Secure Livelihoods Research Consortium

Researching livelihoods and services affected by conflict

Reviewing DRC's poverty estimates, 2005-2012:

Unprecedented GDP growth without trickle down

Report 73

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Cover photo: Members of a local volunteer organisation plant trees in a school yard as part of activities for International Volunteer Day in Goma, eastern Democratic Republic of the Congo (DRC). © UN Photo/Sylvain Liechti

About us

The Secure Livelihoods Research Consortium (SLRC) is a global research programme exploring basic services, and social protection in fragile and conflict-affected situations. Funded by UK Aid from the UK Government (DFID), with complementary funding from Irish Aid and the European Commission (EC), SLRC was established in 2011 with the aim of strengthening the evidence base and informing policy and practice around livelihoods and services in conflict.

The Overseas Development Institute (ODI) is the lead organisation. SLRC partners include: Centre for Poverty Analysis (CEPA), Feinstein International Center (FIC, Tufts University), Focus1000, Afghanistan Research and Evaluation Unit (AREU), Sustainable Development Policy Institute (SDPI), Wageningen University (WUR), Nepal Centre for Contemporary Research (NCCR), Busara Center for Behavioral Economics, Nepal Institute for Social and Environmental Research (NISER), Narrate, Social Scientists' Association of Sri Lanka (SSA), Food and Agriculture Organization (FAO), Women and Rural Development Network (WORUDET), Claremont Graduate University (CGU), Institute of Development Policy (IOB, University of Antwerp) and the International Institute of Social Studies (ISS, Erasmus University of Rotterdam).

SLRC's research can be separated into two phases. Our first phase of research (2011 - 2017) was based on three research questions, developed over the course of an intensive one-year inception phase:

- State legitimacy: experiences, perceptions and expectations of the state and local governance in conflict-affected situations
- State capacity: building effective states that deliver services and social protection in conflict-affected situations
- Livelihood trajectories and economic activity under conflict

Guided by our original research questions on state legitimacy, state capacity, and livelihoods, the second phase of SLRC research (2017-2019) delves into questions that still remain, organised into three themes of research. In addition to these themes, SLRC II also has a programme component exploring power and everyday politics in the Democratic Republic of Congo (DRC). For more information on our work, visit: **www.securelivelihoods.org/what-we-do**

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Acronyms

AEU	Adult Equivalent Unit
AME	Adult Male Equivalence
COICOP	Classification of Individual Consumption by Purpose
DRC	Democratic Republic of the Congo
FAO	Food and Agriculture Organization
FC	Francs congolais
FCT	Food Composition Table
GDP	Gross domestic product
GIC	Growth incidence curves
INS	Institute National de la Statistique (National Institute of Statistics)
MAR	Mean adequacy ratio
PAL	Physical activity levels
PRSP	Poverty Reduction and Strategy Paper
WFP	World Food Programme
WHO	World Health Organization

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Executive summary

Research Question

The first decade of the Democractic Republic of the Congo's (DRC) post-conflict reconstruction period (2004-2013) was marked by an unprecedented economic growth in per capita gross domestic product (GDP) of 3-4% per year, but was this 'peace dividend' translated into widespread poverty reduction within the Congolese population?

Approach

We answer this question by focusing on the percentage of people in poverty (or poverty headcounts) using micro-level data. We use two national household surveys: the first was conducted in 2004-2005, right before the 2006 elections that inaugurated the first post-conflict government; and the second was carried out in 2012-2013, about seven years after the first round.

Both the Institut National de la Statistique (INS) (RDC, 2014) and the World Bank (2016) estimate very high poverty rates; and both point to a significant decrease in poverty between the two survey periods. Using the same datasets, both institutions find that the poverty headcount decreased by five to eight percentage points.

The problem with both estimates, however, is that they cannot be replicated. The World Bank reports its poverty estimates without elaborating on the methodology, nor explaining why they differ from the INS results. Although INS provides more detail on the methodology they followed, this information only enabled us to replicate its 2005 poverty estimates (RDC, 2006), not its 2012 estimates.

