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Carbon tax on milk products and the exact consumer welfare measure in emerging economies

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Abstract

Current milk prices do not account for the emissions, environmental externalities, and the excessive resource use that occur during milk production. Imposing a “carbon tax on food” can be a very effective climate change mitigation policy and the ultimate distributional effect depends heavily on the way the tax is implemented. To offset the regressive financial effect, redistribution measures need to be designed and the financial welfare loss can serve as a first orientation for designing these redistribution measures. Current literature mainly uses estimated elasticities from empirical demand systems to approximate the welfare change which can lead to a substantial bias if the tax rate is sufficiently large. In contrast, we calculate the welfare change by using the Exact Consumer Welfare of a carbon tax on milk for selected emerging economies. We show that on average, consumers in upper-middle-income economies would face a financial welfare loss of 19.4–176.9 USD (in the value of 2017) measured by the compensating variation (CV), depending on the tax scenario. Among a set of 16 emerging economies, consumers in

Abbreviations: AIDS, almost ideal demand system; ARG, Argentina; BRA, Brazil; CH₄, methane; CHN, China; CO₂, carbon dioxide; CS, consumer surplus; CV, compensating variation; EGY, Egypt; FAO, Food and Agriculture Organization; GDP, gross domestic product; GHG, greenhouse gas; ICP, International Comparison Project; IDN, Indonesia; IFCN, International Farm Comparison Network; IND, India; IRN, Islamic Republic of Iran; KOR, South Korea; MEX, Mexico; N₂O, nitrous oxide; NGA, Nigeria; OECD, Organization for Economic Cooperation and Development; PAK, Pakistan; POL, Poland; QAIDS, quadratic almost ideal demand system; RUS, Russia; SD, standard deviation; SO₂, sulfur dioxide; THA, Thailand; TUR, Türkiye; USA, United States of America; USD, United States Dollar; ZAF, South Africa.

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Argentina (ARG) and Türkiye (TUR) face the highest financial welfare losses. We also find that discrepancies between the Exact Consumer Welfare and the consumer surplus are very small. [EconLit Citations: Q11, Q18].

KEYWORDS

carbon tax, consumer welfare change, emerging economies, milk consumption

1 | INTRODUCTION

Annual milk demand is expected to increase by 2% in low-middle, 1.5% in low-income, and 0.4% in high-income economies by 2031 (OECD, 2022). It takes 9 m² of land and 628 litres of fresh water to produce one litre of milk. Further, milk production emits 3.2 kg of CO₂ equivalents per liter (Poore & Nemecek, 2018). Pricing the environmental footprint and shifting these costs to consumers can be a very effective climate change mitigation policy (Springmann et al., 2016). In other words, adding an ad valorem tax proportional to the environmental footprint on food items can be called a “Carbon tax on food.” Public support for such a policy measure is higher when the generated tax revenue is used for redistribution measures, such as income support or health-promoting measures (Fesenfeld et al., 2020). The bases for simulating these redistribution measures is the quantification of the financial welfare losses, which occur after the implementation of a carbon tax on food.

This paper quantifies the financial welfare loss of a carbon tax on milk for consumers in emerging economies. We use the Exact Consumer Welfare measure by Hausman (1981) and compare it to the traditional consumer surplus (CS). We demonstrate that using different welfare measures matters in quantifying the financial welfare loss imposed by a carbon tax on milk.

We focus on emerging economies as the demand for fresh milk is expected to increase the fastest in emerging economies. Fresh milk consumption per capita amounts to 210.66 kg in Türkiye (TUR) and 208.87 kg in Pakistan (PAK) in 2022. While the fresh per capita milk consumption in economies like Brazil (BRA) or South Africa (ZAF) sum up to 79.45 and 33.70 kg, respectively, economies like Nigeria (NGA) and Indonesia (IDN) consume relatively low amounts of fresh milk per capita with 1.01 kg and 4.02 kg in 2022, respectively. For comparison, fresh milk consumption per capita amounts to 99.36 kg in Europe and 65.81 kg in the United States in 2022 (OECD, 2022).

There is extensive literature on the impact of a carbon tax in the energy or transport sector (Andersson, 2019; Best et al., 2020; Hájek et al., 2019). The literature that deals with a carbon tax in the agriculture or food sector is also relatively broad for developed economies (Briggs et al., 2013; Caillavet et al., 2019; Forero-Cantor et al., 2020; Roosen et al., 2022; Säll, 2018) but is limited in the context of emerging or developing economies (Renner et al., 2018; Saelim, 2019; Sofyan, 2011). Further, most of the previous literature uses estimated elasticities from empirical demand systems to approximate the welfare change measured by compensating variation (CV) (Roosen et al., 2022; Säll, 2018). While most studies calculate CVs of a carbon tax on meat products (Roosen et al., 2022; Säll, 2018), only a few calculate CVs for a carbon tax on dairy products. Dogbe and Gil (2018) calculate CVs for carbon tax scenarios for a Spanish region for all food products and find for a stringent carbon tax scenario, that consumers would require an increase of 0.41% in their initial expenditure to maintain current consumption patterns (Dogbe & Gil, 2018). Thereby, they impose restrictions on the functional form of the demand specification and do consider broad food groups instead of specific food groups.

In contrast to previous studies, we use the Exact Consumer Welfare measure by Hausman (1981) to quantify the financial welfare loss derived from an observed demand function by simulating a carbon tax on milk in the

context of 16 emerging economies that account for 55.97% of the total world population and for 28.9% of the world's gross domestic product (GDP). Hereby, we demonstrate that the financial welfare loss using the Exact Consumer Welfare is up to 4.15% lower than the traditional CS. These findings serve as a basis for future simulations of redistribution measures to offset the financially regressive effects of taxation.

The remaining paper is structured as follows. Section 2 provides background information about the environmental impact of milk, the importance of milk for fighting undernutrition, and the demand for milk in emerging economies. We explain the applied method in Section 3, introduce the data in Section 4, and provide results in Section 5. We discuss our results in Section 6 and provide concluding remarks in Section 7.

2 | BACKGROUND

2.1 | Milk consumption and climate change

Overall, the production of one litre of milk is associated with, on average, 9 m² of land use, 3.2 kg of carbon dioxide (CO₂) equivalents greenhouse gas (GHG) emissions, 20 g of sulfur dioxide (SO₂) equivalents of acidifying emissions, 10.7 g of phosphate (PO₄³⁻) equivalents eutrophying emissions, and 628 litres of freshwater withdrawals. Soy milk, which constitutes a prominent alternative to traditional milk, is associated with only 0.7 m² of land use, 1 kg of CO₂ equivalents GHG emissions, and 28 litres of freshwater withdrawals per liter on average. Further, the production of root vegetables is even less resource-intensive, since the production per kilogram requires only, on average, 0.3 m² of land, 0.4 kg of CO₂ equivalents GHG emissions, and 28 litres of freshwater withdrawals (Poore & Nemecek, 2018).

There are various sources of emissions related to the global dairy cattle system. In 2015, three major GHGs related to dairy production were methane (CH₄), nitrogen oxide (N₂O), and carbon dioxide (CO₂). The largest source was CH₄ from enteric fermentation (58.5%), followed by N₂O (20%) and CO₂ (8.9%) emissions from feed production, processing, and transport, as well as CH₄ (4.8%) and N₂O (4.5%) emissions from manure management (FAO, GDP and IFCN, 2019).

While global milk production has increased by 30% between 2005 and 2015, total GHG emissions related to milk production have only increased by 18% due to more efficient dairy production techniques that emit lower GHGs per liter of milk (FAO, GDP and IFCN, 2019). Nevertheless, the ultimate pollution depends highly on where the dairy is produced. For example, milk production in China (CHN) results in higher GHG emissions due to less efficient milk and feed production than in Western Europe or North America (Bai, 2018a). In general, developing dairy regions, such as Sub-Saharan Africa, produce 6.7 kg of CO₂ equivalents per kilogram of fat-and protein-corrected milk. This is in contrast to Western Europe, where only 1.37 kg of CO₂ equivalents are produced for the same amount of milk (FAO, GDP and IFCN, 2019).

