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Working Paper

Carbon footprint, demography, and employment status?

Thünen-Series of Applied Economic Theory - Working Paper, No. 163

Provided in Cooperation with:

University of Rostock, Institute of Economics

Suggested Citation: Carlhoff, Henrik (2019) : Carbon footprint, demography, and employment status?, Thünen-Series of Applied Economic Theory - Working Paper, No. 163, Universität Rostock, Institut für Volkswirtschaftslehre, Rostock

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Thünen-Series of Applied Economic Theory
Thünen-Reihe Angewandter Volkswirtschaftstheorie

Working Paper No. 163

Carbon Footprint, Demography, and Employment Status?

by

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2019

Carbon Footprint, Demography, and Employment Status

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Abstract

This paper investigates the interplay between aging of a society and its carbon dioxide emissions. The existing literature based on US data predicts lower overall emissions due to the lower emission intensity of consumption of a growing old-age share of the population. This conjecture is reexamined by a multivariate approach. The underlying hypothesis is that the individual levels of emissions do not only depend on age but also on income and employment status, which are correlated with age. Thus, bivariate analyses, neglecting other relevant variables, might overstate the decline in emissions for older cohorts. The paper shows that this hypothesis is correct. A bivariate approach overestimates the decline of emissions caused by population aging. Policy decisions favoring a longer work life may reverse the dampening effect of aging on emissions.

JEL-classification: J11, Q54

*I am indebted to Michael Rauscher for helpful suggestions that lead to major improvements of the paper.

1 Introduction

Global greenhouse gas emissions need to be cut drastically within the next decades. The goal laid down in the 2015 Paris Agreement is to cap the rise of average global temperature at 2°C or lower until 2050 compared to the pre-industrial era. The human impact on climate can be divided into its components via the IPAT-identity, $I = PAT$, where I is the impact on the environment, P is population, A is affluence, and T is technology measured by GDP per capita and emissions per unit of GDP, respectively. This identity can be applied to countries as well as to individuals. The individual impact is determined by consumption and its emission intensity. Due to personal needs and restrictions, consumption good bundles change over the individual's life-cycle and therefore the corresponding emissions of greenhouse gases vary as well.

From a demographic perspective, the societal impact would be calculated as the sum of emissions of all cohorts alive. The age composition of a society, however, is not constant. Societies undergoing demographic change age on average. Shares of older people rise relative to shares of younger people. Moreover, life expectancy rises in most countries. In order to identify the impact of aging on greenhouse gas emissions, one has to determine age-specific emissions and analyze the influence of restrictions such as budget constraints.

Several studies identify emission-intensive age groups in cross-country studies. Cole and Neumayer (2004) use dependent (0-14), economically active (15-64) and elderly (65+) as age groups in a linear regression model with IPAT controls. For 86 countries and 24 years (1975-1998) they find an only small, but significant effect of the economically active age group on the emission levels, which becomes insignificant if the average household size is added as a control. A reduction of the average household on the national level by one person leads to 49.9 % additional emissions. Menz and Welsch (2012) propose a similar channel resulting in higher emissions. They use a panel of 26 OECD countries from 1960-2005 and a larger number of age groups than Cole and Neumayer (2004). Their regression results show that age group 60-74 has the most emission-intensive lifestyle, which the authors argue to be caused by a higher probability of older people living alone (and also in larger houses). Furthermore, they find that cohorts born after 1960 are associated with the largest carbon footprints. Different results are reported by Lugauer et al. (2014). They identify the prime-age workers (35-49 years) to be those associated with the highest emissions. They use a two-stage OLS procedure to show that a one percentage point increase in the share of the prime-age workers (instrumented by lagged birth rates) raises emissions by 6.1 percentage points. It follows from their results that 60% of

the actual increase of emissions in their data (46 OECD countries from 1990-2006) is due to the higher share of the prime-age working group.

Age profiles of emissions differ across all goods. Therefore, disaggregation of aggregate CO₂ emissions into good-specific emissions yields further insight. Liddle (2011) studies emissions from transportation and residential energy use for five different age groups, young people under 20 being the benchmark. In transportation, people aged 20-34 consume most emission-intensively while other age groups have lower emissions, the lowest being the group 50-69. Emissions follow a u-shaped age profile for residential energy use, the highest emissions being caused by the groups of people 70+ and 20-34. Zagheni (2011) uses nine different consumption categories of emission-intensive goods to calculate the age-specific emission profiles. Analyzing 2003 Consumer Expenditure data, he shows that the average CO₂ emissions from consumption are hump-shaped with respect to age in the US, the peak being around the age of 62. Combining those age profiles with population forecast, he calculates future levels of emissions. Zagheni concludes that, due to population ageing, there will be a negative effect on overall emissions. The share of people associated with lower emissions is rising compared to the shares of high-emission age groups. He also considered that levels of consumption will change over time with commodity-specific trends. These trends are the same for all cohorts. The joint effect of an aging population and changing consumption leads to a small increase in overall emissions. Other economic factors, e.g. income and employment status, are left out in Zagheni's study. Those variables, e.g. the age-dependent heterogeneity of labor supply or income, are described by Dalton et al. (2008) and O'Neill et al. (2010) to be major determinants of emissions in the future. Both studies use the PET model¹ with different good categories to simulate future paths of emissions with age-specific labor supply. Dalton et al. (2008) developed a multi-dynastical model of households and combine it with three different population scenarios (high, medium, low) for the US until 2100. In the low population scenario, households are small and old and emissions can be reduced by 38% per year. In contrast, in the high population scenario emissions can be reduced up to only 11% with households being large and young. O'Neill et al. (2010) use expenditure data in four categories for 34 countries to

¹ PET stands for Population-Environment-Technology. "The Population-Environment-Technology (PET) model is an intertemporal general equilibrium economic growth model that projects global fossil-fuel based CO₂ emissions over time horizons of a century or more." (Dalton and Goulder (2001), Overview, P.1)

calibrate the PET-model. They state that the effect of reduced labor supply due to aging of the society can cut emissions by 20% until 2100, mainly for industrialized countries.