When we applied the INS's methodology from 2005 to the 2012 survey, we found that the percentage of people in poverty substantially increased from 72% to 81%. This is in sharp contrast to the INS's own reported results, and also runs counter to what we know about the evolution of the DRC's economy.

To produce more accurate poverty estimates and trends, we reviewed the INS methodology and made the following modifications:

- We corrected for erratic sampling weights.
- We imputed rents to all households.
- We improved the method for calculating poverty lines to be used as consumption deflators.
- We corrected for households with suspiciously high or low calorie consumption.

Both the original datasets and the dataset containing the variables with new population weights and deflators can be downloaded (Great Lakes of Africa Centre, 2018) at this website.

Table 1: Reported and replicated percentage of people in poverty, DRC (2005-2012)

	Reported estimates						Data replication based on INS-2005 methodology			Data replication based on improved methodology		
	INS			World Bank								
	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.
Urban	61.8	60.4	-1.4	66.6	62.5	-4.1	64.4	75.5	11.1	61.9	58.6	-3.3
Kinshasa	41.9	36.8	-5.1	56.3	52.8	-3.5	46.6	56.1	9.5	73.7	55.7	-18.0
Rural	75.8	65.2	-10.6	70.5	64.9	-5.6	75.2	84.7	9.6	66.8	69.5	2.6
DRC	71.3	63.4	-7.9	69.3	64.0	-5.3	72.1	81.4	9.3	65.1	65.6	0.5

Source: on the basis of Tables 4 and 7.

Main findings:

- Based on the revised methodology, and in line with both INS and World Bank estimates, our findings suggest that two-thirds of the DRC population are poor. This is a staggering figure, especially given that the measure of poverty adopted essentially pegs poverty to insufficient food intake. In other words, more-or-less two-thirds of the people in the DRC are undernourished.
- The percentage of people in poverty overall did not significantly change between 2005 and 2012. In other words, the decade of unprecedented economic growth in GDP did not visibly translate into increased consumption for the bottom two-thirds of the population. This finding also contradicts both INS and World Bank estimates of a significant reduction in poverty in that period.
- Relying on the proposed methodology, there are important regional differences: poverty decreased spectacularly (by 18 percentage points) in Kinshasa but it increased in other cities and towns as well as in the countryside. The increase was highest in the most remote areas. This result is consistent with casewise evidence on 'kinocentrisme' (De Herdt and Kasongo, 2013) and with analyses that point to a disproportionate weight of Congo's mining sector within the political economy of reconstruction (Englebert, 2014; Marysse and Megersa, 2018).

Implications:

- Our findings highlight the importance of making international and national statistical services more transparent and responsive to the wider public. The possibility of public scrutiny drives the quality and credibility of official poverty estimates. The requirement of transparency may be an important factor to counteract the grip of state representatives and their international counterparts on statistics and resulting knowledge.
- Our findings also lay the ground for further analysis to identify the 'losers' and 'winners' of growth and the underlying mechanisms at play. This is crucial for designing and implementing growth inclusive strategies.

1 Introduction

After the peace treaty was signed in Sun City in 2002, formalising the beginning of a period of political transition, development prospects in the Democratic Republic of the Congo (DRC) were good. Not only did the political landscape stabilise through the adoption of a new constitution in 2005, and the organisation of the first free and fair elections since independence in 2006, the level of official development assistance the country received substantially increased (World Bank 2017). In addition, the country was granted irrevocable debt relief in 2010 for about $12.3 billion (Marysse et al. 2012). Taking gross domestic product (GDP) at face value, the economic peace dividend since 2000 has been substantial: negative growth rates turned positive in less than five years' time, from -7% in 2000 to almost +7% in 2004, and remained high until 2015, with the exception of 2009, the year after the global financial crisis (World Bank 2017). Taking into account population growth estimated at 3%, per capita GDP still increased on average by 3-4% on an annual basis.

The main question is whether, or to what extent, this peace dividend trickled down, and if so, which regions benefitted the most?