2.2 | Milk consumption and undernutrition

Milk constitutes an excellent source of fat, 400 different fatty acids, high-quality protein (including essential amino acids needed by humans), calcium, magnesium, selenium, riboflavin, vitamin B12, and pantothenic acid (FAO, 2014). Thus, many emerging economies recommend milk intake in their national food-based dietary guidelines. However, there exist substantial heterogeneities in recommended milk intake levels—the Islamic Republic of Iran (IRN) recommends an intake of 383.25 kg per year as a mix of milk, cheese, yogurt, and other dairy products while South Korea (KOR) recommends 71.18 kg per year without specification of food items—that reflect the different importance of milk in diets as well as the availability of alternative animal source foods across countries (FAO, 2014; Springmann et al., 2020). One potential reason for relatively low levels of recommended milk intake might be the prevalence of lactose malabsorption, which means that people lack the necessary enzyme for digesting the milk component lactose (FAO, 2014; Storhaug et al., 2017).

Although milk is a nutrient-dense food, the empirical evidence about the nutritional benefits of milk consumption is contested. While there are both observational (Headey et al., 2018) and interventional studies (He et al., 2005), and most of the studies focus on younger age groups (FAO, GDP and IFCN, 2019). A recent meta-analysis of intervention studies concluded that additional intake of milk was associated with higher rates of child growth (in seven out of eight studies) as well as weight gains (in all eight studies) (FAO, GDP and IFCN, 2019). One observational study found statistically significant associations between lower rates of stunting and dairy consumption in children aged 18–23 months in three (Latin America and the Caribbean [−4.4%], South, Central, and Eastern Asia [−4.8%], and Eastern and Southern Africa [−6.6%]) out of five world regions (FAO, GDP and IFCN, 2019; Headey et al., 2018).

The ultimate effect of milk consumption on nutrition depends also on the (non)existence of sufficient food safety standards, which is especially important in the context of emerging economies. The usually unpasteurized consumed milk can be a carrier of zoonotic diseases and can contain adulterants (Garcia et al., 2019). The melamine milk scandal in China in the Year 2008 prompted the implementation of stringent food safety laws in China as well as international re-evaluation of tolerable daily intakes of melamine (Pei et al., 2011; Quan et al., 2017; Wu et al., 2018; Yu, 2012).

2.3 | Milk demand and emerging economies

Figure 1 compares the observed fresh dairy (milk, yogurt, and cream) consumption in 2000, 2010, and 2020 as well as the estimated fresh dairy consumption in 2030. The per capita demand for milk is expected to grow the fastest in emerging economies, mainly due to expected demand increases in India (IND), Pakistan, and Türkiye, triggered by income and population growth (OECD, 2022). In India, fresh dairy consumption is expected to increase (from

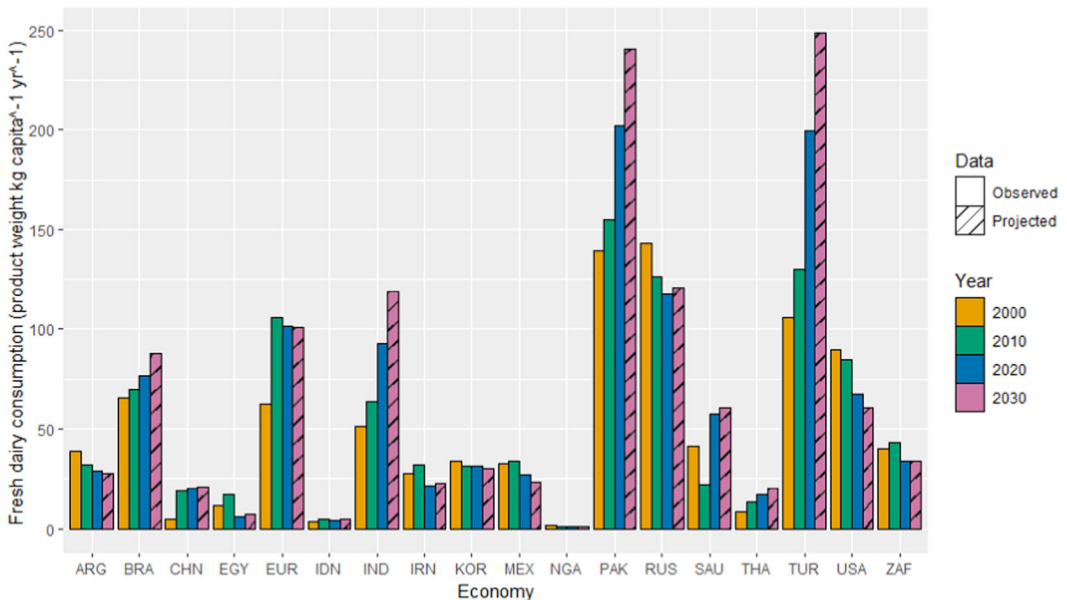


FIGURE 1 Observed fresh dairy consumption (in kilogram per capita and year) in 2000, 2010, and 2020 and projected fresh dairy consumption in 2030 for selected emerging economies. Current and projected consumption levels are obtained from the OECD Agricultural Outlook (OECD, 2022). Poland is missing due to the absence of consumption data.

92.9 kg per capita in 2020 to 118 kg per capita in 2030). In Pakistan, fresh dairy consumption is expected to increase from 202.38 kg per capita in 2020 to 240.74 kg per capita in 2030. In Türkiye, fresh dairy consumption is expected to increase rapidly from almost 200 kg per capita to 248.72 kg per capita. At the same time, fresh dairy consumption is expected to remain more or less constant in economies like Nigeria (around 1.02 kg per capita), Russia (RUS) (around 117 kg per capita), and South Africa (around 3 kg per capita). For comparison, fresh dairy consumption in developed economies like the United States is also expected to drop from 67.46 in 2020 to 60.88 kg per capita in 2030 (OECD, 2022).

Chinese fresh dairy consumption increased rapidly between 2000 and 2010, from 5.01 kg per capita to 18.79 kg per capita, and increased only slightly until 2022 to 20.37 kg per capita and is projected to amount to 21.07 kg per capita in 2030. However, the projected consumption levels should be treated with caution due to uncertain population projections after China has abolished the one-child policy. Further, while the national guidelines for a healthy diet suggest an intake of 110 kg per capita and year, the former Chinese president's vision of supplying every Chinese child with 0.5 litre of milk per day exceeds the national guidelines by 70 kg per capita and year (Bai, 2018a, 2018b).

An important aspect to consider for the carbon tax discussion is the information about the share of overall expenditure consumers in different economies spend on food and milk products. This is broken down in Table 1.

TABLE 1 Food expenditures within total expenditure and average budget shares of fresh and preserved milk within food expenditure for emerging economies.

Economy	Food expenditure within Total expenditure	Budget share of milk Within food expenditure
Lower-middle economy mean	0.21	0.09
CHN	0.12	0.05
EGY	0.17	0.06
IDN	0.25	0.02
IND	0.17	0.18
NGA	0.44	0.00
PAK	0.18	0.27
THA	0.16	0.04
Upper-middle economy mean	0.15	0.07
ARG	0.14	0.08
BRA	0.15	0.07
MEX	0.17	0.05
RUS	0.19	0.07
TUR	0.10	0.10
ZAF	0.14	0.05
Higher-middle economy mean	0.10	0.04
KOR	0.07	0.04
POL	0.14	0.04

Note: Data for Islamic Republic of Iran is missing. Data were obtained from the International Comparison Project (ICP) 2017.

Consumers in lower-middle-income economies spend 21% of their overall expenditure on food, while consumers in higher-income economies spend only 10% of their overall expenditure on food. From their food expenditure, consumers in lower-middle-income economies spend 9% on fresh and preserved milk, while consumers in higher-income economies spend only 4% of their food expenditure on fresh and preserved milk. Interestingly, Pakistani consumers have, with 27%, the highest food expenditures on fresh and preserved milk even though their overall expenditure on food is similar to those of other economies.

