (14) of Table C.1.

As our dependent variable is an indicator of regional price level relative to the price level of the whole country, we have to adjust our control variables accordingly. This is necessary especially in regressions where we pool the indices of various countries. We rely on two transformations. One set of variables is expressed in shares of total national value while a second set of variables is expressed in relative terms. We refer to the latter as relative variables. We consider two specifications of relative variables. We express these relative to the average of all regions and relative to the national value of the respective indicator. Consequently, we obtain two sets of results for all considered data sets. We measure gross value added in services, gross value added in industry, population, and area in shares. Relative variables include disposable income, regional GDP per capita, employment rate, unemployment rate, participation rate, and population density.

C.3 Modelling

We have to adapt our estimation strategy to the type of considered data sets. For panels of regional price levels, we rely on a pooled OLS with clustered standard errors and a between estimator similarly to Costa et al. (2019). For data sets obtained by pooling regional price levels of multiple countries, we consider three types of models. We begin with a simple OLS model. We also consider a simple OLS model combined with White's standard errors to counter the potential effects of heteroskedasticity. Finally, we also consider a model in which we weight observations by the Huber weighting function to account for the potential effects of outlying observations. Combined, all considered specifications of data sets, estimation frameworks, and methodological approaches yield 26 models. Out of these, 12 stem from the DS framework while the remaining 14 are obtained using the BS framework. Among these models, we select the most suitable one and use it for predicting regional price levels.

We obtain a set of 6 models for each specification of the relative variables, i.e., relative to the average of all regions and relative to national value. Out of these 12 models we select the most suitable one for predicting the regional price levels of countries covered by the expanded sample. Tables C.2 and C.3 present the final models. All models were obtained using the previously described iterative approach. Differences in the specification of relative variables do not cause significant variation in the specification of final models. We can observe the biggest difference

Table C.2 Demand–supply framework

	All available countries			Only countries covered by OECD, Eurostat		
	OLS	OLS-heteroskedasticity	Robust	OLS	OLS-heteroskedasticity	Robust
	(1)	(2)	(3)	(4)	(5)	(6)
Income	0.140^{***}	0.172^{***}	0.161^{**}		0.124	0.145^{***}
	(0.050)	(0.047)	(0.076)		(0.076)	(0.053)
Area	0.475^{***}			0.588^{***}		
	(0.128)			(0.115)		
Participation rate				0.190^{**}		0.131
				(0.092)		(0.131)
Population					0.392^{***}	0.253^{***}
					(0.127)	(0.063)
Regional GDP	0.072^{**}		0.027	0.135^{***}	0.079^{*}	0.049^{***}
	(0.033)		(0.030)	(0.021)	(0.045)	(0.016)
Capital		6.739^{***}	5.173^{**}			
		(2.292)	(2.208)			
Unemployment rate		-0.038^{*}	−0.020			
		(0.020)	(0.013)			
Constant	77.366^{***}	87.372^{***}	82.724^{***}	63.720^{***}	76.981^{***}	64.917^{***}
	(3.280)	(6.389)	(6.012)	(8.425)	(3.740)	(10.944)
Observations	210	210	210	179	179	179
R^2	0.256	0.213		0.348	0.277	
Adjusted R^2	0.245	0.202		0.337	0.265	
Residual Std. Error	9.783 (df = 206)	10.057 (df = 206)	4.394 (df = 205)	8.203 (df = 175)	8.634 (df = 175)	4.567 (df = 174)
F Statistic	23.609^{***} (df = 3; 206)	18.637^{***} (df = 3; 206)		31.094^{***} (df = 3; 175)	22.386^{***} (df = 3; 175)	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table C.3 Demand–supply framework (relative transformation to national values)

	All available countries			Only countries covered by OECD, Eurostat		
	OLS	OLS-heteroskedasticity	Robust	OLS	OLS-heteroskedasticity	Robust
	(1)	(2)	(3)	(4)	(5)	(6)
Income	0.118**	0.173***	0.169*	0.134**	0.108*	0.204***
	(0.050)	(0.046)	(0.099)	(0.059)	(0.062)	(0.066)
Area	0.451***			0.584***		
	(0.125)			(0.114)		
Regional GDP	0.077**		0.017	0.095***	0.079**	0.035*
	(0.032)		(0.033)	(0.032)	(0.040)	(0.021)
Capital		6.924***	5.853***			
		(2.350)	(2.051)			
Unemployment rate	−0.047**	−0.056***	−0.036***		−0.025**	
	(0.019)	(0.017)	(0.012)		(0.012)	
Population					0.388***	0.207***
					(0.130)	(0.069)
Constant	84.536***	89.426***	85.132***	74.164***	81.873***	74.807***
	(4.305)	(5.676)	(7.689)	(3.858)	(3.878)	(4.776)
Observations	210	210	210	179	179	179
R^2	0.295	0.250		0.338	0.285	
Adjusted R^2	0.281	0.239		0.327	0.268	
Residual Std. Error	9.548 (df = 205)	9.824 (df = 206)	4.620 (df = 205)	8.261 (df = 175)	8.614 (df = 174)	4.272 (df = 175)
F Statistic	21.405*** (df = 4; 205)	22.828*** (df = 3; 206)		29.831*** (df = 3; 175)	17.309*** (df = 4; 174)	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

between models based on data obtained from the OECD and Eurostat databases, i.e. models (4), (5), and (6). For these models, the change in the specification of relative variables results in the inclusion of income, participation rate, or unemployment rate. These changes require further attention as we prefer models based on this sample due to methodological issues raised by the inclusion of China. Nevertheless, we believe that we can choose a suitable model for predicting regional price levels from among all estimated models.

We rely on model (6) in Table C.3 to predict regional price levels of countries in the expanded sample. We choose this model for several reasons. First, we prefer models based on a narrower sample of countries for which we have data for control variables from the OECD and Eurostat regional databases. This is due to the potential limitations imposed by the comparability of data from the National Bureau of Statistics of China with those from the OECD and Eurostat regional databases. Second, we reject simple OLS models as these are likely to be affected by heteroskedasticity and outlying observations in the data. Third, we choose to rely on the robust model due to the presence of outlying observations. Fourth, we choose the model which contains variables identified consistently as significant predictors of regional price levels across all considered models. Income and regional GDP appear to be the strongest predictors. In addition, we consider the share of population living in a given region as a significant predictor. This decision stems from the fact that it is identified as such in outlier and heteroskedasticity robust models based on the OECD/Eurostat sample. This reasoning leads us to choose model (6) as the most suitable for predicting regional price levels in the expanded sample.