In this paper, we answer this question by scrutinising two national household surveys. The surveys were carried out in 2004-2005, right before the 2006 elections that inaugurated the first post-conflict government; and in 2012-2013, about seven years after the first round. Although household surveys are relevant instruments to evaluate welfare and poverty at the micro level, different issues hinder their measurement and monitoring. These issues can be grouped under two headings, each denoting a different research objective.

The first set of issues speaks to the lack or varying quality of metadata and transparency on precise survey implementation and analysis (Thontwa et al., 2017). Knowledge about the magnitude or dynamics of wellbeing and poverty is a politically sensitive issue for governments committed to improving the social conditions of their citizens. The fact that, in many cases, national statistical administrations are heavily involved in these exercises also raises the question of how independent their work is from political influence. However, for official poverty estimates and trends to be credible, they should stand up to public scrutiny. This paper's first objective, therefore, is to replicate and interpret the official poverty data in light of the methodological choices made.

Using the above-mentioned datasets, the Institut National de la Statistique (INS) (RDC, 2014) as well as the World Bank (2016) have published monetary indicators of poverty. Surprisingly, the World Bank reported its poverty estimates without discussing its methodology. The INS, on the other hand, provided more detail on the methodology for 2005, which allowed us to generally replicate the poverty estimates for that year (RDC 2006), but we were not able to completely reproduce the 2012 estimates published by the INS on the basis of the underlying dataset (RDC, 2014: 101). We thus largely followed the INS reported methodology for 2005 to reconstruct what would have been their poverty estimate for 2012 had they applied the same methodology. Unexpectedly, our replication analysis yields completely different results from the INS and the World Bank on the poverty dynamics between 2005 and 2012. We found that the percentage of people in poverty did not substantially decrease, rather it increased substantially.

To explain the discrepancy, we focus on methodological problems and pitfalls in the survey data and poverty methodology. Aiming to produce more accurate estimates of wellbeing and poverty, this paper's second objective is to introduce changes to the INS methodology given available datasets. More specifically, we propose to correct for erratic sampling; to fully impute rents to homeowners; to improve the method for calculating poverty lines and to use them as consumption deflators. Moreover, we argue that due correction should be made for households with suspiciously high or low calorie consumption. On the one hand, and in line with (Deaton and Kozel, 2005) in the case of India, the proposed repairs can only be considered 'a poor substitute for the collection of clean, credible, and comprehensive data' (2005: 196). On the other hand, we hope the proposed changes will be used in future estimations of wellbeing and poverty.

After applying these changes, we find that poverty estimates differ considerably both from INS and World Bank results. More specifically, we find that the official 2005 poverty levels were overestimated, and that, over time, contrary to both INS and World Bank estimates, the percentage of people in poverty did not substantially decrease nor increase: it essentially remained the same. Further analysis suggests that Kinshasa stands out as a double exception, registering both high and equitable growth in household consumption, whereas the rest of the country showed very little evidence of economic growth trickling down as registered by per capita GDP. This result is consistent with casewise evidence on 'kinocentrisme' (De Herdt and Kasongo, 2013) and with analyses that attribute a disproportionate weight to the mining sector in the political economy of post-conflict DRC (Englebert, 2014; Marysse and Megersa, 2018).

The paper is structured as follows: after presenting the two datasets in Section 2, we go through the replication exercise in Section 3. Section 4 details our proposal to improve the existing methodology, while Section 5 presents the impact of these improvements on the initial (replicated) INS results. In Section 6, we briefly discuss the trickle down question, before presenting our conclusions in Section 7.

2 The data: Two national-level household surveys

This paper uses two cross-sectional datasets on household consumption in the DRC collected by the INS in 2004-2005 and 2012-2013.[1] The sample size covers 12,087 households for the 2005 round and 21,403 households for the 2012 round, each following a sample design that seeks representativity per sector (statutory cities, provincial towns and villages) at the provincial level.[2] Both survey rounds follow the same methodology, Enquête 1-2-3 (henceforth 123 Survey), where each number refers to a separate phase: (1) employment, (2) informal sector, and (3) consumption. This paper mainly relies on the third phase, which comprises diary and recall data on twelve consumption categories following the Classification of Individual Consumption by Purpose (COICOP). Whereas the diary data relate to an average period of 15 days, the recall period stretches to 6 or 12 months, depending on the module. As reported in Table 2, both surveys' primary data amounts to 3,244,982 individual consumption lines for which quantities, local selling units, unit prices and total expenditures have been recorded by 33,490 different households in total.