3 | METHODOLOGY

3.1 | Theory

3.1.1 | CS

CS is a widely used concept of measuring consumer welfare as only information about the prices and quantities are needed. As specified in Equation 1, it is based on the uncompensated Marshallian demand function. In Figure 2, CS is defined as the area ABCDE below the Marshallian demand curve and above the price line p_0 (Deaton & Muellbauer, 1980; Hausman, 1981). A price change results in an income and substitution effect, but for the CS used demand function can only capture the substitution effect. Thus, to quantify the monetary welfare change, we need to use welfare measures that can capture both the income and substitution effect. Further, we run into an integrability problem when using CS, as only information about price and quantities are sufficient to calculate the CS. This means that we cannot integrate such a function back to a corresponding expenditure function as we lack information about the income. Hence, the CS might not be the most appropriate welfare measure (Shin & Burke, 2010).

$$CS = \int_{p_0}^{p_1} q(p) dp = \frac{p_1 - p_0}{2} (q_1 + q_0). \quad (1)$$

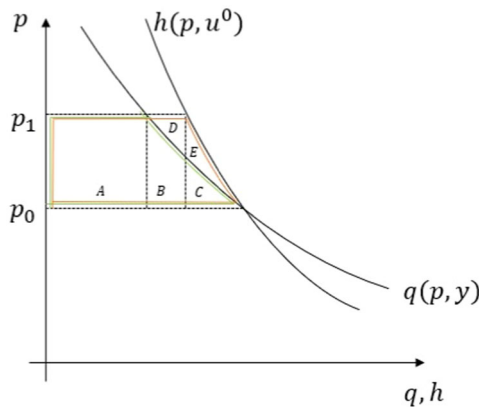


FIGURE 2 Schematic representation of the difference between the Exact compensating variation (area ABC framed in green color) proposed by Hausman (1981) and the traditional consumer surplus (area ABCDE framed in orange color). Adapted from Hausman (1981); and Shin and Burke (2010).

3.1.2 | CV

An alternative welfare measure is the so-called CV.¹ Compared with the CV, CS does not consider the income effect, and hence the discrepancy between CV and CS depends on the income effect. CV is defined as the amount consumers would need to receive as compensation for a price increase to be as well off as before (Deaton & Muellbauer, 1980; Roosen et al., 2022; Saelim, 2019; Säll, 2018; Shin & Burke, 2010), is represented by the area ABC in Figure 2, and is formally defined in Equation 2a. As the CV is based on the compensated Hicksian demand functions, we are able to capture the income and substitution effect, and are thus, more precise than the CS (Madden et al., 2007).

$$CV = E(p_1, U_0) - E(p_0, U_0), \quad (2a)$$

Or in an integrated form:

$$CV = \int_{p_0}^{p_1} \frac{\partial E(p_0, U_0)}{\partial p_i} = \int_{p_0}^{p_1} h(p_0, U_0) dp_i. \quad (2b)$$

In practice, we could use the Taylor expansion to approximate $E(p_1, U_0)$ (Yu, 2014). The first-order expansion is

$$E(p_1, U_0) \approx E(p_0, U_0) + \frac{\partial E(p_0, U_0)}{\partial p} (p_1 - p_0). \quad (3)$$

We obtain the compensated demand function $h(p_0, U_0)$ by taking the derivative of the expenditure function with respect to price, also known as Shepard's Lemma (see Equation 6), which enables us to rewrite the formula for the CV:

$$\frac{\partial E(p_0, U_0)}{\partial p} = h(p_0, U_0). \quad (4)$$

Substituting (4) and (5) into (3), we have

$$CV \approx h(p_0, U_0)(p_1 - p_0). \quad (5)$$

Clearly, Equation (5) could cause a large bias when the high-order terms are ignored.

Usually, researchers avoid the integrability problem by employing the almost ideal demand system (AIDS) (Forero-Cantor et al., 2020; Säll & Gren, 2015) or the quadratic almost ideal demand system (QAIDS) (Roosen et al., 2022; Saelim, 2019). However, both demand systems are sometimes subjected to restrictions on the demand function parameters a priori and are not derived from observed data (Shin & Burke, 2010). In contrast, by using the method proposed by Hausman (1981), we are able to choose a more flexible functional form that best fits observational data (Hayes & Porter Hudak, 1987; Shin & Burke, 2010).

Hausman (1981) provides an exact measure for consumer welfare as the CV that allows us to evaluate the monetary welfare effects of a carbon tax on milk. After estimating an observed demand function, we derive the unobserved indirect utility function by integrating the demand function. We retrieve the expenditure function by inverting the indirect utility function and use the expenditure function to calculate the CV. Ultimately, we compare the obtained results to the traditional CS in Equation 1.

¹Equivalent Variation (EV) is defined as the new utility after price change and is another measure for welfare change. We do not consider EV in this study since we assume reference utility for the consumer should be defined at the original level.

3.1.3 | Marshallian demand and exact welfare

The Marshallian demand curve is specified as a function that explains milk consumption per capita q_{it} in country i and year t with consumer price p , income Y , a vector of control variables Z , and a country effect v , while β_0 , β_1 , β_2 , and γ constitute the coefficients to be estimated. Further, the error term ϵ_{it} is the normally distributed random error term (see the following equation):

$$\log(q_{it}) = \beta_0 + \beta_1 \log(p_{it}) + \beta_2 \log(Y_{it}) + \gamma Z_{it} + v_i + \epsilon_{it}. \quad (6)$$

Equation (6) is a classical demand function, and the literature often assumes that consumers are price takers. That is, we can argue that price is exogenous.

The imposition of a carbon tax τ relative to the initial price p_0 would lead to price p_1 defined as follows:

$$p_{i,1} = p_{i,0} + \tau_i p_{i,0}. \quad (7)$$

Following (Hausman, 1981), we can obtain the indirect utility function by integrating the demand function from Equation (5):

$$V(P_{it}, Y_{it}) = -e^{(\gamma Z_{it} + v_i)} \frac{P_{it}^{1+\beta_1}}{1 + \beta_1} + \frac{Y_{it}^{1-\beta_2}}{1 - \beta_2}. \quad (8)$$

As the expenditure function E_0 is the inverse of the indirect utility function, specified in Equation (8), we can plug the inverse of Equation (8) into Equation (2a) and after rearranging, we obtain the following specification for the CV:

$$CV(p_0, p_1, Y_0) = \left\{ (1 - \beta_2) \left[\frac{e^{(\gamma Z_{it} + v_i)}}{1 + \beta_1} (p_0^{1+\beta_1} - p_1^{1+\beta_1}) \right] + Y_0^{1-\beta_2} \right\}^{\frac{1}{1-\beta_2}} - Y_0. \quad (9)$$

3.2 | Estimation method

Our aim is to quantify the relationship between milk consumption in kilogram per capita and year, price, income, population, and urbanization rate. We build a small panel dataset from the Years 2000–2019 for 16 emerging economies. We estimated Equation (6) both with fixed-effects and random-effects models. However, the result of the Hausmann test suggests using a fixed effect model over a random effect model (p value < 2.2e-16).²

4 | DATA

The baseline year of our welfare calculation is 2019. We select milk consumption data per capita, GDP per capita, and population data from 16 main emerging economies between the Years 2000 and 2019 from the Food and Agriculture Organization (FAO) and the World Bank databases. As the definitions for the classification of emerging economies differ across international organizations, we select the emerging economies which are classified as

²We use the statistical software R version 4.2.2 and a set of various packages. In detail, we utilize the packages "countrycode" (Keyes, 2022), "dplyr" (Wickham et al., 2022a), "tidyverse" (Wickham, 2022b), and "readxl" (Wickham & Bryan, 2022) for data processing and cleaning. We use the functions of the package "plm" (Croissant & Millo, 2022) and "AER" (Kleiber & Zeileis, 2021) for the statistical analysis. We use the functions of the packages "ggplot2" (Wickham, 2022), "ggpubr" (Kassambara, 2022) and "grid" (Murrell, 2022) for graphical illustrations of the results.

emerging economies across most of the definitions. Poland (POL) and South Korea are considered as high-income economies nowadays but were classified as emerging economies within the period 2000–2019 (Casanova, 2020). Retail prices for 2011 and 2017 are obtained from the International Comparison Program (ICP) database, which we use together with the FAO milk price index to approximate retail prices for the remaining years between 2000 and 2019.³ Further, we complement our study with tax levels as the percentage change in food prices for milk commodities, differentiated by region and retrieved from a global modeling study (Springmann et al., 2016).