Table C.4 Balassa–Samuelson framework—multiple countries

	OLS	OLS-heteroskedasticity	Robust
	(1)	(2)	(3)
Income	0.361***	0.361***	0.373***
	(0.047)	(0.030)	(0.028)
Services	0.003	0.003	0.016
	(0.031)	(0.053)	(0.019)
Industry	0.003	0.003	−0.003
	(0.015)	(0.016)	(0.008)
Constant	2.942***	2.942***	2.903***
	(0.209)	(0.153)	(0.130)
Observations	153	153	153
R^2	0.305	0.305	
Adjusted R^2	0.291	0.291	
Residual Std. Error (df = 149)	0.080	0.080	0.043
F Statistic (df = 3; 149)	21.830***	21.830***	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table C.5 Balassa–Samuelson framework—panel data

	USA		Poland	
	Pooled OLS	Between	Pooled OLS	Between
	(1)	(2)	(3)	(4)
Income	0.318***	0.321***	0.201***	0.222***
	(0.047)	(0.059)	(0.014)	(0.073)
Services	0.027	0.033	−0.184***	−0.224*
	(0.046)	(0.040)	(0.027)	(0.133)
Industry	−0.073***	−0.075***	−0.094***	−0.116*
	(0.021)	(0.020)	(0.014)	(0.064)
Constant	3.074***	3.069***	3.335***	3.164***
	(0.184)	(0.252)	(0.091)	(0.473)
Observations	459	51	195	15
R^2	0.647	0.657	0.371	0.472
Adjusted R^2	0.644	0.635	0.361	0.328
Residual Std. Error	0.050 (df = 455)		0.021 (df = 191)	
F Statistic	277.477*** (df = 3; 455)	29.956*** (df = 3; 47)	37.600*** (df = 3; 191)	3.273* (df = 3; 11)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table C.6 Balassa–Samuelson framework—multiple countries (national values)

	OLS	OLS-heteroskedasticity	Robust
	(1)	(2)	(3)
Income	0.366***	0.366***	0.366***
	(0.046)	(0.039)	(0.028)
Services	0.015	0.015	0.017
	(0.031)	(0.050)	(0.020)
Industry	0.006	0.006	−0.0002
	(0.015)	(0.017)	(0.007)
Constant	2.955***	2.955***	2.947***
	(0.203)	(0.224)	(0.126)
Observations	153	153	153
R^2	0.313	0.313	
Adjusted R^2	0.299	0.299	
Residual Std. Error (df = 149)	0.079	0.079	0.044
F Statistic (df = 3; 149)	22.645***	22.645***	

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table C.7 Balassa–Samuelson framework—panel data (national values)

	USA		Poland	
	Pooled OLS	Between	Pooled OLS	Between
	(1)	(2)	(3)	(4)
Income	0.318***	0.321***	0.199***	0.222***
	(0.047)	(0.059)	(0.014)	(0.073)
Services	0.028	0.033	−0.179***	−0.224*
	(0.046)	(0.040)	(0.027)	(0.133)
Industry	−0.073***	−0.075***	−0.093***	−0.116*
	(0.021)	(0.020)	(0.014)	(0.064)
Constant	3.074***	3.070***	3.364***	3.177***
	(0.184)	(0.251)	(0.091)	(0.469)
Observations	459	51	195	15
R^2	0.647	0.657	0.366	0.472
Adjusted R^2	0.645	0.635	0.356	0.328
Residual Std. Error	0.050 (df = 455)		0.022 (df = 191)	
F Statistic	278.451*** (df = 3; 455)	29.956*** (df = 3; 47)	36.788*** (df = 3; 191)	3.273* (df = 3; 11)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

We also consider the BS framework as an alternative approach to modelling regional price levels. The BS framework yields 14 models, 7 per each specification of relative variables. Tables C.4, C.5, C.6, and C.7 present complete estimation results from all considered specifications. In the original study, Costa et al. (2019) deploy the methodology based on panel data of US regional price levels. As we can see from columns (1) and (2) of Tables C.5 and C.7 in this specification, the methodology provides a better fit to the data compared to the DS framework. However, a similar methodological approach seems less suitable when we use it on a panel of Polish regional price levels. This is evident from the lower goodness of fit and coefficients which differ in both magnitude and direction from those obtained for the USA. Columns (3) and (4) of Tables C.5 and C.7 present complete estimation results. Furthermore, when deployed on a data set of pooled regional price levels from different countries, the methodology does not seem superior to the DS framework. Consequently, we believe that relying solely on the DS framework for predicting the regional price levels of the expanded sample is sufficient.

C.4 Housing costs

We also consider an alternative set of models based solely on price levels that account for housing price differences. We are led by the concern that housing prices might be a significant determinant of regional price differences. Consequently, we

Table C.8 Demand–supply framework: restricted sample

	OLS (1)	OLS-heteroskedasticity (2)	Robust (3)
Regional GDP	0.109***		
	(0.037)		
Area	0.920***		
	(0.147)		
Participation rate			0.162
			(0.163)
Income	0.131**	0.251***	0.221***
	(0.065)	(0.033)	(0.060)
Capital		−0.257	3.607
		(3.973)	(2.261)
Population		0.563**	0.283***
		(0.222)	(0.089)
Constant	71.204***	71.872***	59.037***
	(4.391)	(3.267)	(12.412)
Observations	143	143	143
R^2	0.395	0.260	
Adjusted R^2	0.382	0.244	
Residual Std. Error	8.676 (df = 139)	9.590 (df = 139)	4.482 (df = 138)
F Statistic (df = 3; 139)	30.209***	16.304***	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

remove Germany, Slovakia, and the UK from the sample as their price levels either do not cover housing prices or we are unable to determine if they do. We thus re-estimate the complete set of models relying only on countries whose respective price levels cover housing price variation. This yields six models.