The main objective of this paper is to further investigate the age-specific carbon footprint à la Zagheni (2011) by considering additional variables emphasized by Dalton et al. (2008) and O'Neill et al. (2010). A multivariate approach to age-specific CO₂ emissions is needed due to the nature of consumption, which depends on many other variables besides age. Several adjustments are to be made to Zagheni's model. First, unemployment and retirement need to be considered as factors affecting the emission profiles, as individuals without jobs tend to consume less compared to employed people. Second, the shapes of the CO₂ emissions profiles might change over time due to changes in the macroeconomic environment. We apply the simple and multivariate models to datasets from two different years, 2003 and 2014, and compare the corresponding age profiles. Third, policy decisions regarding the extension of the work life may have an important impact and shift the peak of the individual emissions profile to the right. Future changes in participation rates of older age groups could raise overall emissions substantially. Policies are not explicitly examined, but the effect of changing age-specific employment shares on overall emissions is investigated. On aggregate these three effects could lead to a revision of Zagheni's conclusion.

The remainder of the paper is organized as follows. First, the process of data generation is explained as the translation from monetary spending to consumption related emissions is not trivial. Next, the simple and multivariate models are presented and their results are compared. Afterwards, the effect of changing age-specific employment shares is analyzed. The paper concludes with an interpretation of the empirical results and a summary of their implications.

2 Data

We use data from the 2003 and 2014 Consumer Expenditure Surveys² for the US. Eight broad consumption categories are taken to approximate energy-intensive goods: food, clothes, gasoline, natural gas, electricity, air flights, tobacco, and furniture. Furthermore, the datasets contain information on age, employment status, financial assets, total expenditures of consumers and many more. For simplicity only single-person households are considered. This avoids the economy of scale bias of household size described by Nelson (1988). The use of equivalence scales for multi-person households is possible, but more common if consumption

² The Consumer Expenditure Survey is published annually by the Bureau of Labor Statistics (2018). Public-use microdata can be found at https://www.bls.gov/cex/pumd_data.htm#stata.

is aggregated or if income is the dependent variable. Using equivalence scales for consumption of multi-person households inflates the sum of overall consumption and emissions compared to the observed data. It is questionable if scale effects of larger households would be represented correctly in the regressions. Such effects are obviously excluded if only single-person households are used, but this avoids problems regarding the estimation procedure of the scale parameters. The overall emission level from the relevant goods can be interpreted as an upper bound. Quarterly expenditures are calculated based on the interview files³.

To translate expenditures into CO₂-equivalent emissions, informations from several sources are combined. As in Zagheni (2011), the Economic Input-Output Life Cycle Assessment Model (EIO-LCA) created by Carnegie Mellon University Green Design Institute (2018) is used for coefficients of the year 2003. Unfortunately, later versions are not available. Therefore, input-output tables from the World Input-Output Database (WIOD)⁴ published by Timmer et al. (2015) are used, which include emissions of different greenhouse gases⁵ (GHG) from production of each sector. Intersectoral relationships from the input-output tables are translated from Dollar values into CO₂-equivalent emissions by

$$e_{ij} = \frac{a_{ij}}{b_j}, \quad (1)$$

where a_{ij} are inputs required from sector j for production in sector i and b_j is the CO₂-equivalent emission of sector j per US-Dollar of its output. The matrix E includes all intersectoral relationships e_{ij} . The input-output model in terms of emissions is $Ex + f = x$, where x is representing emissions from production and f final demand, and by rearranging terms we get $x = (I - E)^{-1} f$. Additional emissions from additional demand can be calculated as

$$\Delta x = (I - E)^{-1} \Delta f. \quad (2)$$

This is done for the years 2003 and 2009⁶ and the percentage changes of the coefficients are calculated for all categories of goods. To get 2014 conversion factors, the percentage change from 2003 to 2009 is linearly extrapolated up to 2014. This percentage change is applied to the 2003 EIO-LCA model coefficients. This is done since the EIO-LCA model uses a finer differentiation of goods, e.g., food and tobacco are in the same category in the WIOD input-output tables, but in the EIO-LCA model they are not. Therefore, their conversion factors differ

³ The public-use microdata contains interview and diary files. The diary files are not included because it wasn't possible to calculate the same expenditures for the overlapping households in both files.

⁴ Environmental accounts have been provided by Genty et al. (2012) available at: <http://www.wiod.org/release13>.

⁵ The CO₂ equivalents from the GHGs are calculated using the coefficients shown in Table 8 in the appendix.