Table 2: Data description, DRC (2005-2012)

	2005	2012	Total
Number of households	12,087	21,403	33,490
Number of recorded transactions:			
Food	880,499	1,467,566	2,348,065
Drinks	54,279	91,335	145,614
Clothes	47,597	33,316	80,913
Housing	128,201	139,156	267,357
Equipment	55,145	82,265	137,410
Health	35,643	27,601	63,244
Transport	13,640	18,066	31,706
Communication	1,655	14,967	16,622
Leisure	17,304	15,118	32,422
Education	9,543	7,234	16,777
Catering	8,545	9,236	17,781
Services	41,639	45,432	87,071
Total	1,293,690	1,951,292	3,244,982

Source: 123 Survey (2005) and (2012).

1 Although both 123 Survey rounds were spread over two years, for convenience we will simply refer to 2005 for the first and 2012 for the second round, which are the years when most households were surveyed. The data and metadata can be downloaded from the National Datasets on Livelihoods platform on the IOB website.

2 In anticipation of the ongoing process of decentralisation which became official by 2015, the 2012 sampling design was based on 26 provinces compared to 11 provinces in 2005.

The 123 Survey methodology applied to the DRC largely adopts the 'better' standards of the survey industry, with unit records of individual consumption being accessible, as opposed to only aggregate household data or even grouped data (see Park and Wang, 2001). The methodology's reliance on 15-day diaries with not less than six enumerator visits to supervise this process also follows best practice. In addition, the 123 questionnaire comprises a list with more than 200 food items, which, apart from daily purchases, also accommodated other types of food transactions, like gifts received or given in kind, and self-produced food. On the contrary, conversion rates for local selling units were not readily available and have been only occasionally collected in 2005. This was done much more systematically in 2012. The reverse is true for rent imputation of homeowners: this procedure was fairly complete for the 2005 round, while more incomplete in 2012.

3 Replication of official results

Based on the first round of 123 Survey data, the country elaborated its first Poverty Reduction and Strategy Paper (PRSP) in 2006, which presented a detailed analysis of poverty, including its spatial variation and determinants. To address the variation in cost of living, this poverty diagnostic relied on per capita urban (420 Francs congolais (FC)) and rural (268 FC) poverty lines (RDC 2006). In 2014, a similar poverty analysis was conducted for the final report of the 123 Survey's second wave. The 2014 report (RDC 2014) used three poverty lines per adult equivalent unit respectively, for the capital city of Kinshasa (2,929 FC), other urban areas (2,189 FC) and rural areas (1,583 FC). To allow comparability with the first wave, the report also estimated a combined poverty line for Kinshasa and other urban areas (see Table 3). For both years, official poverty thresholds were set following a two-step procedure of first calculating a food poverty line based on the observed food basket needed for minimal calorie intake, after which a non-parametric non-food allowance was added.

Table 3: Official poverty lines in FC per person per day, DRC (2005-2012)

	2005	2012	2012/2005
Urban	420	2,375	5.66
Kinshasa		2,929	
Other		2,189	
Rural	268	1,583	5.92

Source: RDC (2006, 2014).

Table 4 presents regional poverty levels of 2005 and 2012 as officially reported by INS and the World Bank as well as our best replication of INS calculations. As mentioned, the World Bank published its own poverty estimates (World Bank, 2016, 2018),[3] which are different from the INS figures for reasons not explained in the report.[4] While the core dataset is exactly the same, the results between both institutions differ substantially in some areas. This is the case in Kinshasa and Bas-Congo where the World Bank's poverty levels are respectively higher by around 15 percentage points and lower by 7.5 percentage points. Given the similar size and direction of these corrections in 2005 and 2012, the change in poverty remains more or less the same for both provinces. For Bandundu, Sud-Kivu, Maniema and Kasai-Occidental on the contrary, the World Bank revisions

3 We were only able to access a draft version of the DRC poverty assessment (World Bank 2016), but the data presented in the report were used in 2018 for the DRC systematic country diagnostic and they are consistent with the PovCalNet dataset (though the 2005 survey results are reported as 2004).