We can identify slight differences between the selected model and the models based solely on price levels that account for variations in housing prices. Tables C.8 and C.9 present the additional models. Focusing on the robust models, we can see that they include controls for income and population similarly to the selected model. However, they include controls for participation rate and capital (dummy) instead of regional GDP. Nevertheless, these are statistically insignificant in the final model. Moreover, removing the last added variable, i.e., population, results in models where the participation rate becomes insignificant. The chosen model is thus more stable. The overlap between the alternative models and the chosen model, combined with the higher stability of the latter, leads us to rely on the selected model rather than to adopt an alternative specification based solely on price levels that account for housing prices.

Table C.9 Demand–supply framework: restricted sample (relative transformation to national values)

	OLS	OLS-heteroskedasticity	Robust
	(1)	(2)	(3)
Regional GDP	0.111***		
	(0.038)		
Area	0.884***		
	(0.148)		
Income	0.129**	0.206***	0.216***
	(0.065)	(0.045)	(0.065)
Population		0.549***	0.289**
		(0.192)	(0.130)
Participation rate		0.190*	0.184
		(0.105)	(0.184)
Capital			3.767
			(2.459)
Constant	72.354***	58.063***	58.213***
	(4.284)	(9.151)	(14.744)
Observations	143	143	143
R^2	0.386	0.275	
Adjusted R^2	0.373	0.259	
Residual Std. Error	8.737 (df = 139)	9.495 (df = 139)	4.453 (df = 138)
F Statistic (df = 3; 139)	29.139***	17.567***	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

C.5 Predicted regional price levels

Table C.10 presents predicted regional price levels. The expanded sample consists of the following nine countries: Canada, Chile, Denmark, Greece, Hungary, Mexico, Spain, Sweden, and Switzerland. We obtained all data for the prediction of regional price levels from the OECD regional database. The size of the expanded sample was determined by the availability of regional data from the OECD regional database and its compatibility with the LIS database. We omit the following countries from the expanded sample: Belgium, Finland, Ireland, and Lithuania. Even though the coverage of the OECD regional database permits the prediction of regional price levels, the obtained indices are all above the value of 100. This is illogical as all regions cannot have regional price levels higher than the price level of the whole country. We therefore choose not to include these countries in the expanded sample.

Table C.10 Expanded sample—predicted price levels

Year	Country	Region	Price level
2017	Canada	CA10: Newfoundland and Labrador	98.7202
2017	Canada	CA11: Prince Edward Island	95.76577
2017	Canada	CA12: Nova Scotia	96.45491
2017	Canada	CA13: New Brunswick	96.47892
2017	Canada	CA24: Quebec	100.6581
2017	Canada	CA35: Ontario	106.6226
2017	Canada	CA46: Manitoba	97.28432
2017	Canada	CA47: Saskatchewan	100.5862
2017	Canada	CA48: Alberta	105.987
2017	Canada	CA59: British Columbia	102.8179
2017	Canada	CA60: Yukon	105.7747
2017	Canada	CA61: Northwest Territories	106.6979
2017	Canada	CA62: Nunavut	98.22854
2009	Chile	CL01: Tarapacá	98.93391
2009	Chile	CL02: Antofagasta	107.4201
2009	Chile	CL03: Atacama	96.04036
2009	Chile	CL04: Coquimbo	93.36402
2009	Chile	CL05: Valparaíso	97.74001
2009	Chile	CL06: O'Higgins	95.44691
2009	Chile	CL07: Maule	92.91577
2009	Chile	CL08: Bío-Bío	93.73846
2009	Chile	CL09: Araucanía	90.50333
2009	Chile	CL10: Los Lagos	94.23354
2009	Chile	CL11: Aysén	99.38771
2009	Chile	CL12: Magallanes	100.41
2009	Chile	CL13: Santiago Metropolitan	114.0118
2009	Chile	CL14: Los Ríos	90.5204
2009	Chile	CL15: Arica y Parinacota	92.37924
2009	Chile	CL16: Ñuble	75.38635
2016	Denmark	DK011: City of Copenhagen	104.7763
2016	Denmark	DK012: Copenhagen suburbs	105.1243
2016	Denmark	DK013: North Zealand	103.8478
2016	Denmark	DK014: Bornholm	98.59853
2016	Denmark	DK021: East Zealand	100.7909
2016	Denmark	DK022: West and South Zealand	100.6832
2016	Denmark	DK031: Fyn	99.98646
2016	Denmark	DK032: South Jutland	102.1292
2016	Denmark	DK041: West Jutland	100.9075
2016	Denmark	DK042: East Jutland	102.4688
2016	Denmark	DK050: North Jutland	100.9955
2010	Greece	EL30: Attica	110.0522
2010	Greece	EL41: North Aegean	98.60566

Table C.10 (continued)

Year	Country	Region	Price level
2010	Greece	EL42: South Aegean	100.5974
2010	Greece	EL43: Crete	96.20161
2010	Greece	EL51: Eastern Macedonia, Thrace	96.05009
2010	Greece	EL52: Central Macedonia	100.0249
2010	Greece	EL53: Western Macedonia	98.33193
2010	Greece	EL54: Epirus	97.62172
2010	Greece	EL61: Thessaly	97.95688
2010	Greece	EL62: Ionian Islands	98.34122
2010	Greece	EL63: Western Greece	96.87123
2010	Greece	EL64: Central Greece	96.81635
2010	Greece	EL65: Peloponnese	97.76139
2015	Hungary	HU11: Budapest	111.2145
2015	Hungary	HU12: Pest	101.7867
2015	Hungary	HU21: Central Transdanubia	100.7829
2015	Hungary	HU22: Western Transdanubia	101.3946
2015	Hungary	HU23: Southern Transdanubia	97.39658
2015	Hungary	HU31: Northern Hungary	96.76056
2015	Hungary	HU32: Northern Great Plain	97.71643
2015	Hungary	HU33: Southern Great Plain	98.90935
2017	Ireland	IE04: Northern and Western	97.22988
2017	Ireland	IE05: Southern	105.5749
2017	Ireland	IE06: Eastern and Midland	110.6051
2018	Mexico	ME01: Aguascalientes	102.6132
2018	Mexico	ME02: Baja California Norte	106.8855
2018	Mexico	ME03: Baja California Sur	111.1036
2018	Mexico	ME04: Campeche	104.2002
2018	Mexico	ME05: Coahuila	104.3997
2018	Mexico	ME06: Colima	102.7993
2018	Mexico	ME07: Chiapas	86.66227
2018	Mexico	ME08: Chihuahua	103.4255
2018	Mexico	ME09: City of Mexico	118.1074
2018	Mexico	ME10: Durango	96.00118
2018	Mexico	ME11: Guanajuato	97.22126
2018	Mexico	ME12: Guerrero	89.50931
2018	Mexico	ME13: Hidalgo	93.84711
2018	Mexico	ME14: Jalisco	104.1265
2018	Mexico	ME15: Mexico	99.34189
2018	Mexico	ME16: Michoacan	95.54003
2018	Mexico	ME17: Morelos	94.74385
2018	Mexico	ME18: Nayarit	97.85336
2018	Mexico	ME19: Nuevo Leon	110.2055
2018	Mexico	ME20: Oaxaca	89.96226