⁶ Environmental accounts are only available until 2009.

but have the same relative change from 2003 to 2014 (almost 30%). For all fossil sources of energy, e.g., gasoline, coal and natural gas, emissions per unit are a physical constant, and emissions per US-Dollar can change only if prices change. CO₂-equivalent⁷ emissions per unit are divided by the average prices per unit⁸ for respective goods⁹. Conversion factors for the relevant goods are shown in Table 1. Table 1

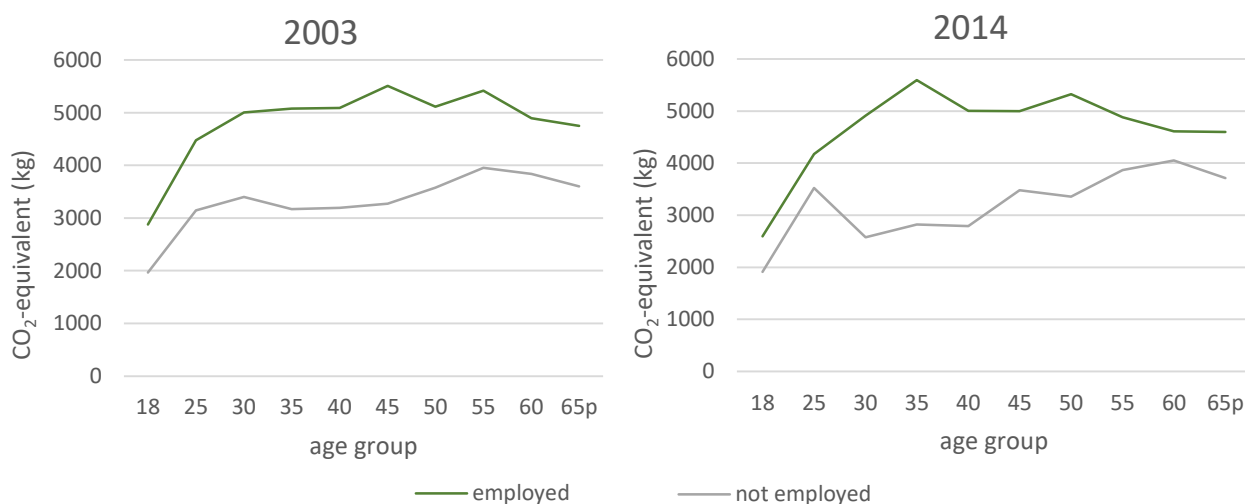
Table 1: CO₂-equivalent emissions (kg) per US-Dollar spent

	Food	Clothes	Electricity	Air flights	Furniture	Tobacco	Gasoline	Natural Gas
2003	1.70	0.96	9.37	1.98	0.62	0.31	5.505	5.133
2014	1.19	0.53	6.07	1.50	0.31	0.22	2.561	4.207

Source: 2003: Carnegie Mellon University Green Design Institute (2018). 2014: own calculations.

Applying the coefficients to the expenditure data and separating individuals by employment status, we can depict the impact of employment on emissions. A very broad concept of employment is used here. Employed and self-employed people are counted as employed, everyone else is not employed (including persons that do not work because they are old, sick, or do not want to work without being officially counted as unemployed).

Figure 1: Average CO₂-equivalent emissions for persons employed and not employed in 2003 and 2014 by age groups



Age group shows the minimum age of five (seven for age 18 to 24) year age groups, 65p: 65 and older.

⁷Conversion factors are calculated from data of the U.S. Environmental Protection Agency (available at: https://www.epa.gov/sites/production/files/2015-11/documents/emission-factors_nov_2015.pdf)

⁸Calculations use average annual retail prices from the Energy Information Administration (available at: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPM0_PTE_NUS_DPG&f=M and <https://www.eia.gov/dnav/ng/hist/n3010us3m.htm>)

⁹Additional information on calculations for gasoline and natural gas can be found Table 9 in the appendix.

3 The Simple and the Multivariate Approach

3.1 OLS regressions and evaluation method

We distinguish bivariate and multivariate models. For each good considered, the two models are estimated separately. To replicate the use of the average consumption of one-year cohorts in Zagheni's version in regressions, emissions from consumption of good j by individual i are estimated using only age and its square as covariates:

$$emission_{ij} = \beta_{0j} + \beta_{1j} age_i + \beta_{2j} age_i^2 + u_i. \quad (3)$$

The second model is the multivariate approach which includes unemployment and income with control variables retirement and financial stock¹⁰ as additional regressors:

$$emission_{ij} = \gamma_{0j} + \gamma_{1j} age_i + \gamma_{2j} age_i^2 + \delta_{1j} notemployed_i + \delta_{2j} income_i \\ + \theta_1 retired_i + \theta_2 financialstock_i + \varepsilon_i. \quad (4)$$

The results from these regressions are used to calculate the age-specific change of emissions in both models, holding other factors constant in the second approach. For each good the marginal impact of age on emissions is calculated, i.e.

$$\frac{d emission_j}{d age} = \beta_{1j} + 2\beta_{2j} age \quad \text{and} \quad \frac{d emission_j}{d age} = \gamma_{1j} + 2\gamma_{2j} age \quad (5)$$

respectively. These results are used to address over- or underestimation of emissions for older or younger shares of the population. The age at the intersection of those functions is called the crossover-age. For higher ages than the crossover-age, the multivariate model estimates a higher marginal effect from age on emissions than the simple model.