4 Several attempts to get in touch with the principal investigators of the World Bank working on the DRC have proven to be unsuccessful.

are very unequal in size or direction between both years, which seriously nuances the poverty reduction performance in the first two provinces while sketching a more precarious picture for the latter two. Regarding sector performance, the World Bank estimates that urban (resp. rural) poverty in 2005 is approximately five percent points higher (resp. lower) compared to the INS headcounts. As a result, the poverty reduction observed over the period considered, according to the World Bank's method, is more equally distributed across both sectors, though slightly more pronounced in rural areas. Overall, the World Bank concludes that the percentage of people in poverty declined with 5.3 percentage points, compared to the INS's 7.9 percentage points. In terms of per person poverty according to the international 1.9 PPP$ 'extreme poverty' line (which is higher than the 'national' poverty lines in the DRC), the World Bank reports a decline of 17.4 percentage points, from 94.3% to 76.9% between 2005-2012 (World Bank, 2016: 36, also in PovCalNet). Given that the World Bank data was published without providing a detailed methodological note, it is impossible to interpret these differences or to assess its estimates in comparison to those published by the INS.

Column (c) replicates the INS methodology (RDC, 2006) as closely as possible by using the original data for 2005 and 2012. However, we are not able to completely replicate the INS results. While our results are close to the average poverty level in 2005 (71.3 versus 72.1), important differences remain, especially for the urban sector (61.8 versus 64.4) and especially for Kinshasa (41.9 versus 46.6). Notwithstanding this correspondence, the most important message of the replication exercise is that the reported and replicated results completely diverge for 2012, which in turn affects any trend analysis over the period considered. Indeed, whereas INS reports a decline in the percentage of poor people, with 7.9 percentage points for the DRC as a whole, our findings, replicating the INS 2005 methodology, suggest that the percentage of people in poverty increased by 9.3 percentage points.[5] In other words, if we accepted the INS method as it is, we should conclude that more than four-fifths of all DRC inhabitants were poor in 2012 and that only the provinces of Bandundu, Equateur and North-Kivu and South-Kivu kept their (already high) 2005 poverty level.

Did poverty increase or decrease between 2005 and 2012? The divergence between the reported and replicated figures calls for an in-depth analysis of the methodology applied, to which we turn in the next section.

5 Extending our replication exercise to the other FGT poverty measures (Foster et al., 1984) largely boils down to the same conclusion that (i) correspondence is much better for 2005 than 2012, and (ii) poverty largely evolves in opposite direction.

Table 4: Replication of the official poverty headcounts (%), DRC (2005-2012)

	Reported estimates						Data replication		
	(a)			(b)			(c)		
Method	INS			World Bank			INS		
Metadata	available			not available			available		
N sample	33,490			33,490			33,490		
	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.
Urban	61.8	60.4	-1.4	66.6	62.5	-4.1	64.4	75.5	11.1***
Rural	75.8	65.2	-10.6	70.5	64.9	-5.6	75.2	84.7	9.6***
Kinshasa	41.9	36.8	-5.1	56.3	52.8	-3.5	46.6	56.1	9.5***
Bas-Congo	70.1	56.9	-13.2	62.2	49.3	-12.9	69.3	79.3	10.0***
Bandundu	88.5	74.6	-13.9	(85.0)	77.2	(-7.8)	90.2	91.1	0.9
Equateur	93.7	77.3	-16.4	(90.3)	76.4	(-13.9)	91.1	90.4	-0.6
Orientale	75.9	56.9	-19.0	(70.3)	55.2	(-15.1)	71.9	79.4	7.4***
Nord-Kivu	72.8	52.4	-20.4	69.4	49.0	-20.4	75.6	75.4	-0.2
Maniema	59.4	62.9	3.5	49.3	63.5	14.2	57.8	86.4	28.6***
Sud-Kivu	84.8	60.2	-24.6	80.0	62.9	-17.1	82.8	84.6	1.7
Katanga	69.5	66.6	-2.9	(69.3)	62.9	(-6.4)	70.0	82.7	12.7***
Kasai-Oriental	62.7	78.6	15.9	58.6	75.9	17.3	62.1	89.9	27.8***
Kasai-Occidental	55.4	74.9	19.5	49.0	74.7	25.7	59.1	87.6	28.5***
DRC	71.3	63.4	-7.9	69.3	64.0	-5.3	72.1	81.4	9.3***