We display descriptive statistics on aggregated level in Table 2 and on disaggregated level in Appendix Tables A1 and A2. Across time and economies, 80.39 (SD: 62.49) kg of milk is consumed on average. Further, the price per kilogram milk is 1.66 (SD: 0.83) on average. The GDP per capita, measured in USD, amounts to 6747.96 (SD: 6006.59) USD across years and economies on average. Population amounts to 253829622.96 (SD: 393782646.88) people on average and the share of people living in urban areas amounts to 60.14 (SD: 18.58)%.

5 | RESULTS

5.1 | Regression results

As a first step, we display the regression results in Table 3. As expected, the price elasticity of demand for a normal good like milk is estimated to be -0.27 and the income elasticity of demand is estimated to be 0.29 . It is difficult to compare this price elasticity to other studies, as other studies display price elasticities for aggregated food groups usually. These price elasticities for food (Moz-Christofoletti & Pereda, 2021; Muhammad et al., 2011; Saelim, 2019) tend to be lower, suggesting that demand for fresh milk is less price sensitive compared with broader food groups. Regarding the income elasticity, we also obtain a lower value compared with similar studies that display the income elasticity for dairy, suggesting that fresh milk consumption is not as income sensitive other dairy products (Colen et al., 2018). Milk consumption per capita decreases substantially by 2.55% with a 1% increase in population. Interestingly, milk consumption per capita decreases only by 0.01% with a 1% increase in urbanization, and this effect is statistically insignificant. The negative signs for population and urbanization are plausible due to the scale effect, meaning that milk consumption per capita within an economy decreases after reaching a certain saturation point. Coefficients for consumer price, GDP per capita and population are highly statistically significant.

5.2 | CV

In the second step, we use these coefficients to calculate the exact CV as suggested by Hausman (1981). We display the results in Table 4. The larger the simulated tax rate, the larger is the calculated CV for all emerging economies. Interestingly, the CV is relatively moderate in lower and higher middle-income economies, while the CV is relatively higher in upper-middle-income economies. On average, consumers in lower-middle-income economies would face a financial welfare loss of 5.12 USD in the lowest tax scenario and 46.69 USD in the highest tax scenario. Consumers in upper-middle-income countries would face a financial welfare loss of 19.39 USD in the lowest and 176.88 USD in the highest scenario. In particular, consumers in Argentina (ARG) would experience a financial welfare loss of 33.89 USD in the 10% tax scenario and up to 308.79 USD in the 100% tax scenario, which is more than 50% higher than the average welfare loss in this economy group. Ultimately, higher middle-income

³The price is defined as USD in 2017.

TABLE 2 Descriptive statistics for data from the Years 2000 to 2019 for 16 emerging economies.

Variable	Mean	SD	P0	P25	P50	P75	P100
Quantity kg	80.39	62.49	1.21	23.12	61.97	141.54	224.43
P cons USD	1.66	0.83	0.49	1.11	1.48	1.94	4.72
GDP pc USD	6747.96	6006.59	450.65	2139.94	5658.01	9348.37	33447.16
Pop	253829622.96	393782646.88	36870796.00	61854046.00	99598998.50	191453189.75	1407745000.00
Urb rate	60.14	18.58	27.67	42.97	61.14	75.20	91.99

Source: Own calculation.

TABLE 3 Regression coefficients of a fixed effect panel model for panel data for 16 emerging economies for the period between 2000 and 2019.

	Milk consumption in kg Per capita per year
Log (consumer price)	-0.27* (0.10)
Log (GDP pc)	0.29** (0.10)
Log (population)	-2.55*** (0.31)
Urbanization rate	-0.01 (0.01)
R	0.29
Adjusted R ²	0.24
Num. obs.	320

Source: Own calculation.

*Significance levels: $p < 0.05$.

** $p < 0.01$; *** $p < 0.001$.

economies face a financial welfare loss of 11.04 USD in the lowest and 100.89 USD in the highest tax scenario, on average.

5.3 | CS

Finally, we compare the obtained results to the traditional CS. We illustrate the comparison of the CV and the CS for all four tax scenarios in Figure 3. Additionally, we display the absolute and relative difference for only three tax scenarios in Figure 4 as the difference in the lowest tax scenario is almost negligible (see Figure 3a). Overall, we find that our results across all countries and scenarios are consistent with microeconomic theory as the Exact Consumer Welfare measure is larger than the CS in absolute terms.

5.4 | Discrepancy between CV and CS

While the difference between the Exact Consumer Welfare measure and CS varies across countries and scenarios in absolute terms (see Figure 4a), the difference becomes more uniform in relative terms (see Figure 4b). Overall, the difference between the Exact Consumer Welfare measure and the CS does not exceed 4.15%. We find the most substantial differences for Nigeria and South Korea across all tax scenarios (0.21% in the 20% scenario, 1.17 and 1.18 in the 50% scenario, and 4.15 in the 100% scenario). Further, we find the lowest difference for Pakistan, amounting to only 0.03%, 0.59, and 3.02% in the 20%, 50%, and 100% tax scenarios, respectively.

The relatively small discrepancy between CV and CS could result from either the relatively small budget share of milk consumption in total household expenditure or the habit persistence of milk consumption. These two factors could lead to a small income effect in the Slutsky equation.

TABLE 4 Results of the compensating variation by Hausman (1981) for four different tax scenarios.

Economy	Tax scenario with tax rate equal to			
	10%	20%	50%	100%
Lower-middle mean	-5.12	-10.12	-24.46	-46.68
CHN	-7.95	-15.70	-37.99	-72.64
EGY	-4.89	-9.66	-23.38	-44.68
IDN	-0.70	-1.38	-3.34	-6.39
IND	-8.71	-17.20	-41.55	-79.28
IRN	-4.32	-8.54	-20.66	-39.51
NGA	-0.20	-0.39	-0.94	-1.79
PAK	-11.38	-22.45	-54.15	-103.02
THA	-2.85	-5.64	-13.64	-26.10
Upper-middle mean	-19.39	-38.30	-92.61	-176.88
ARG	-33.89	-66.93	-161.77	-308.79
BRA	-19.98	-39.47	-95.45	-182.32
MEX	-12.81	-25.30	-61.21	-117.00
RUS	-19.31	-38.14	-92.25	-176.28
TUR	-24.48	-48.36	-116.91	-223.26
ZAF	-5.87	-11.59	-28.05	-53.63
Higher-middle mean	-11.04	-21.82	-52.78	-100.89
KOR	-2.50	-4.95	-11.98	-22.92
POL	-19.58	-38.68	-93.58	-178.86

Source: Own calculation.

6 | DISCUSSION

6.1 | Application of carbon tax rates

As we presented only general findings in the previous section, we were also curious about the performance of the Exact Consumer Welfare measure relative to the CS in a more realistic carbon tax scenario. We use the carbon tax from Springmann et al. (2016). They calculate the carbon tax based on emission intensities for each world region and food commodity, combined with the respective social costs of carbon. We map our set of economies to the regions proposed by Springmann et al. (2016) and apply the respective carbon tax, summarized in Table 5.

On average, we find a financial welfare loss of 10.51 USD for lower-middle, 41.84 USD for upper-middle, and 14.73 USD for higher-middle-income economies (see Table 6). The differences between the Exact Consumer Welfare measure and the CS is negligible in both absolute and relative terms (see Table 6 and Figure 5). Future research could base the calculations on more recent, more differentiated, and sophisticated carbon tax scenarios.