Datasets from different years are used. The 2003 dataset is used to discuss Zagheni's results and to show the bias of the results of the simple approach. To control for stability of the relation between emissions and age, the exercise is repeated with the 2014 dataset.

3.2 Regression results and age profiles

Table 2 and Table 3 show the estimated regression results for the four most relevant goods, the peak-ages of emissions, and crossover-ages in 2003 and 2014. Regarding the emissions from food and gasoline consumption in 2003, the crossover-age is lower than the peak-age¹¹ of

¹⁰ Financial stock includes all financial assets recorded in the datasets, e.g. savings and stocks.

¹¹ The age with maximum consumption can be calculated as $-\frac{\beta_1}{2\beta_2}$ and for the control model respectively. Graphical presentation can be found in Figure 3 and Figure 4 in the Ippendix.

emissions. For emissions from natural gas and electricity consumption, the opposite is observed.

Table 2: 2003 - regression results

	food		gasoline		natural gas		electricity	
age	48.349*	31.085*	37.668*	28.612*	21.838*	19.648*	93.178*	80.296*
	(2.666)	(2.708)	(2.627)	(2.752)	1.509	(1.693)	(3.650)	(4.230)
age ²	-0.492*	-0.326*	-0.460*	-0.354*	-0.169*	-0.150*	-0.773*	-0.650*
	(0.025)	(0.027)	(0.024)	(0.027)	(0.015)	(0.019)	(0.037)	(0.045)
not employed		-233.538*		-502.416*		-92.679*		-216.643*
		(28.927)		(32.121)		(18.151)		(48.441)
retired		272.317*		368.591*		115.355*		251.608*
		(35.050)		(35.072)		(27.631)		(62.311)
income		10.533*		4.726*		1.773*		8.110*
		(0.774)		(0.592)		(0.291)		(1.096)
financial stock		1.398*		0.547		-0.414		-0.102
		(0.645)		(0.648)		(0.332)		(0.914)
constant	301.614*	447.972*	397.435*	515.728*	-280.611*	-261.901*	-983.406*	-873.715*
	(62.109)	(56.329)	(62.183)	(61.028)	(30.036)	(31.597)	(74.763)	(76.669)
R ²	0.0453	0.1519	0.0785	0.1288	0.0365	0.0470	0.0870	0.1166
peak-age	49.17	47.74	40.92	40.41	64.63	65.49	60.25	61.80
crossover-age	51-52		42-43		58-59		52-53	

N=8480, *: significantly different from zero ($\alpha=0.01$), standard errors in parentheses.

If the simple model is used to project the change of emission of a one-year age cohort over the life-cycle, the influence of age seems to be overestimated. In a society undergoing demographic change with population aging, overall emissions are projected to decline while the multivariate model suggests rising emissions. Results for the analysis of the data from 2014 are similar in regard to over- and underestimation of emissions. Other results such as the relationship of the peak-age of emissions and the crossover-age are different. For food and electricity, the qualitative relationship does not change but the peak-ages are further apart and the crossover-age moves into the opposite direction of the peak-age, resulting in a higher distance from the peaks to the crossover-age. Changes are visible for emissions from gasoline and natural gas consumption. The sequence of peak and crossover-age is inverted. This indicates, that age-specific behavior changes over time. Figure 2 shows the estimated age profiles for both models

of CO₂-equivalent emissions summarized for eight goods in 2003 and 2014. The profiles in 2014 are flatter than in 2003. This indicates a declining effect of age on emissions. Forecasting emissions and presuming constant age-specific behavior with a changed age structure ignores the influence of a changed economic environment.

Table 3: 2014 - regression results

	food		gasoline		natural gas		electricity	
age	33.044*	19.662*	41.660*	32.838*	17.522*	15.696*	78.213*	71.528*
	(3.131)	(3.175)	(2.591)	(2.558)	(1.700)	(1.830)	(3.889)	(4.086)
age ²	-0.360*	-0.241*	-0.451*	-0.342*	-0.136*	-0.123*	-0.629*	-0.560*
	(0.030)	(0.032)	(0.024)	(0.025)	(0.017)	(0.020)	(0.038)	(0.042)
not employed		-245.947*		-485.160*		-84.521*		-57.826
		(33.310)		(27.151)		(18.005)		(51.041)
retired		336.057*		270.595*		118.730*		26.127
		(39.956)		(33.308)		(25.437)		(64.442)
income		9.162*		3.550*		1.734*		3.293*
		(0.593)		(0.439)		(0.277)		(0.652)
financial stock		-0.0003		0.0004		0.0000		0.0005
		(0.0005)		(0.0005)		(0.0003)		(0.0007)
constant	808.289*	885.108*	51.793	194.652*	-196.702*	-186.957*	-667.424*	-616.890*
	(73.852)	(71.235)	(61.065)	(59.083)	(35.516)	(36.396)	(84.215)	(85.302)
R ²	0.0253	0.1493	0.529	0.1261	0.0219	0.0405	0.0659	0.0750
peak-age	45.94	40.83	46.15	48.07	64.37	63.59	62.13	63.91
crossover-age	56-57		40-41		71-72		47-48	