Notes: All data in adult equivalent units. Numbers between brackets result from visual inspection of Figure 2.2 (World Bank 2016), where exact changes in poverty headcount are missing for four provinces.

+ = significant at .10, * = significant at .05, ** = significant at .01, *** = significant at .001.

Source: RDC (2006, 2014); World Bank (2016); 123 Survey data (2005 and 2012).

4 Improving the methodology for wellbeing comparisons

4.1 Recalibrating sampling frames

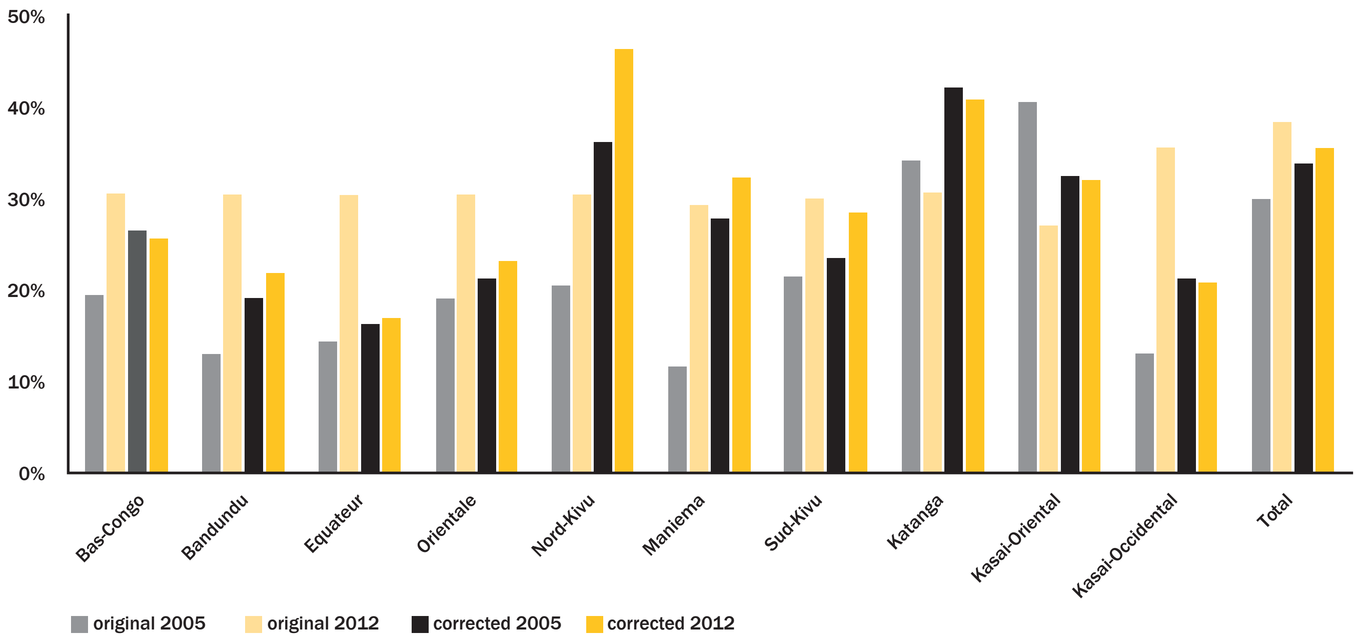
Without routine registration, and given that the country's latest population census goes back to 1984, fielding a representative household survey in the DRC is not straightforward. Indeed, one needs reliable demographic data to be associated with the selected sampling units to estimate how many population units they represent (Gelman, 2007; Little, 2004). Marivoet and De Herdt (2017) document the high volatility in population data used underneath the sampling frames of the latest national household surveys conducted in the DRC. Clearly, over time, very different fertility or mortality assumptions appear to have been used to estimate the distribution of the Congolese population. Figure 1 shows the provincial urbanisation rates for both rounds of the 123 Survey as reflected by the original design weights added to the surveys (see striped bars). Taken at face value, the extent of urbanisation seems to have changed dramatically between 2005 and 2012. The World Bank reports that '[t]he country's average urban growth rate in the last decade was 4.1% […]; if this trend continues, the urban population will double in only 15 years' (World Bank, 2018: 1-2). Overall, the country's urbanisation rate went from 30% to almost 40% between 2005 and 2012, a difference which could equally be observed in the provinces of Bas-Congo, Orientale, Nord-Kivu and Sud-Kivu. In Bandundu, Equateur, Maniema and Kasai-Occidental, we note an increase by more than 15% over the period of seven years. Conversely, Katanga and Kasai-Oriental would have experienced a period of de-urbanisation; at a low rate for Katanga and more pronounced for Kasai-Oriental.