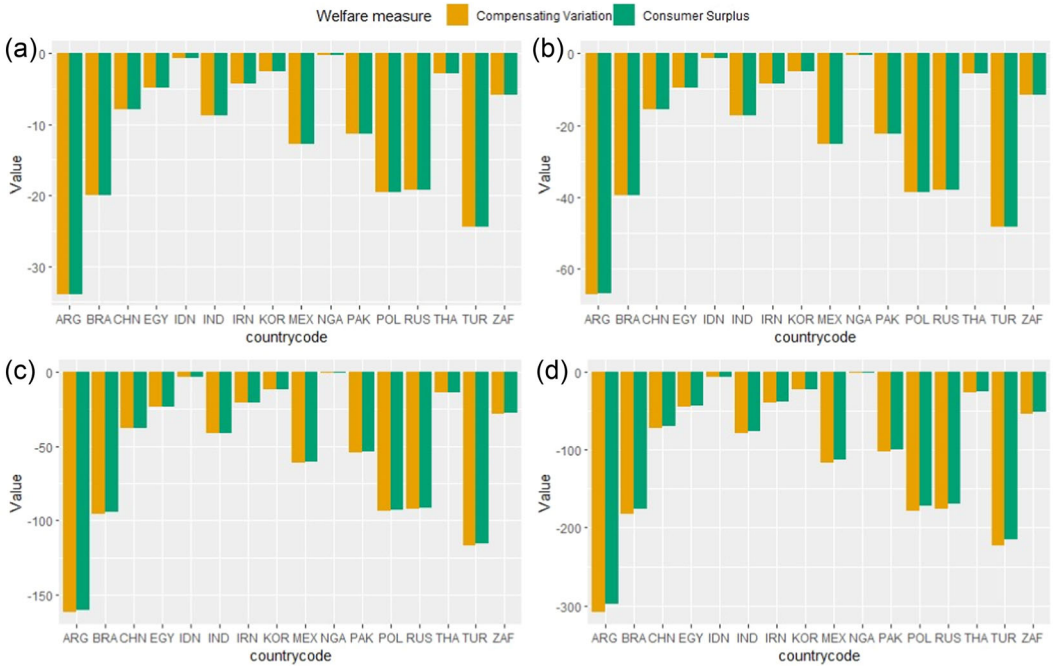


FIGURE 3 Comparison of compensating variation by Hausman (1981) and consumer surplus for 10% (a), 20% (b), 50% (c), and 100% (d) tax scenarios. Source: Own calculation.

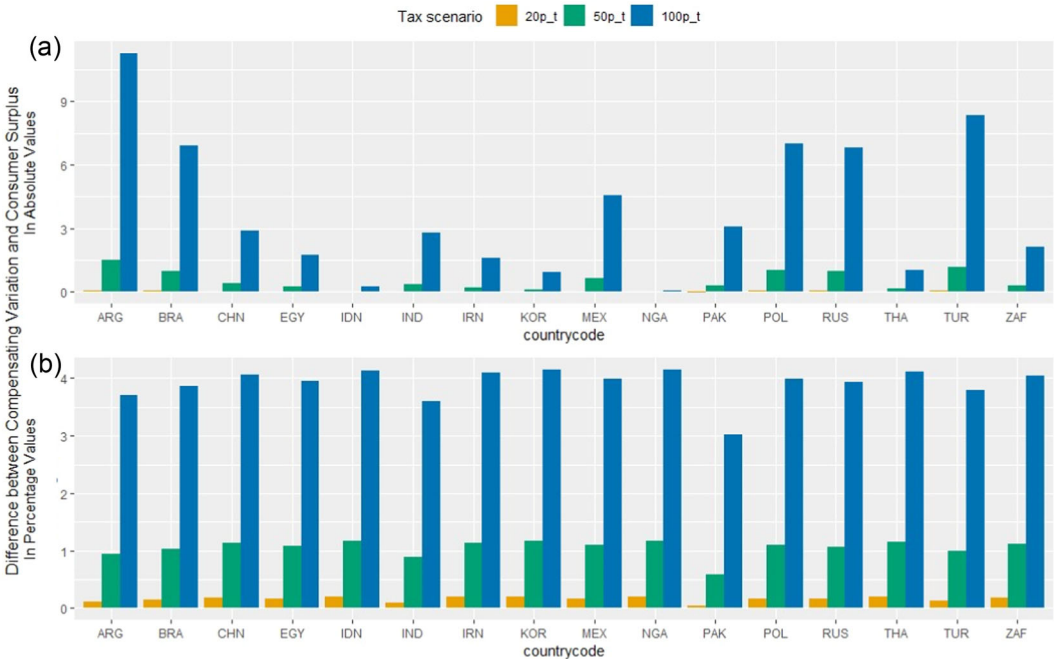


FIGURE 4 Difference between compensating variation by Hausman (1981) and consumer surplus in absolute (a) and relative (b) values for the 20%, 50%, and 100% tax scenarios. The 10% is not displayed here due to zero difference compared with the consumer surplus. Source: Own calculation.

TABLE 5 Emerging economy classification, adapted from Springmann et al. (2016).

Income class	Economy	Tax rate in %
Low-middle	CHN, EGY, IDN, IND, IRN, NGA, PAK, THA	0.208
Upper-middle	ARG, BRA, MEX, RUS, TUR, ZAF	0.219
Higher-middle	POL, KOR	0.134

Note: Assumption: Türkiye classifies as an upper-middle-income economy.

TABLE 6 Results of the compensating variation by Hausman (1981), consumer surplus, and differences between both measurements in absolute and percentage values for the Carbon tax scenario by Springmann et al. (2016).

Economy	Compensating variation (CV)	Consumer surplus (CS)	Difference between CV and CS in	
			Absolute value	Relative value
Lower-middle country mean	-10.51	-10.50	0.01	0
CHN	-16.32	-16.28	0.03	0
EGY	-10.04	-10.02	0.02	0
IDN	-1.43	-1.43	0.00	0
IND	-17.87	-17.85	0.02	0
IRN	-8.87	-8.85	0.02	0
NGA	-0.40	-0.40	0.00	0
PAK	-23.32	-23.33	-0.01	0
THA	-5.86	-5.85	0.01	0
Upper-middle country mean	-41.84	-41.77	0.07	0
ARG	-73.12	-73.01	0.10	0
BRA	-43.12	-43.05	0.08	0
MEX	-27.64	-27.59	0.06	0
RUS	-41.67	-41.59	0.08	0
TUR	-52.83	-52.74	0.09	0
ZAF	-12.67	-12.64	0.03	0
Higher-middle country mean	-14.73	-14.72	0.01	0
POL	-26.12	-26.11	0.02	0
KOR	-3.34	-3.34	0.00	0

Source: Own calculation.

6.2 | Methodological issues

There are also some drawbacks related to the Exact Consumer Welfare measure. First, this method becomes very complicated for multiple price changes as we cannot recover the complete expenditure function in case of multiple price changes (Irvine & Sims, 1998; Shin & Burke, 2010). Hence, we chose to focus only on one commodity rather than extending the analysis to a more comprehensive assessment that would include highly processed dairy products with a higher carbon footprint than fresh dairy products. Producing 1 kg of cheese releases 21 kg of CO₂

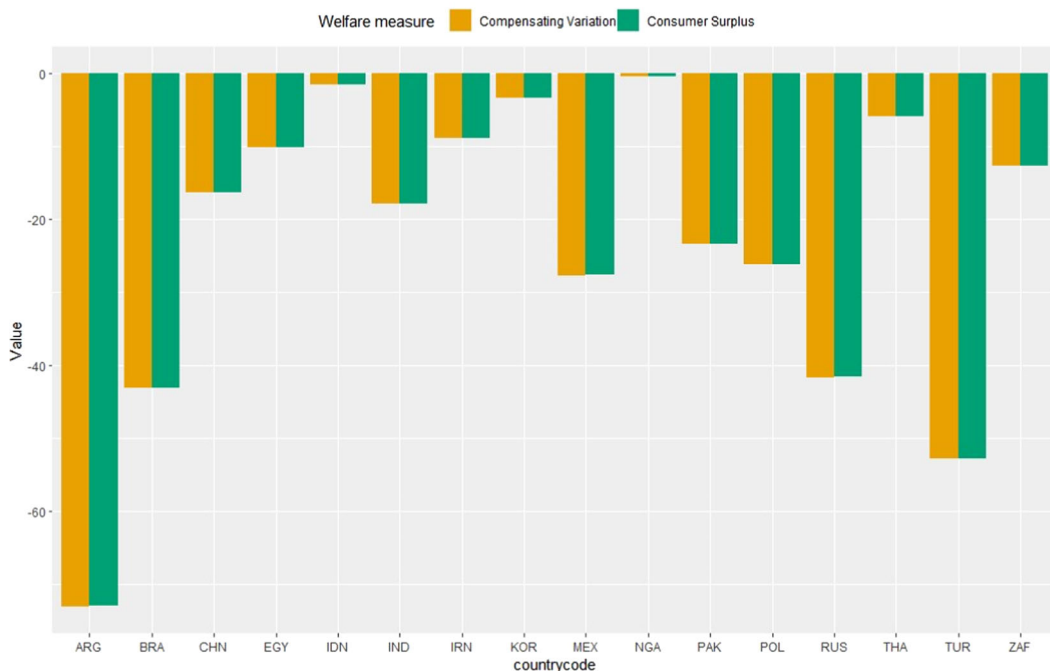


FIGURE 5 Comparison of compensating variation by Hausman (1981) and consumer surplus. Source: Own calculation.

equivalents, while the production of one litre of milk releases only 3 kg of CO₂ equivalents. Moreover, a comprehensive study would also consider more food groups, including animal source-based food such as different kinds of meat with a higher carbon footprint than dairy or fruits and vegetables with a lower carbon footprint. The production of beef and lamb meat is associated with 60 kg and 24 kg of CO₂ equivalents, respectively. Further, the production of a kilogram of apples or a kilogram of root vegetables is associated with 0.4 CO₂ equivalents (Poore & Nemecek, 2018).