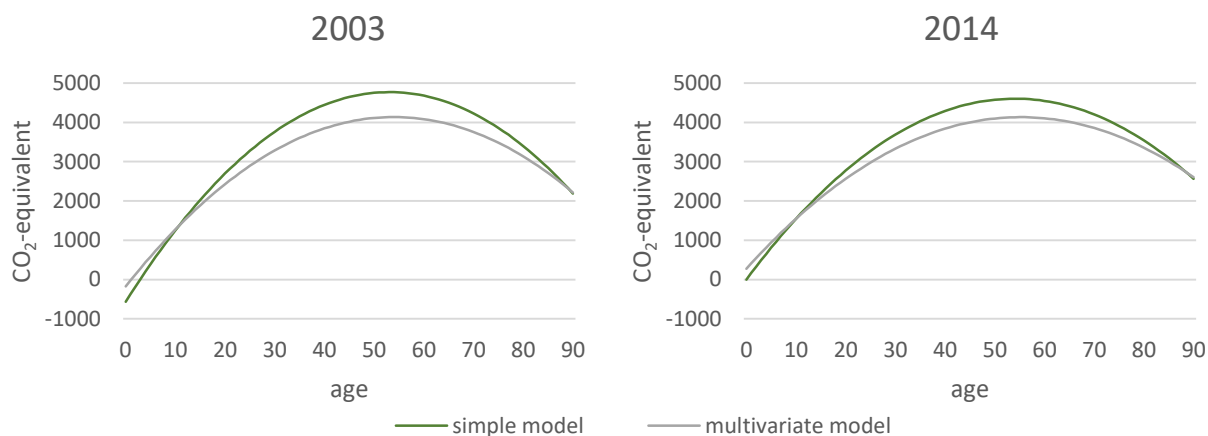
N=7207, *: significantly different from zero ($\alpha=0.01$), standard errors in parentheses.

The age profiles derived from the multivariate approach are flatter than those derived from the simple model in both years. The discrepancy is caused by economic factors such as income and the employment status. As age and economic factors are correlated, the simple model suffers from omitted variable bias. From these results the marginal effect of age on emissions in both models is calculated as described in chapter 3.1. The change of emissions with respect to age from both models can be compared.

For all goods considered, this comparison gives the same result: The simple model estimates stronger impact of age on emissions than the multivariate model. For the young part of the

population, an additional year results in a higher increase of emissions than in the multivariate model, for older people a larger reduction of emissions is estimated.

Figure 2: Profile of CO₂-equivalent emissions with respect to age.



Own calculations, CO₂-equivalent emissions in kg.

Table 4 lists crossover-ages of the four most relevant goods in 2003 and 2014 and the percentage of the population older than the crossover-age. From a demographic perspective it should be noted that the share of the population older than the crossover-age rose from 2003 to 2014 and it is predicted to rise even further from 2014 to 2025.

Table 4: Crossover-age and population forecast

good		food		gasoline		natural gas		electricity	
year (t)		2003	2014	2003	2014	2003	2014	2003	2014
crossover-age (v)		51-52	56-57	42-43	40-41	58-59	71-72	52-53	47-48
Pop. (%) over v	t	25.9	24.3	39.3	46.0	17.6	8.1	24.6	36.8
	t+11	31.3	28.5	43.4	47.7	21.6	11.0	29.9	39.0

Data for the year 2025 is published by U.S. Census Bureau (2018a) and is available at: <https://www.census.gov/data/datasets/2017/demo/popproj/2017-popproj.html>

4 Shifts in age-specific unemployment

4.1 Treatment regressions

The structure of the datasets bears the problem that all individual variables are not observed over a longer time span. The employment status is defined at the date of the interview, e.g. an individual that was not employed at this day but worked during the twelve months prior to this

date is counted as not employed. In contrast, the income variable is defined as income of the last twelve months prior to the interview and the consumption variable covers the past three months. Therefore, the effects of income and employment status on the individual budget constraint and therefore consumption might not be represented correctly. Unfortunately, it is not possible to correct for this bias within the datasets. Moreover, since the dataset is a pure cross-section, single individuals are either employed or not employed, the counterfactual cannot be observed. That would be the case if the dataset would be panel data. Analyzing the effect of the employment status on consumption in a ceteris-paribus fashion ignores the obvious change in income resulting from a change of the employment status. Usual OLS estimates may significantly underestimate the effect of employment status on consumption. These simultaneous changes can be addressed by treatment regressions (Heckman (1979)). The probability of the treatment, in this case not being employed, is estimated by individual characteristics. In the first step, a probit regression is done for the binary variable of *notemployed*:

$$\Pr(\textit{notemployed} = 1|X) = \beta_0 + \beta_1 \textit{age} + \beta_2 \textit{age}^2 + \beta_3 \textit{male} + \beta_4 \textit{dsave} + \beta_5 \textit{stocks} + u,$$

where *male* is a dummy (man=1, woman=0). The variable *dsave* is the change of savings in the last 12 months prior to the interview. Accumulating higher savings in the last 12 months might indicate that the individual was employed and able to save out of income while dissaving implies lower income due to possible unemployment. The dichotomous variable *stocks* indicates if an individual holds any kind of bonds or stocks. It is a proxy for wealth income of individuals. Including metric information on income leads to collinearity problems in the second step of the estimation. Information on the change of savings and other financial assets are available only for the 2014 CES and a replication in the 2003 dataset was not possible. Therefore, only the 2014 dataset is used here. From the probit regression, the hazard ratios are computed for each observation. The hazard ratio is then used as a further covariate in the OLS regressions for each consumption good. In such a linear regression the coefficient for *notemployed* describes the average treatment effect (ATE).