Table C.10 (continued)

Year	Country	Region	Price level
2018	Mexico	ME21: Puebla	92.80914
2018	Mexico	ME22: Queretaro	105.0509
2018	Mexico	ME23: Quintana Roo	104.7711
2018	Mexico	ME24: San Luis Potosi	97.59236
2018	Mexico	ME25: Sinaloa	101.041
2018	Mexico	ME26: Sonora	106.3328
2018	Mexico	ME27: Tabasco	94.66546
2018	Mexico	ME28: Tamaulipas	101.0535
2018	Mexico	ME29: Tlaxcala	92.74003
2018	Mexico	ME30: Veracruz	92.46332
2018	Mexico	ME31: Yucatan	97.5833
2018	Mexico	ME32: Zacatecas	92.50267
2016	Spain	ES11: Galicia	98.11442
2016	Spain	ES12: Asturias	98.97003
2016	Spain	ES13: Cantabria	98.51241
2016	Spain	ES21: Basque Country	106.4487
2016	Spain	ES22: Navarra	103.8939
2016	Spain	ES23: La Rioja	99.75518
2016	Spain	ES24: Aragon	100.8381
2016	Spain	ES30: Madrid	108.4251
2016	Spain	ES41: Castile and León	99.27493
2016	Spain	ES42: Castilla-La Mancha	95.4504
2016	Spain	ES43: Extremadura	93.57689
2016	Spain	ES51: Catalonia	105.766
2016	Spain	ES52: Valencia	98.16798
2016	Spain	ES53: Balearic Islands	100.0443
2016	Spain	ES61: Andalusia	97.01303
2016	Spain	ES62: Murcia	94.89593
2016	Spain	ES63: Ceuta	95.52056
2016	Spain	ES64: Melilla	93.45343
2016	Spain	ES70: Canary Islands	95.50952
2005	Sweden	SE110: Stockholm County	106.9833
2005	Sweden	SE121: Uppsala County	99.92458
2005	Sweden	SE122: Södermanland County	97.68507
2005	Sweden	SE123: Östergötland County	98.01582
2005	Sweden	SE124: Örebro County	101.6316
2005	Sweden	SE125: Västmanland County	91.6798
2005	Sweden	SE211: Jönköping County	91.91602
2005	Sweden	SE212: Kronoberg County	84.10201
2005	Sweden	SE213: Kalmar County	90.37291
2005	Sweden	SE214: Gotland County[a]	100
2005	Sweden	SE221: Blekinge County	117.3939

Table C.10 (continued)

Year	Country	Region	Price level
2005	Sweden	SE224: Skåne County	106.7662
2005	Sweden	SE231: Halland County	96.38962
2005	Sweden	SE232: Västra Götaland County	85.16772
2005	Sweden	SE311: Värmland County	95.91653
2005	Sweden	SE312: Dalarna County	97.5075
2005	Sweden	SE313: Gävleborg County	97.52356
2005	Sweden	SE321: Västernorrland County	97.74374
2005	Sweden	SE322: Jämtland County	96.97864
2005	Sweden	SE331: Västerbotten County	97.17067
2005	Sweden	SE332: Norrbotten County	98.06129
2013	Switzerland	CH01: Lake Geneva Region	102.4161
2013	Switzerland	CH02: Espace Mittelland	101.4
2013	Switzerland	CH03: Northwestern Switzerland	101.7021
2013	Switzerland	CH04: Zurich	105.7185
2013	Switzerland	CH05: Eastern Switzerland	99.96211
2013	Switzerland	CH06: Central Switzerland	101.551
2013	Switzerland	CH07: Ticino	97.91239

[a]The regional price level of Gotland County is assumed to be equal to national price level. Due to high value of disposable income per capita, predictions using our model that include Gotland County yield illogical values. The remaining variables used for the prediction of Swedish regional price levels were based on all regions, including Gotland County

D Complete results

See Tables D.1, D.2 and D.3.

Table D.1 Gini coefficients and impact of regional price levels

Country	Year	Source of RPL	Household income		Per capita income		Equalised income	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Australia	2010	Mishra and Ray (2014)	0.399 (0.381,0.393)	0.387	0.359 (0.339,0.352)	0.345	0.344 (0.324,0.337)	0.33
Austria	2007	Matzka and Nachbagauer (2009)	0.355 (0.346,0.361)	0.354	0.305 (0.298,0.313)	0.305	0.284 (0.276,0.291)	0.284
Canada	2017	Predicted	0.376 (0.374,0.383)	0.378	0.332 (0.329,0.337)	0.333	0.311 (0.308,0.317)	0.313
Chile	2009	Predicted	0.476 (0.478,0.493)	0.485	0.473 (0.473,0.49)	0.481	0.449 (0.451,0.465)	0.458
China	2002	Brandt and Holz (2006)	0.398 (0.389,0.399)	0.394	0.449 (0.441,0.451)	0.446	0.418 (0.409,0.42)	0.414
China	2013	Brandt and Holz (2006)	0.394 (0.384,0.396)	0.39	0.431 (0.421,0.434)	0.428	0.401 (0.39,0.403)	0.396
Czechia	2007	Cadil et al. (2014)	0.323 (0.319,0.332)	0.326	0.248 (0.248,0.261)	0.255	0.246 (0.244,0.257)	0.251
Czechia	2013	Kocourek et al. (2016)	0.324 (0.319,0.333)	0.326	0.259 (0.257,0.272)	0.265	0.253 (0.25,0.265)	0.257
Czechia	2013	Kramulová et al. (2016)	0.324 (0.319,0.333)	0.326	0.258 (0.257,0.272)	0.265	0.252 (0.25,0.265)	0.257
Denmark	2016	Predicted	0.343 (0.342,0.345)	0.343	0.258 (0.257,0.261)	0.259	0.252 (0.251,0.255)	0.253
Germany	1994	Roos (2006)	0.325 (0.319,0.335)	0.327	0.29 (0.284,0.301)	0.293	0.261 (0.255,0.271)	0.263
Germany	2016	Weinand and von Auer (2020)	0.355 (0.35, 0.362)	0.356	0.310 (0.304, 0.317)	0.311	0.290 (0.285, 0.298)	0.291