Second, the Exact Consumer Welfare measure proposed by Hausman (1981) would be difficult to implement in the case of complex demand functions (Irvine & Sims, 1998; Shin & Burke, 2010). Since we focus only on one food commodity, we argue that a simple, linear demand function is sufficient. In fact, milk is usually regarded as a normal good, which is also confirmed by our regression result (positive income elasticity). However, if we would include other food groups that are, for example, luxury goods, a more complex, nonlinear model might be required and alternative welfare measurements would be more appropriate.

6.3 | Choice of regressors

Contrary to most of the animal source-based food demand literature, we only find a small and insignificant effect of urbanization in the demand estimation. We argue that in our demand specification, the effect that urbanization has on milk consumption can be already explained by our substantial population coefficient (Gouel & Guimbard, 2018).

In fact, evidence of whether urbanization itself is changing food demand is mixed. Several studies include urbanization in their food demand estimations but acknowledge that urbanization affects consumption rather through accompanying variables, such as differences in physical activity levels, raising opportunity costs of food preparation (especially for women), occupations, incomes, and different food prices between urban and rural areas

(Cockx et al., 2018; Colen et al., 2018; McCullough et al., 2022). Arguments in favor of including urbanization in food demand estimations are that consumers in urban areas have a higher exposure to product advertisements and to Western culture, which is characterized by higher consumption levels of animal-sourced food (Milford et al., 2019; York & Gossard, 2004).

Further, the evidence about differences in consumption patterns between urban and rural residents is contested as well. A study that estimated the environmental footprint of changing diets in China between 1997 and 2011 finds substantial differences between urban and rural residents. He et al. (2018) show that cereal consumption declined and meat consumption increased at higher rates for rural residents compared with urban residents. However, they mention that consumption patterns of rural and urban residents converge, implying that the shift in diets could be attributed to other variables, such as income (He et al., 2018). Another study investigates the changing consumption patterns of rural–urban migrants in Tanzania found no significant effect on the intake of fats, animal-source foods, and dietary diversity after relocating from rural to urban areas. Nevertheless, after moving to urban areas, residents consumed fewer staples and more high-sugar and ready-to-eat foods (Cockx et al., 2018). Hence, we argue that urbanization might have a more substantial effect on staples or ultraprocessed meats, and to a lesser extent on the consumption of milk.

6.4 | Heterogeneity between economies

Usually, cross-country analyses of food demand analyses demonstrate that price and income elasticities vary from country to country, given differences in dietary preferences and availability of food. Colen et al. (2018) find that average income elasticities for dairy vary across the African continent, most notably 21.94% between the North and other parts of Africa (Colen et al., 2018).

However, we find that for the purposes of this paper, one price and income elasticity for one food item, which is in line with economic theory, are sufficient. We allow for a certain degree of heterogeneity by including a country fixed effect v_i (see Equation 3), which is also incorporated in the Exact Consumer Welfare calculation (see Equation 2a). A more comprehensive food demand estimation should nevertheless appropriately account for regional heterogeneities in price and income elasticities in the future.

6.5 | Distributional effects of a carbon tax on milk

Taxes imposed on consumption goods are financially regressive at first glance. However, many papers demonstrated that the ultimate distributional impact depends highly on the tax design and that a carbon tax can be even financially progressive under well-designed redistribution measures (Klenert et al., 2022; Saelim, 2019; Säll, 2018). The most commonly considered redistribution measurements are a uniform lump-sum redistribution of the tax revenue or the combination of a subsidy on healthy and environmentally friendly food groups. Springmann et al. (2016) show in a global modeling study that the optimal carbon tax scenario would include a subsidy on fruits and vegetables in 88% of middle-income countries. This optimal scenario could prevent up to 18.39 thousand deaths in low- and middle-income economies in Africa and up to 197.78 thousand deaths in low- and middle-income economies in the Western Pacific due to diet-related diseases (Springmann et al., 2016).

On the country level, we find only a few studies that simulated redistribution measures for revenues from a carbon tax on food in emerging economies. In the case of Thailand (THA), in a scenario where carbon tax revenues would be used for increasing pensions for elderly people, the lowest quintile would receive a welfare gain of 2.8% (Saelim, 2019). A targeted transfer via the local social welfare program could reduce poverty incidences and emission outcomes simultaneously in Mexico (MEX) (Renner et al., 2018). In Brazil, a revenue-neutral lump-sum

transfer would lead to compensation for low- and high-income households of 0.7 and 0.02% of their expenditure, respectively (Moz-Christofolletti & Pereda, 2021). A study from 2011 found that in the case of Indonesia, revenue recycling generated by a carbon tax on food would lead to a positive net benefit for the four lowest-income groups and a negative net benefit for the four highest-income groups (Sofyan, 2011).

7 | CONCLUSIONS

A carbon tax on milk generates a financial welfare loss, and there are different theoretical concepts to quantify such a welfare loss. We use the Exact Consumer Welfare measure to calculate the monetary consequences of a carbon tax on milk across emerging economies. We find that on average, upper-middle-income economies experience a higher financial welfare loss than lower and higher-middle-income economies. Particularly, Argentina and Türkiye are the two countries with relatively high welfare losses due to a possible carbon tax on milk products. Methodologically, we also confirm that the discrepancy between CV and CS is very small, though CV is slightly larger than CS in terms of absolute values. We limit the analysis to milk and a simple demand function since the application of the Exact Consumer Welfare to multiple price changes or complex demand functions is not trivial. Further, we do not allow for differences in price and income elasticities across emerging economies. Additionally, we do not incorporate any redistribution measures. To further increase the public acceptance of a carbon tax on milk and food in general, our theoretically consistent results can serve as a basis for simulating different types of income support to offset the financially regressive effects of taxation. The design of a carbon tax on milk should exploit advantages for the climate and nutrition and compensate consumers for the anticipated financial welfare loss. Future research should incorporate multiple food groups, account for national heterogeneities, and emphasize designing effective redistribution measurements.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available on GitHub at https://github.com/wehnerjasmin/carbon_tax_milk_exact_consumer_welfare.

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PEER REVIEW

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APPENDIX A

TABLE A1 Descriptive statistics for relevant variables and each country for the Years 2000 and 2019.