Taking a long-term perspective, by adding the population data underneath other national surveys since 2001 (not shown in Figure 1), Marivoet and De Herdt (2017) conclude that these demographic evolutions are erratic.[6] As a result, any trend analysis based on these surveys risks measuring changes in sample design rather than changes in the variables of interest. As a solution, the authors propose to stabilise the sampling frames using a post-stratification technique based on an interpolation of the 1984 census distribution and a 2012 benchmark derived from vaccination and school enrolment data.

Applying this technique, we find that the extent of urbanisation has been underestimated in the 2005 survey, while being overestimated in the 2012 round,

6 Indeed, whereas an occasional re-definition of areas would be perfectly legitimate, the volatile nature of such changes over a longer time renders this explanation very unlikely.

Figure 1: Variation in provincial urbanisation rates according to the original and corrected sampling weights, DRC (2005-2012)



Notes: The province of Kinshasa has formally no rural sector (i.e. urbanisation rate equal to 100%), and therefore is not displayed on this figure.
Source: Adapted from Marivoet and De Herdt (2017) by only selecting the urbanisation rates of the 123 Survey data (2005 and 2012).

and that urbanisation in the DRC would have evolved much less dramatically than the INS reported. Given the magnitude of variation across years and types of weights, the bias in results due to the erratic sampling frames can be expected to be most pronounced in Bandundu, Equateur, Nord-Kivu, Maniema and both Kasai provinces, which we will check further in this paper.

4.2 Imputing house rents

Apart from food, housing outlays take up an important share in overall consumption in most developing countries including the DRC. However, when households own their house, there is no corresponding outlay for the house rent paid by renters – though owners do derive a rental value from occupying their dwelling. To address this issue, one typically imputes a house rent based on the house's characteristics and the effective rents paid by renters, for which several techniques are proposed in the literature (for an overview, see Balcazar et al., 2014).

Although the INS did impute housing rents to homeowners, there are important issues to mention. First, we lack information about the precise imputation technique INS adopted. It is thus impossible for us to replicate their exercise. Secondly, whereas nearly each household in 2005 was given either an effective or an imputed house rent, it was not the case in 2012, where rent was imputed to only to 6% of the households. Thus, more than 89% were 'missing' a(n imputed) rent in 2012.[7] Thirdly, INS worked with effective house rents paid by renters; which means it only imputed rents to homeowners. This approach has the disadvantage of making the rent fluctuate more for renters compared to homeowners. This may be the result of factors affecting housing quality not captured by the rent imputation model. It may also stem from factors not related to housing quality, like the identity of the renter or the relationship between the renter and owner. For these reasons, we propose to impute rents to both renters and owners.