Table D.1 (continued)

Country	Year	Source of RPL	Household income		Per capita income		Equalised income	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Greece	2010	Predicted	0.363	0.367	0.334	0.338	0.323	0.327
			(0.357,0.378)		(0.327,0.349)		(0.316,0.338)	
Hungary	2015	Predicted	0.337	0.344	0.27	0.281	0.258	0.268
			(0.333,0.354)		(0.268,0.294)		(0.258,0.279)	
India	2004	Chakrabarty et al. (2018)	0.491	0.491	0.489	0.485	0.471	0.469
			(0.487,0.495)		(0.481,0.489)		(0.465,0.472)	
India	2011	Chakrabarty et al. (2018)	0.501	0.499	0.493	0.49	0.478	0.476
			(0.495,0.503)		(0.486,0.494)		(0.472,0.479)	
Ireland	2017	Predicted	0.359	0.361	0.304	0.307	0.286	0.289
			(0.348,0.373)		(0.293,0.32)		(0.276,0.301)	
Italy	2004	Pittau et al. (2011)	0.352	0.36	0.338	0.352	0.315	0.328
			(0.351,0.368)		(0.342,0.362)		(0.318,0.337)	
Italy	2008	Pittau et al. (2011)	0.351	0.358	0.332	0.345	0.311	0.323
			(0.349,0.368)		(0.335,0.356)		(0.313,0.334)	
Japan	2008	SBJ (2016)	0.379	0.379	0.347	0.348	0.327	0.328
			(0.366,0.392)		(0.336,0.361)		(0.316,0.339)	
Mexico	2018	Predicted	0.424	0.431	0.438	0.447	0.402	0.41
			(0.427,0.435)		(0.442,0.451)		(0.406,0.414)	
Poland	2004	Rokicki and Hewings (2019)	0.348	0.349	0.352	0.354	0.313	0.315
			(0.346,0.353)		(0.351,0.358)		(0.312,0.319)	
Poland	2007	Rokicki and Hewings (2019)	0.354	0.355	0.34	0.343	0.308	0.31
			(0.352,0.358)		(0.339,0.346)		(0.306,0.313)	
Poland	2010	Rokicki and Hewings (2019)	0.355	0.357	0.338	0.342	0.307	0.31

Table D.1 (continued)

Country	Year	Source of RPL	Household income		Per capita income		Equalised income	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
			(0.354,0.36)		(0.339,0.345)		(0.307,0.313)	
Russia	2000	Gluschenko (2006)	0.463	0.464	0.408	0.409	0.410	0.410
			(0.453, 0.475)		(0.396, 0.422)		(0.398, 0.422)	
Slovakia	2010	Radvansky et al. (2012)	0.34	0.341	0.266	0.27	0.259	0.262
			(0.333,0.348)		(0.261,0.279)		(0.254,0.269)	
Spain	2016	Predicted	0.374	0.378	0.354	0.359	0.335	0.34
			(0.372,0.384)		(0.352,0.366)		(0.334,0.347)	
Sweden	2005	Predicted	0.328	0.326	0.259	0.257	0.238	0.236
			(0.322,0.33)		(0.254,0.262)		(0.232,0.24)	
Switzerland	2013	Predicted	0.345	0.346	0.325	0.327	0.293	0.294
			(0.337,0.355)		(0.318,0.335)		(0.285,0.304)	
UK	1999	Baran and O'Donoghue (2002)	0.392	0.394	0.362	0.365	0.342	0.345
			(0.390,0.398)		(0.360,0.369)		(0.341,0.349)	
UK	2004	Ball and Fenwick (2004)	0.388	0.392	0.359	0.363	0.338	0.342
			(0.388,0.396)		(0.359,0.368)		(0.338,0.347)	
UK	2004	Wingfield et al. (2005)	0.388	0.392	0.359	0.363	0.338	0.342
			(0.388,0.396)		(0.359,0.368)		(0.338,0.347)	
UK	2010	ONS (2010)	0.379	0.381	0.349	0.351	0.331	0.333
			(0.377,0.386)		(0.346,0.355)		(0.328,0.338)	
UK	2016	ONS (2016)	0.383	0.385	0.354	0.355	0.334	0.336
			(0.379,0.391)		(0.349,0.361)		(0.33,0.343)	
USA	2008	Bureau of Economic Analysis (2019)	0.408	0.41	0.396	0.398	0.367	0.369
			(0.407,0.413)		(0.395,0.401)		(0.366,0.372)	

Table D.1 (continued)