The values of variables predicted by the OLS regressions are used to calculate overall emissions in the US for a population of 300 Million. Average consumption of five-year age groups¹² separated into employed and not employed is calculated from the treatment regressions. We multiply average group-specific emissions with the respective number of people, which was

¹² Different for: age 0-17, 18-24 and Age 65 and older.

derived using population shares published by the US Census Bureau (2018b) and information on the age-specific employment status from the CES data¹³. Overall emissions are the sum of emissions of all groups. Finally, we assume that in each age group the share of persons employed is raised by one percent and calculate the resulting change in overall emissions.

4.2 Results of the treatment regressions

Results from the probit regression are shown in Table 5. Most variables show the expected signs. The impact of age on the probability of not being employed is u-shaped over the life-cycle, men have a lower probability of not being employed and owning stocks has a negative impact. The change of savings has an unexpected positive but small influence on the probability of not being employed.

Table 5: Margins for probability of unemployment from probit regression

	age	age ²	male	dsave	stocks
<u>d notemployed</u>	-0.02324**	0.000337**	-0.01788*	0.00124**	-0.1169**
dx	(0.001430)	(0.000014)	(0.009520)	(0.00051)	(0.0448)

significance levels: **: $\alpha=0.05$, *: $\alpha=0.1$, standard errors in parentheses.

From the OLS regressions with hazard ratio we get the ATE for the most relevant goods as shown in Table 6.

Table 6: 2014 - Average Treatment Effects (in kg CO₂-equivalent emissions)

	food	Gasoline	natural gas	electricity
ATE	389.844**	-544.276***	-188.024*	147.282

significance levels: ***: $\alpha=0.01$; **: $\alpha=0.05$; *: $\alpha=0.10$, complete regression results: Table 10 in the appendix

The estimated emissions for all eight goods with a population of 300 million is about 4.4 billion metric tons, which is roughly 65% of US overall CO₂-equivalent emissions in 2014¹⁴. If the number of people in each age group¹⁵ that is not employed is reduced by one percent, this leads to an increase of emissions about of 3.524 million kg CO₂-equivalent per year, i.e. by 0.08%. This effect can be decomposed into age-specific effects. Table 7 shows the percentage change of emissions in different age groups as a response to a one percentage decrease in the share of

¹³ No other information on age-specific unemployment was available.

¹⁴ EPA calculated the CO₂ equivalent emissions as 6.76 billion metric tons in 2014 for the US (information available at: <https://cfpub.epa.gov/ghgdata/inventoryexplorer/#allsectors/allgas/gas/all>)

¹⁵ Exception: Age group 0-17 is per definition not unemployed. Because of the low representation in single households they are excluded for the purpose of this analysis.

not employed people in each age group. The potential increases of CO₂-equivalent emissions are larger for older than for younger people.

Table 7: Percentage change of CO₂-equivalent emissions as a response to a decline in unemployment or inactivity

age	18-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65+
$\frac{d CO_2e}{d notemployed}$ (%)	0.13	0.03	0.03	0.04	0.06	0.07	0.07	0.09	0.10	0.19

Age group 0-17 is not shown. People in this age group are per definition employed, therefore a decline in unemployment is not possible.

5 Conclusion

In this paper a multivariate analysis of the age-specific carbon footprint is performed and the results are compared to those of a simple model à la Zagheni. Furthermore, the effects of changes in age-specific employment shares on the overall emission levels are calculated.

The main conclusion is that a simple model using only age to explain emissions overstates the impact of age. The multivariate approach shows that the age profile is flatter if other relevant variables, in particular economic factors, are controlled for. This indicates that a substantial part of the decline of emissions after peak-age 62 in Zagheni's model is a result of economic inactivity, e.g. unemployment and reduced income, rather than of aging. Changing the age structure in a way predicted by demographic forecasts, the multivariate model projects higher overall emissions as a response to population aging than the simple model because shares of population older than the crossover-age rise.

There are also important insights regarding the forecast of future emissions based on simple models that use only age to explain emissions. First, using age-specific consumption from the simple model at one point of time to project future emissions perpetuates the error of overestimating the decline of emissions due to aging. To get reliable forecasts with the multivariate model, future age-specific employment shares and income have to be estimated. Second, the comparison of the results from 2003 and 2014 indicates a declining effect of age on emissions, visible through the flatter age profile of emission. In summary, future cohorts that reach a certain age will behave differently from current cohorts at the same age.

Activating labor market policies in countries with aging societies target those parts of the population that are associated with lower carbon footprints. A simple model with age as the only explanatory variable by assumption excludes the possibility that emissions rise due to

higher labor participation of elderly. The results derived in this paper show that the increases in employment significantly raise overall emissions, especially for older age groups. This trade-off of economic vs. environmental policy in an aging society should be considered further.

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Appendix

Table 8: Global Warming Potentials

Gas	CO ₂	CH ₄	N ₂ O	NO _x	CO	NM VOC
GWP	1	25	298	4.5	3	3.4

Source: IPCC 2007 (Forster et al. 2007) and for CO: Fuglested et al. (1996).