Variable	Country	Mean	SD	P0	P25	P50	P75	P100
Quantity kg	ARG	183.06	19.47	139.36	170.06	184.44	191.99	224.43
	BRA	131.73	13.71	109.23	119.75	137.03	143.20	149.74
	CHN	22.57	5.83	9.45	21.85	23.25	26.63	29.56
	EGY	46.28	12.25	24.80	36.77	45.00	54.89	66.40
	IDN	7.06	2.54	4.35	4.78	6.29	9.53	11.31
	IND	63.76	8.93	47.68	59.24	63.08	70.86	77.87
	IRN	41.49	20.56	17.63	22.87	40.90	59.85	66.53
	KOR	18.09	9.81	6.67	8.73	17.73	26.90	33.70
	MEX	99.38	9.71	87.73	90.33	98.94	109.04	110.29
	NGA	4.57	3.52	1.21	1.31	3.84	7.51	12.57
	PAK	130.52	31.99	84.94	103.69	132.56	157.09	172.33
	POL	173.40	13.20	152.90	165.07	168.05	181.59	198.35
	RUS	148.27	12.28	129.30	138.94	145.31	156.32	172.68
	THA	18.98	5.20	11.67	14.58	17.89	23.21	30.17
	TUR	144.26	18.67	105.53	131.76	143.56	156.75	179.15
	ZAF	52.76	5.37	40.08	49.69	52.66	55.65	62.97

TABLE A1 (Continued)

Variable	Country	Mean	SD	P0	P25	P50	P75	P100
P cons USD	ARG	1.80	0.67	0.66	1.12	1.87	2.40	2.79
	BRA	1.47	0.58	0.58	0.97	1.52	1.86	2.33
	CHN	2.78	0.86	1.22	1.98	2.97	3.49	3.97
	EGY	1.37	0.42	0.75	0.99	1.32	1.76	2.01
	IDN	1.42	0.38	0.76	1.09	1.49	1.62	2.16
	IND	0.92	0.27	0.50	0.68	1.02	1.13	1.22
	IRN	1.26	0.51	0.54	0.83	1.32	1.58	2.25
	KOR	2.86	1.08	1.23	1.65	3.16	3.56	4.72
	MEX	1.40	0.20	1.11	1.29	1.34	1.46	1.84
	NGA	2.72	1.09	1.23	1.93	2.62	3.14	4.70
	PAK	1.26	0.25	0.93	1.07	1.13	1.51	1.72
	POL	0.96	0.27	0.53	0.82	1.00	1.16	1.35
	RUS	1.22	0.45	0.49	0.87	1.26	1.57	1.84
	THA	1.52	0.38	0.95	1.09	1.71	1.80	2.04
	TUR	1.89	0.47	1.05	1.53	1.96	2.16	2.69
	ZAF	1.65	0.39	0.92	1.48	1.63	1.95	2.20
	GDP pc USD	ARG	9524.41	3974.52	2707.99	6900.41	9599.59	12958.89
BRA		7935.32	3459.61	2839.49	4530.32	8762.03	10268.02	13245.39
CHN		4795.22	3219.30	959.36	1692.23	4191.35	7731.17	10143.86
EGY		2178.71	846.89	979.83	1372.90	2193.34	2911.83	3437.27
IDN		2506.11	1235.31	748.26	1235.03	2691.80	3628.71	4135.23
IND	1202.47	554.56	450.65	693.87	1216.39	1592.26	2086.27	

(Continues)

TABLE A1 (Continued)

Variable	Country	Mean	SD	P0	P25	P50	P75	P100
	IRN	5583.95	1934.18	2202.56	4622.09	5787.64	6490.54	8703.25
	KOR	22945.88	6842.92	11563.04	18475.03	23581.30	28866.31	33447.16
	MEX	9026.02	1216.33	7075.36	7900.53	9279.62	9966.79	10928.96
	NGA	1890.78	816.93	567.93	1203.26	2060.83	2401.00	3222.69
	PAK	1012.45	350.22	511.90	730.14	946.45	1290.76	1621.58
	POL	10928.21	3762.52	4501.48	7686.49	12512.99	13868.25	15732.31
	RUS	8845.44	4531.59	1771.65	5018.05	9207.13	11561.02	15974.62
	THA	4596.77	1864.98	1893.26	2835.58	4728.00	5962.24	7814.38
	TUR	8861.13	2973.24	3142.95	7117.66	9623.03	10957.30	12614.99
	ZAF	6134.51	1672.31	2797.07	5669.77	6441.70	6988.89	8810.89
Population	ARG	40784703.75	2503901.13	36870796.00	38792685.50	40635619.50	42785116.50	44938712.00
	BRA	194149200.30	11173192.33	174790339.00	185596950.75	194800071.00	203190747.75	211049519.00
	CHN	1336715500.00	45225608.78	1262645000.00	1301808750.00	1334482500.00	1373860000.00	1407745000.00
	EGY	83177681.25	9866836.71	68831561.00	75185700.25	81948016.50	90929138.25	100388076.00
	IDN	240709424.70	18639002.16	211513822.00	225538517.50	240227390.00	255941871.25	270625567.00
	IND	1219996989.90	96916308.58	1056575548.00	1143113309.50	1226003690.00	1299238674.00	1366417756.00
	IRN	7372991.40	5278375.57	65623397.00	69559578.50	73343676.00	77722378.75	82913893.00
	KOR	49473879.50	1518605.23	47008111.00	48159050.50	49430973.50	50813731.00	51764822.00
	MEX	113223693.85	9121951.87	98899845.00	105632632.75	113278423.50	120730915.50	127575529.00
	NGA	158367497.60	24629396.57	122283853.00	137978865.50	156414071.00	177588061.75	200963603.00
	PAK	178165397.95	23057502.20	142343583.00	159394179.75	177475126.50	196335497.25	216565317.00
	POL	38096059.45	99415.10	37965475.00	38005404.25	38091907.50	38169639.25	38258629.00

TABLE A1 (Continued)

Variable	Country	Mean	SD	P0	P25	P50	P75	P100
	RUS	143982797.35	1087706.20	142742366.00	143027454.75	143943491.50	144482579.00	146596869.00
	THA	66799851.50	2050418.45	62952639.00	65310967.50	67030933.00	68507690.75	69625581.00
	TUR	72623985.35	6280181.68	63240196.00	67880328.25	71824199.00	77554299.75	83429607.00
	ZAF	51284313.55	4298737.14	44967713.00	47733348.75	50846990.00	54754730.25	58558267.00
Urb rate	ARG	90.68	0.89	89.14	89.99	90.77	91.41	91.99
	BRA	84.13	1.75	81.19	82.76	84.19	85.56	86.82
	CHN	48.34	7.68	35.88	42.18	48.55	54.57	60.31
	EGY	42.90	0.13	42.70	42.79	42.91	43.02	43.08
	IDN	49.26	4.38	42.00	45.74	49.52	52.80	55.98
	IND	30.86	2.11	27.67	29.15	30.76	32.48	34.47
	IRN	70.11	3.52	64.04	67.39	70.34	72.96	75.39
	KOR	81.32	0.67	79.62	81.26	81.55	81.74	81.94
	MEX	77.64	1.78	74.72	76.23	77.67	79.07	80.44
	NGA	43.02	5.13	34.84	38.86	43.03	47.20	51.16
	PAK	34.91	1.21	32.98	33.93	34.89	35.87	36.91
	POL	60.93	0.62	60.04	60.37	60.95	61.48	61.79
	RUS	73.76	0.38	73.34	73.45	73.66	73.98	74.59
	THA	42.09	6.16	31.39	37.10	43.20	47.13	50.69
	TUR	70.40	3.42	64.74	67.69	70.53	73.21	75.63
	ZAF	61.91	3.13	56.89	59.40	61.95	64.44	66.86

Source: Own calculation.

TABLE A2 Descriptive statistics for relevant variables and each year for 16 emerging economies.

Variable	Year	Mean	SD	P0	P25	P50	P75	P100
Quantity kg	2000	84.82	68.57	6.09	26.78	60.68	131.35	224.43
	2001	83.90	66.99	6.14	27.07	61.04	125.13	217.46
	2002	81.73	61.79	6.30	30.32	60.66	123.33	198.35
	2003	83.54	61.69	7.81	25.95	62.94	134.77	196.90
	2004	82.10	58.34	8.03	28.90	63.87	133.12	181.64
	2005	86.15	62.16	7.41	26.62	64.59	140.45	185.41
	2006	86.92	61.52	8.33	25.95	67.52	147.56	182.71
	2007	89.91	63.27	11.12	27.86	69.41	150.29	194.62
	2008	89.76	64.93	7.00	27.98	71.03	146.87	202.06
	2009	89.91	65.33	7.95	28.71	67.81	149.27	191.44
	2010	71.70	61.99	1.30	20.66	50.44	127.71	186.17
	2011	72.69	63.06	1.60	20.34	51.38	137.68	180.22
	2012	74.43	64.32	1.57	20.74	52.18	145.19	185.74
	2013	76.32	66.85	1.53	22.30	50.58	145.67	183.48
	2014	75.83	65.53	1.54	20.76	51.92	138.62	187.58
	2015	75.12	65.65	1.32	17.06	55.00	133.59	193.63
2016	75.02	64.45	1.27	17.38	56.95	135.90	180.58	
2017	75.52	63.63	1.24	19.25	60.46	135.98	170.26	
2018	76.03	64.90	1.22	18.74	60.65	138.89	174.74	
2019	76.36	66.95	1.21	21.10	56.94	139.66	181.58	
2000	1.10	0.38	0.49	0.94	1.10	1.29	1.82	
P cons USD	2001	1.03	0.40	0.51	0.73	0.98	1.22	1.94
	2002	0.96	0.42	0.50	0.57	0.92	1.19	2.03