Country	Year	Source of RPL	Household income		Per capita income		Equalised income	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
USA	2009	Bureau of Economic Analysis (2019)	0.404	0.406	0.395	0.397	0.363	0.365
			(0.403,0.409)		(0.394,0.4)		(0.362,0.368)	
USA	2010	Bureau of Economic Analysis (2019)	0.406	0.408	0.396	0.397	0.364	0.366
			(0.406,0.411)		(0.394,0.4)		(0.363,0.368)	
USA	2011	Bureau of Economic Analysis (2019)	0.414	0.416	0.403	0.404	0.373	0.375
			(0.414,0.419)		(0.401,0.407)		(0.372,0.378)	
USA	2012	Bureau of Economic Analysis (2019)	0.414	0.417	0.402	0.404	0.373	0.375
			(0.414,0.42)		(0.401,0.407)		(0.372,0.378)	
USA	2013	Bureau of Economic Analysis (2019)	0.415	0.418	0.402	0.403	0.373	0.375
			(0.415,0.421)		(0.399,0.406)		(0.371,0.379)	
USA	2014	Bureau of Economic Analysis (2019)	0.417	0.419	0.41	0.411	0.378	0.38
			(0.416,0.422)		(0.408,0.414)		(0.377,0.383)	
USA	2015	Bureau of Economic Analysis (2019)	0.414	0.417	0.407	0.408	0.375	0.377
			(0.414,0.419)		(0.406,0.411)		(0.374,0.38)	
USA	2016	Bureau of Economic Analysis (2019)	0.419	0.421	0.406	0.407	0.377	0.378
			(0.418,0.424)		(0.405,0.41)		(0.376,0.381)	
USA	2017	Bureau of Economic Analysis (2019)	0.421	0.423	0.407	0.408	0.378	0.38
			(0.42,0.426)		(0.405,0.411)		(0.377,0.383)	

Table D.2 Decile ratios and impact of regional price levels

Country	Year	Source of RPL	90/10 ratio		90/50 ratio		80/20 ratio	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Australia	2010	Mishra and Ray (2014)	4.854	4.53	2.149	2.037	2.901	2.779
			(4.413,4.655)		(1.992,2.093)		(2.716,2.846)	
Austria	2007	Matzka and Nachbagauer (2009)	3.644	3.625	1.837	1.829	2.287	2.265
			(3.498,3.762)		(1.789,1.873)		(2.208,2.338)	
Canada	2017	Predicted	4.142	4.167	1.925	1.93	2.546	2.556
			(4.075,4.267)		(1.903,1.964)		(2.502,2.604)	
Chile	2009	Predicted	7.287	7.549	2.944	2.977	3.453	3.602
			(7.272,7.927)		(2.884,3.103)		(3.512,3.669)	
China	2002	Brandt and Holz (2006)	7.187	6.986	2.756	2.713	3.824	3.799
			(6.797,7.165)		(2.658,2.773)		(3.714,3.878)	
China	2013	Brandt and Holz (2006)	7.267	7.043	2.463	2.42	3.687	3.631
			(6.786,7.306)		(2.358,2.5)		(3.511,3.755)	
Czechia	2007	Cadil et al. (2014)	2.928	2.973	1.708	1.75	1.986	2.004
			(2.891,3.062)		(1.709,1.784)		(1.967,2.046)	
Czechia	2013	Kocourek et al. (2016)	2.993	3.041	1.741	1.759	1.986	2.004
			(2.934,3.159)		(1.712,1.806)		(1.954,2.044)	
Czechia	2013	Kramulová et al. (2016)	2.989	3.041	1.738	1.759	1.975	2.004
			(2.934,3.159)		(1.712,1.806)		(1.954,2.044)	
Denmark	2016	Predicted	2.962	2.971	1.669	1.674	2.068	2.073
			(2.948,2.996)		(1.664,1.685)		(2.062,2.084)	
Germany	1994	Roos (2006)	3.269	3.315	1.772	1.792	2.096	2.106
			(3.174,3.418)		(1.733,1.835)		(2.052,2.173)	
Germany	2016	Weinand and von Auer (2020)	3.705	3.716	1.85	1.863	2.273	2.29
			(3.611, 3.839)		(1.824, 1.903)		(2.241, 2.347)	

Table D.2 (continued)

Country	Year	Source of RPL	90/10 ratio		90/50 ratio		80/20 ratio	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Greece	2010	Predicted	4.417	4.443	1.949	1.95	2.613	2.635
			(4.18,4.685)		(1.871,2.025)		(2.534,2.737)	
Hungary	2015	Predicted	3.071	3.228	1.755	1.787	2.067	2.156
			(3.06,3.382)		(1.714,1.864)		(2.068,2.241)	
India	2004	Chakrabarty et al. (2018)	9.423	9.422	3.32	3.298	4.317	4.298
			(9.158,9.674)		(3.22,3.373)		(4.208,4.386)	
India	2011	Chakrabarty et al. (2018)	10.092	9.897	3.358	3.337	4.372	4.292
			(9.578,10.24)		(3.265,3.405)		(4.192,4.392)	
Ireland	2017	Predicted	3.446	3.575	1.804	1.811	2.34	2.334
			(3.362,3.743)		(1.735,1.905)		(2.233,2.469)	
Italy	2004	Pittau et al. (2011)	3.895	4.285	1.957	1.987	2.422	2.596
			(4.019,4.466)		(1.912,2.051)		(2.534,2.693)	
Italy	2008	Pittau et al. (2011)	3.841	4.192	1.93	1.961	2.386	2.585
			(4.001,4.382)		(1.897,2.033)		(2.528,2.647)	
Japan	2008	SBJ (2016)	4.701	4.63	1.971	1.97	2.682	2.687
			(4.401,5.008)		(1.902,2.046)		(2.554,2.841)	
Mexico	2018	Predicted	6.12	6.497	2.521	2.564	3.136	3.243
			(6.365,6.646)		(2.52,2.607)		(3.195,3.289)	
Poland	2004	Rokicki and Hewings (2019)	4.022	4.037	1.954	1.959	2.401	2.41
			(3.969,4.117)		(1.938,1.985)		(2.379,2.439)	
Poland	2007	Rokicki and Hewings (2019)	3.769	3.787	1.941	1.947	2.329	2.337
			(3.732,3.85)		(1.927,1.972)		(2.316,2.364)	
Poland	2010	Rokicki and Hewings (2019)	3.858	3.886	1.951	1.967	2.363	2.38

Table D.2 (continued)