Table 9 Overview for calculations of Emission factors for natural gas and gasoline

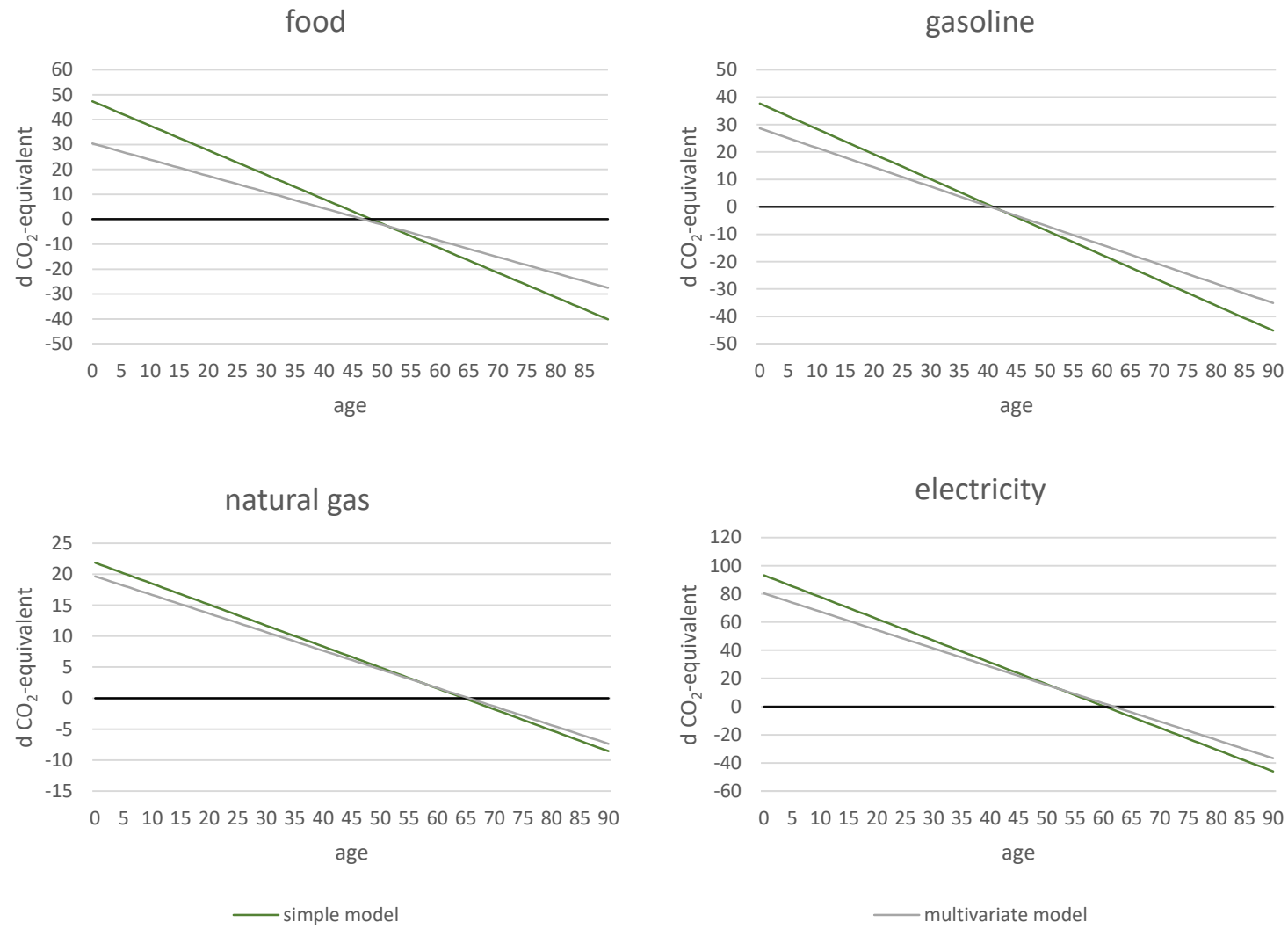
	Average price of natural gas (tscf)	Kg CO ₂ -equivalent per tscf of natural gas	CO ₂ -equivalent/\$ spent on natural gas
2003	10.62 \$	54.496	5.133
2014	12.95 \$		4.207
	Average price of gasoline	Kg CO ₂ -equivalent per gallon of gasoline	CO ₂ -equivalent/\$ spent on gasoline
2003	1.60 \$	8.813	5.505
2014	3.44 \$		2.561

Table 10 2014 Treatment regression - OLS results

	food	gasoline	natural gas	electricity	clothes	furniture	tobacco	air flights
age	16.292*** (4.404)	31.826*** (3.988)	13.911*** (2.665)	70.408*** (5.814)	1.0566 (0.7862)	0.501 (0.879)	1.077*** (0.227)	0.305 (1.604)
age ²	-0.188*** (0.594)	-0.325*** (0.054)	-0.094*** (0.036)	-0.581*** (0.0784)	-0.226** (0.011)	-0.009 (0.012)	-0.009*** (0.003)	-0.017 (0.0216)
unemployed	-389.844** (178.381)	-544.276*** (161.256)	-188.024* (107.945)	147.282 (235.524)	36.311 (31.817)	9.890 (35.640)	-12.932 (9.161)	20.355 (65.025)
retired	329.417*** (43.585)	272.900*** (39.445)	122.683*** (26.366)	16.755 (57.548)	17.014** (7.758)	9.610 (8.718)	-3.096 (2.227)	48.159*** (15.906)
income	8.801*** (0.320)	3.543*** (0.289)	1.720*** (0.193)	3.109*** (0.422)	0.870*** (0.057)	0.589*** (0.064)	0.004 (0.016)	1.466*** (0.117)
financial stock	-0.0003 (0.0005)	0.0003 (0.0004)	-0.00004 (0.0003)	0.0005 (0.0006)	-0.0001 (0.0001)	0.0002** (0.0001)	-0.00003 (0.00002)	0.0002 (0.0002)
hazard	89.201 (102.131)	34.405 (92.326)	60.330 (61.803)	-117.388 (134.848)	-24.953 (18.216)	-7.239 (20.406)	9.782* (5.245)	-14.327 (37.230)
constant	915.201*** (103.554)	194.652** (59.083)	-186.957** (36.396)	-660.156*** (136.726)	30.946* (18.490)	7.143 (20.677)	-10.567** (5.332)	43.610 (37.726)