TABLE A2 (Continued)

Variable	Year	Mean	SD	P0	P25	P50	P75	P100
	2003	1.07	0.43	0.54	0.69	1.09	1.34	2.00
	2004	1.24	0.63	0.61	0.79	1.09	1.47	2.85
	2005	1.34	0.65	0.65	0.95	1.08	1.61	2.98
	2006	1.58	1.08	0.72	1.01	1.12	1.67	4.72
	2007	1.80	1.00	0.86	1.16	1.35	2.06	4.09
	2008	1.86	0.89	0.91	1.33	1.68	1.95	4.17
	2009	1.67	0.67	0.86	1.22	1.57	1.95	3.18
	2010	1.93	0.79	1.06	1.34	1.73	2.35	3.85
	2011	2.02	0.63	1.20	1.44	2.10	2.40	3.26
	2012	2.19	0.91	1.14	1.64	2.06	2.32	4.49
	2013	2.22	0.92	1.06	1.81	1.88	2.39	4.65
	2014	2.23	1.00	1.11	1.70	1.84	2.37	4.70
	2015	1.93	0.84	0.93	1.51	1.57	2.03	3.63
	2016	1.71	0.65	0.87	1.36	1.60	1.75	3.43
	2017	1.78	0.72	1.11	1.35	1.58	1.75	3.70
	2018	1.71	0.69	1.14	1.33	1.52	1.72	3.51
	2019	1.74	0.66	1.02	1.38	1.47	1.98	3.45
GDP pc USD	2000	3564.75	3299.26	450.65	914.57	2691.22	4731.86	12263.47
	2001	3472.58	3220.49	456.43	976.90	2536.14	5327.09	11563.04
	2002	3103.57	3267.44	469.01	1086.43	2290.10	3051.59	13159.67
	2003	3485.28	3554.23	539.32	1044.19	2667.12	4352.85	14672.42

(Continues)

TABLE A2 (Continued)

Variable	Year	Mean	SD	P0	P25	P50	P75	P100
	2004	4103.17	3994.52	622.45	1126.68	3196.76	5582.22	16482.75
	2005	4848.94	4695.03	717.68	1267.11	4018.25	6388.90	19398.49
	2006	5531.46	5216.51	805.73	1639.77	4830.37	7215.68	21730.95
	2007	6513.51	5840.19	906.54	1877.60	5842.79	9236.60	24083.34
	2008	7141.34	5621.96	880.21	2223.57	6033.97	10247.66	21387.71
	2009	6374.93	4732.21	920.31	2302.87	6121.35	8571.57	19139.12
	2010	7680.64	5666.26	972.60	2990.09	7403.39	10691.85	23079.26
	2011	8823.51	6337.58	1154.53	3415.79	8757.07	12947.90	25097.59
	2012	8971.39	6383.01	1146.10	3570.72	8403.41	12551.94	25459.17
	2013	9222.52	6794.20	1151.67	3483.71	7507.29	12885.34	27179.52
	2014	9104.51	7023.05	1274.67	3450.77	7309.78	12440.65	29252.93
	2015	8307.64	6742.84	1339.01	3410.88	7136.12	9964.06	28737.44
	2016	8071.13	6734.17	1533.92	3387.47	7043.85	9282.02	29280.44
	2017	8772.27	7389.65	1621.58	3384.02	7751.26	10622.26	31600.73
	2018	8942.40	7688.08	1515.78	3554.77	8225.16	10250.89	33447.16
	2019	8923.70	7284.71	1347.95	3891.73	8392.68	10093.23	31902.42
Pop	2000	227712618.81	369397159.41	36870796.00	58966507.00	83865703.00	153645236.50	1262645000.00
	2001	230557438.38	373556554.85	37275644.00	59496933.50	85225407.00	153782818.75	1271850000.00
	2002	233340099.12	377598242.32	37681743.00	59963003.75	86584904.00	157046652.00	1280400000.00
	2003	236078612.06	381538039.54	38087866.00	60385482.75	87953561.00	160272339.25	1288400000.00
	2004	238795992.81	385416727.67	38182222.00	60767107.00	89343503.50	163500143.25	1296075000.00

TABLE A2 (Continued)

Variable	Year	Mean	SD	P0	P25	P50	P75	P100
	2005	241510539.38	389287133.60	38165445.00	61108282.00	90764387.50	166759782.25	1303720000.00
	2006	244219956.44	393084096.65	38141267.00	61481771.00	92216912.50	170058807.75	1311020000.00
	2007	246916477.12	396786855.10	38120560.00	61916489.50	93701313.50	173388690.75	1317885000.00
	2008	249627968.88	400432014.99	38125759.00	62343103.00	95225676.50	176744328.50	1324655000.00
	2009	252328759.94	403990001.97	38151603.00	62769378.75	96799337.50	180115833.75	1331260000.00
	2010	255003275.88	407449925.46	38042794.00	63200515.75	98427102.50	183496891.50	1337705000.00
	2011	257759129.81	410962819.73	38063255.00	63639724.00	100112359.50	186883761.25	1345035000.00
	2012	260623258.56	414715385.98	38063164.00	64085141.50	101848198.00	190281916.75	1354190000.00
	2013	263474990.31	418379504.19	38040196.00	64530170.50	103615905.00	193704575.25	1363240000.00
	2014	266297991.25	421918208.35	38011735.00	64965107.00	105389902.50	197169695	1371860000.00
	2015	269067832.44	425322425.50	37986412.00	65382481.50	107150400.00	200688154.50	1379860000.00
	2016	271818138.62	428692413.53	37970087.00	65780397.00	108890225.00	204264281	1387790000.00
	2017	274579008.75	432123790.96	37974826.00	66159800.50	110609958.00	207851921.25	1396215000.00
	2018	277197059.12	435208574.35	37974750.00	66519470.50	112307192.00	210159062	1402760000.00
	2019	279683311.56	438011058.66	37965475.00	66858752.50	113981802.50	212428468.50	1407745000.00
Urb rate	2000	55.81	20.46	27.67	35.62	59.3	73.69	89.14
	2001	56.28	20.29	27.92	36.74	59.56	73.77	89.33
	2002	56.77	20.11	28.24	37.95	59.84	73.85	89.51
	2003	57.25	19.94	28.57	39.17	60.06	73.95	89.69
	2004	57.74	19.76	28.9	40.41	60.28	74.06	89.86
	2005	58.22	19.59	29.23	41.66	60.49	74.17	90.03

(Continues)

TABLE A2 (Continued)

Variable	Year	Mean	SD	P0	P25	P50	P75	P100
	2006	58.70	19.42	29.57	42.29	60.71	74.28	90.2
	2007	59.16	19.24	29.91	42.51	60.92	74.39	90.37
	2008	59.62	19.07	30.25	42.72	61.14	74.5	90.53
	2009	60.08	18.9	30.59	42.93	61.35	74.61	90.69
	2010	60.54	18.75	30.93	43.76	61.56	74.72	90.85
	2011	60.95	18.62	31.28	44.61	61.76	74.83	90.99
	2012	61.34	18.5	31.63	45.4	61.96	74.94	91.12
	2013	61.73	18.39	32	46.17	62.16	75.07	91.25
	2014	62.13	18.28	32.38	46.97	62.36	75.21	91.38
	2015	62.52	18.18	32.78	47.8	62.55	75.36	91.5
	2016	62.91	18.08	33.18	48.62	62.76	75.52	91.63
	2017	63.30	17.99	33.6	49.44	62.98	75.95	91.75
	2018	63.69	17.9	34.03	50.25	63.21	76.4	91.87
	2019	64.09	17.81	34.47	51.04	63.58	76.83	91.99

Source: Own calculation.

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