Country	Year	Source of RPL	90/10 ratio		90/50 ratio		80/20 ratio	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
			(3.831,3.944)		(1.947,1.988)		(2.356,2.406)	
Russia	2000	Gluschenko (2006)	6.778	6.866	2.558	2.574	3.358	3.392
			(6.298, 7.549)		(2.435, 2.696)		(3.256, 3.551)	
Slovakia	2010	Radvansky et al. (2012)	3.195	3.25	1.73	1.765	2.097	2.112
			(3.096,3.391)		(1.719,1.808)		(2.057,2.168)	
Spain	2016	Predicted	5.163	5.254	1.998	2.018	2.791	2.882
			(5.05,5.589)		(1.979,2.078)		(2.808,2.957)	
Sweden	2005	Predicted	2.876	2.821	1.637	1.625	2.008	1.974
			(2.773,2.865)		(1.606,1.643)		(1.949,2)	
Switzerland	2013	Predicted	3.519	3.569	1.844	1.862	2.257	2.251
			(3.411,3.715)		(1.812,1.907)		(2.19,2.326)	
UK	1999	Baran and O'Donoghue (2002)	4.627	4.675	2.131	2.155	2.86	2.878
			(4.593,4.755)		(2.123,2.186)		(2.839,2.921)	
UK	2004	Ball and Fenwick (2004)	4.378	4.413	2.115	2.138	2.664	2.679
			(4.341,4.49)		(2.107,2.17)		(2.636,2.717)	
UK	2004	Wingfield et al. (2005)	4.387	4.413	2.113	2.138	2.661	2.679
			(4.341,4.49)		(2.107,2.17)		(2.636,2.717)	
UK	2010	ONS (2010)	4.11	4.146	2.074	2.088	2.514	2.519
			(4.076,4.246)		(2.058,2.124)		(2.484,2.559)	
UK	2016	ONS (2016)	4.125	4.176	2.045	2.059	2.545	2.549
			(4.061,4.272)		(2.016,2.099)		(2.509,2.594)	
USA	2008	Bureau of Economic Analysis (2019)	5.669	5.695	2.147	2.175	3.094	3.112
			(5.615,5.784)		(2.155,2.198)		(3.083,3.145)	

Table D.2 (continued)

Country	Year	Source of RPL	90/10 ratio		90/50 ratio		80/20 ratio	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
USA	2009	Bureau of Economic Analysis (2019)	5.378 (5.332,5.482)	5.406	2.153 (2.154,2.199)	2.176	3.008 (2.986,3.047)	3.013
USA	2010	Bureau of Economic Analysis (2019)	5.58 (5.524,5.701)	5.616	2.182 (2.174,2.216)	2.195	3.09 (3.051,3.115)	3.082
USA	2011	Bureau of Economic Analysis (2019)	5.711 (5.623,5.802)	5.711	2.247 (2.237,2.282)	2.26	3.142 (3.119,3.183)	3.15
USA	2012	Bureau of Economic Analysis (2019)	5.718 (5.676,5.843)	5.757	2.218 (2.223,2.266)	2.242	3.176 (3.154,3.217)	3.187
USA	2013	Bureau of Economic Analysis (2019)	5.649 (5.586,5.812)	5.703	2.224 (2.218,2.277)	2.248	3.137 (3.094,3.17)	3.133
USA	2014	Bureau of Economic Analysis (2019)	5.808 (5.772,5.966)	5.868	2.295 (2.299,2.35)	2.326	3.092 (3.067,3.14)	3.102
USA	2015	Bureau of Economic Analysis (2019)	5.673 (5.646,5.828)	5.736	2.274 (2.286,2.334)	2.308	3.055 (3.032,3.103)	3.069
USA	2016	Bureau of Economic Analysis (2019)	5.841 (5.773,5.977)	5.877	2.255 (2.249,2.3)	2.277	3.112 (3.11,3.182)	3.148
USA	2017	Bureau of Economic Analysis (2019)	5.867 (5.793,5.981)	5.889	2.268 (2.266,2.315)	2.293	3.185 (3.157,3.226)	3.188

Table D.3 Poverty headcount ratios and impact of regional price levels

Country	Year	Source of RPL	40% line		50% line		60% line	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Australia	2010	Mishra and Ray (2014)	7.49 (5.629,6.617)	6.08	14.36 (13.37,14.74)	14.06	22.1 (20.55,22.2)	21.26
Austria	2007	Matzka and Nachbagauer (2009)	4.98 (4.108,5.482)	4.76	9.79 (8.848,10.668)	9.74	15.9 (14.88,16.95)	15.91
Canada	2017	Predicted	6.72 (6.326,7.172)	6.74	12.38 (11.65,12.84)	12.23	19.34 (18.84,20.18)	19.46
Chile	2009	Predicted	9.78 (9.9,10.66)	10.28	16.17 (16.38,17.29)	16.82	23.43 (23.57,24.59)	24.05
China	2002	Brandt and Holz (2006)	11.07 (10.17,11.39)	10.83	18.21 (17.15,18.61)	17.92	25.55 (24.59,26)	25.41
China	2013	Brandt and Holz (2006)	13.73 (12.78,14.44)	13.77	20.24 (19.18,20.83)	20	26.76 (25.8,27.69)	26.94
Czechia	2007	Cadil et al. (2014)	2.57 (2.023,2.953)	2.47	5.57 (4.799,6.007)	5.4	10.99 (10.08,11.56)	10.83
Czechia	2013	Kocourek et al. (2016)	2.61 (2.219,3.387)	2.78	5.76 (5.175,6.83)	5.97	11.11 (10.56,12.37)	11.35
Czechia	2013	Kramulová et al. (2016)	2.67 (2.219,3.387)	2.78	5.58 (5.175,6.83)	5.97	11.05 (10.56,12.37)	11.35
Denmark	2016	Predicted	3.12 (2.988,3.202)	3.1	6.13 (5.973,6.321)	6.15	12.78 (12.55,13.04)	12.8
Germany	1994	Roos (2006)	4.04 (3.446,4.654)	4.03	7.57 (7.105,8.634)	7.95	13.26 (12.3,14.33)	13.31
Germany	2016	Weinand and von Auer (2020)	5.13 (4.677, 5.584)	5.10	10.02 (9.352, 10.577)	9.91	16.37 (15.52, 16.98)	16.30

Table D.3 (continued)