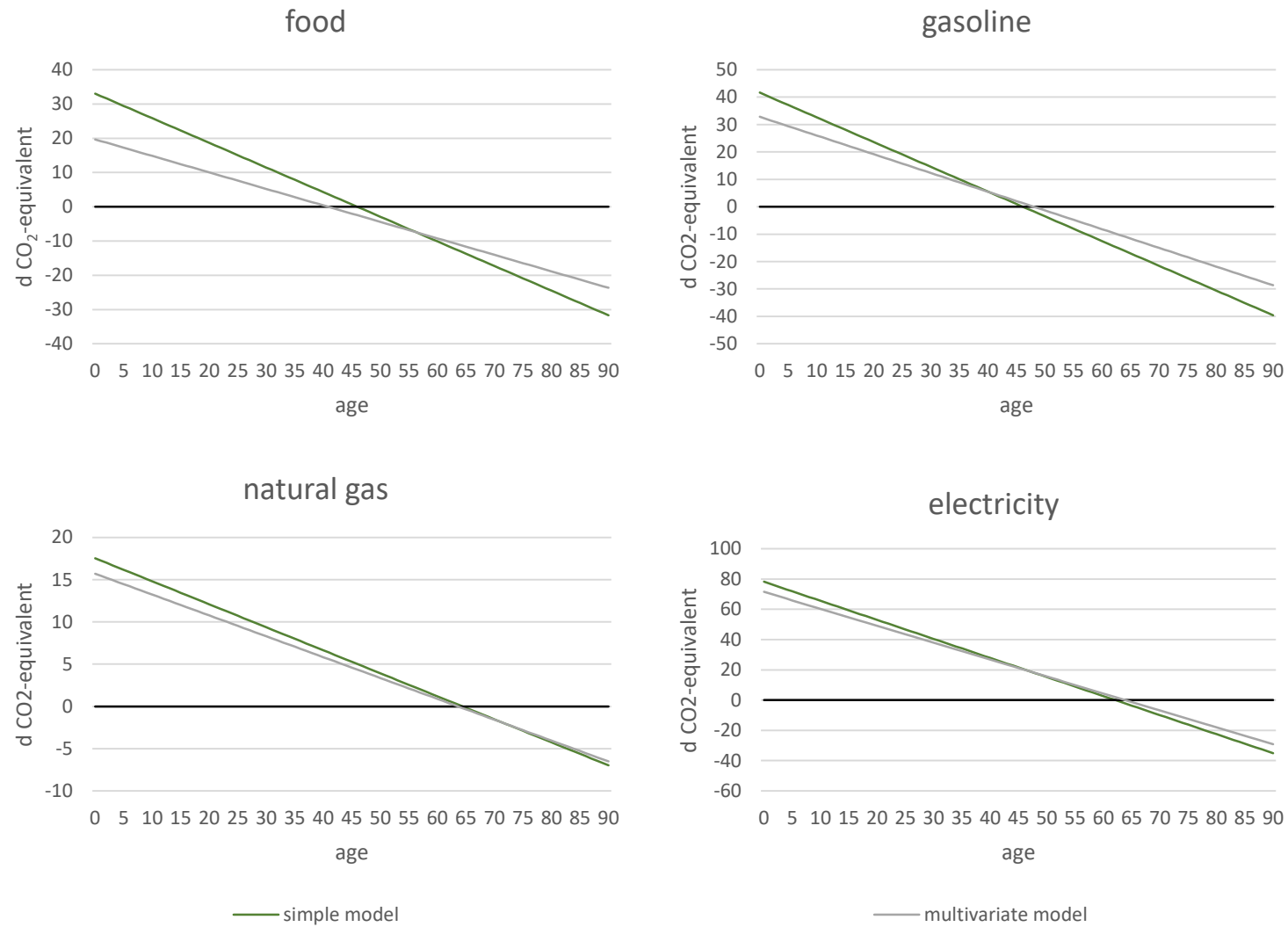
N=7207, significance levels: ***: $\alpha=0.01$; **: $\alpha=0.05$; *: $\alpha=0.10$, standard errors in parenthesis

Figure 3: 2003 - estimated change in CO₂-equivalent emissions



Own calculations, d CO₂-equivalent in kg.

Figure 4: 2014 - estimated change in CO₂-equivalent emissions



Own calculations, d CO₂-equivalent in kg

Figure 5: Overall CO₂-equivalent emissions (kg) in 2003 and 2014 in different age groups



The graphs in Figure 5 compare the emissions in 2003 and 2014 (in kg, vertical axis) for different five-year age groups (different for 18-24, horizontal axis with maximum age in group).