Country	Year	Source of RPL	40% line		50% line		60% line	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Greece	2010	Predicted	7.83	8.18	13.53	14.02	20.5	21.28
			(7.229,9.157)		(12.64,15.11)		(19.68,22.53)	
Hungary	2015	Predicted	2.64	2.86	6.12	6.58	11.97	13.13
			(2.107,3.686)		(5.421,7.799)		(11.31,14.59)	
India	2004	Chakrabarty et al. (2018)	12.8	12.57	19.12	19.19	26.14	26.54
			(12.06,13.25)		(18.44,19.91)		(25.84,27.15)	
India	2011	Chakrabarty et al. (2018)	13.46	13.32	19.87	19.72	26.88	26.66
			(12.82,13.86)		(19.11,20.24)		(26.03,27.2)	
Ireland	2017	Predicted	3.52	3.48	8.74	9.36	16.39	17.23
			(2.786,4.268)		(7.743,10.529)		(15.19,18.72)	
Italy	2004	Pittau et al. (2011)	5.66	6.78	9.88	11.96	16.82	19.77
			(5.816,7.796)		(10.75,13.1)		(18.53,21.47)	
Italy	2008	Pittau et al. (2011)	5.53	6.52	9.88	12.29	17.1	19.64
			(5.536,7.516)		(10.92,13.29)		(18.15,21.09)	
Japan	2008	SBJ (2016)	8.8	8.62	15.05	15.32	21.27	21.18
			(7.325,10.191)		(13.47,16.9)		(19.34,22.76)	
Mexico	2018	Predicted	9.46	10.3	15.25	16.04	22.14	22.98
			(9.99,10.59)		(15.68,16.47)		(22.55,23.43)	
Poland	2004	Rokicki and Hewings (2019)	5.8	5.84	10.74	10.83	17.24	17.3
			(5.544,6.141)		(10.47,11.21)		(16.81,17.73)	
Poland	2007	Rokicki and Hewings (2019)	4.93	4.95	9.23	9.2	15.51	15.56
			(4.721,5.174)		(8.884,9.505)		(15.14,16.04)	
Poland	2010	Rokicki and Hewings (2019)	5.02	5.02	9.67	9.62	16.15	16.29

Table D.3 (continued)

Country	Year	Source of RPL	40% line		50% line		60% line	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
			(4.74,5.293)		(9.278,9.951)		(15.84,16.72)	
Russia	2000	Gluschenko (2006)	11.16	10.97	17.03	17.08	24.15	23.89
			(9.79, 12.24)		(15.67, 18.74)		(22.48, 25.62)	
Slovakia	2010	Radvansky et al. (2012)	4.58	4.55	8.11	8.03	13.67	13.44
			(3.866,5.323)		(7.053,8.937)		(12.4,14.5)	
Spain	2016	Predicted	10.33	10.83	15.26	15.73	22.12	22.57
			(10.01,11.56)		(14.86,16.57)		(21.57,23.36)	
Sweden	2005	Predicted	2.8	2.64	6.02	5.6	12.35	11.97
			(2.387,2.946)		(5.218,6.013)		(11.33,12.53)	
Switzerland	2013	Predicted	3.82	3.81	8.78	8.74	14.97	14.78
			(3.277,4.405)		(7.788,9.619)		(13.78,15.98)	
UK	1999	Baran and O'Donoghue (2002)	5.89	5.91	13.1	13.2	21.75	21.82
			(5.534,6.249)		(12.61,13.78)		(21.15,22.39)	
UK	2004	Ball and Fenwick (2004)	5.35	5.28	11.37	11.27	19.16	19.07
			(4.96,5.583)		(10.77,11.73)		(18.53,19.63)	
UK	2004	Wingfield et al. (2005)	5.35	5.28	11.44	11.27	19.22	19.07
			(4.96,5.583)		(10.77,11.73)		(18.53,19.63)	
UK	2010	ONS (2010)	5.24	5.25	9.76	9.79	17.14	17.26
			(4.877,5.611)		(9.331,10.284)		(16.71,17.95)	
UK	2016	ONS (2016)	5.81	5.85	10.25	10.43	17.66	17.59
			(5.452,6.319)		(9.8,11)		(16.98,18.33)	
USA	2008	Bureau of Economic Analysis (2019)	11.21	11.13	17.48	17.31	24.27	24.26
			(10.84,11.41)		(17.01,17.67)		(23.9,24.58)	

Table D.3 (continued)

Country	Year	Source of RPL	40% line		50% line		60% line	
			Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
USA	2009	Bureau of Economic Analysis (2019)	9.99 (9.583,10.131)	9.85	16.08 (15.52,16.18)	15.87	23.12 (22.65,23.32)	22.99
USA	2010	Bureau of Economic Analysis (2019)	10.52 (10.21,10.75)	10.48	16.72 (16.27,16.91)	16.59	23.73 (23.31,24.01)	23.67
USA	2011	Bureau of Economic Analysis (2019)	10.35 (9.95,10.48)	10.21	16.6 (16.03,16.67)	16.34	23.9 (23.51,24.19)	23.84
USA	2012	Bureau of Economic Analysis (2019)	10.68 (10.26,10.79)	10.54	17.13 (16.48,17.11)	16.78	24.36 (23.83,24.53)	24.19
USA	2013	Bureau of Economic Analysis (2019)	10.33 (9.96,10.6)	10.28	17 (16.29,17.07)	16.65	24.18 (23.52,24.36)	23.97
USA	2014	Bureau of Economic Analysis (2019)	10.27 (9.94,10.47)	10.22	16.42 (15.83,16.48)	16.18	23.68 (23.13,23.79)	23.47
USA	2015	Bureau of Economic Analysis (2019)	9.95 (9.602,10.154)	9.89	16.12 (15.44,16.07)	15.73	23.18 (22.54,23.25)	22.88
USA	2016	Bureau of Economic Analysis (2019)	10.78 (10.39,10.93)	10.65	17.04 (16.7,17.37)	17.01	24.09 (23.86,24.55)	24.19
USA	2017	Bureau of Economic Analysis (2019)	10.8 (10.32,10.9)	10.57	17.31 (16.78,17.52)	17.15	24.62 (24.17,24.9)	24.53

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Declarations

Competing interests There indeed are no competing interests to declare.

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