7 Following detailed inspection, some form of house rent imputation appears to be added to the aggregate outlay file for housing, yet without this imputation being added to the file with individual expenditures. As a result, there is no consistent correspondence between the official disaggregated and aggregated data on housing outlays. In any case, around 2,500 households do not have any housing outlays at all, neither in the individual nor in the aggregate expenditure module.

We estimate the natural logarithm of paid house rents against the indicator function of a set of house characteristics (Balcazar et al., 2014). In total, nine housing characteristics were retained for this exercise: material used for wall, floor and roof; the number of rooms and sleeping rooms; the type of energy used for cooking; the type of water supply; the type of sanitation; and the type of rubbish collection. We apply this estimation model to nine different housing regions, defined by combining data on land cover, topography and social environment.

We estimate house rents for both waves and all housing regions at the same time, incorporating the effect of changes in prices over time with a dummy variable. We also interact a time dummy with the sector dummies to account for diverging relative prices between Kinshasa, the other urban and rural areas, assuming that, for example, an increasing presence of newcomers – among them expatriates – might influence the housing market independently from changes in housing quality. The combined estimation for both years has the double advantage of improving the estimation robustness of housing characteristics and measuring the dynamics of housing quality over time, independent from price changes.

More specifically, we estimate rent as:

$$\begin{aligned} \ln(\text{RENT}) = \alpha_0 + \alpha_1 f(x_i, x_j, \dots) + \alpha_2\,\text{YEAR} \\ + \alpha_{3m}\,\text{SECTOR} + \alpha_{4n}\,\text{ZONE} \\ + \alpha_{5q}\,\text{YEAR} * \text{SECTOR} + \varepsilon \end{aligned}$$

Where:

$f(x_i, x_j, \dots)$ = function of housing characteristics x

YEAR = dummy variable for '2005' (base) or '2012'

SECTOR = set of m (=2) dummy variables for 'Kinshasa' (base), 'other urban' or 'rural'

ZONE = set of n (=3) dummy variables for 'Savanna highland' (base), 'Savanna lowland', 'Tropical highland' or 'Tropical lowland'

We use the regression coefficients (see results in Appendix A) to fit and impute house rents to both homeowners and renters. Thus, we obtain an almost full coverage of households with an imputed house rent (100% for 2005 and 98% for 2012), which reflects the market's valuation of housing quality for both of the years and the different regions.

Table 5: Mean effective and imputed monthly house rents (nominal FC) per housing zone according to initial and revised rent imputation procedure, DRC (2005-2012)

		INS procedure				Revised procedure		
	Sample N	2005		2012		2005	2012	2012/ 2005
		effective	imputed	effective	imputed			
N	33,490	1,555	10,311	1,093	1,310	12,084	21,016	
% in sample N	100%	13%	85%	5%	6%	100%	98%	
Kinshasa	9%	9,025	12,816	61,977	92,188	7,054	48,161	6.83
Urban Savanna Highlands	13%	3,592	3,306	19,961	20,722	2,406	12,677	5.27
Urban Savanna Lowlands	11%	3,901	2,557	13,501	7,927	1,999	9,097	4.55
Urban Tropical Highlands	5%	4,923	2,797	20,040	11,164	3,253	13,841	4.25
Urban Tropical Lowlands	8%	2,642	3,570	20,456	20,002	1,927	14,072	7.30
Rural Savanna Highlands	16%	1,162	798	2,719	4,110	700	1,813	2.59
Rural Savanna Lowlands	16%	1,242	1,305	2,356	2,201	667	1,771	2.66
Rural Tropical Highlands	6%	886	1,512	2,969	3,951	983	2,943	3.00
Rural Tropical Lowlands	16%	1,124	955	6,859	4,312	1,006	2,491	2.48
Total	99%	4,939	4,672	29,953	6,231	1,694	8,869	5.24

Notes: For the INS procedure, mean monthly house rents (FC) were obtained by using the initial sampling weights; the revised procedure relied on the corrected sampling weights as described above. Given the low coverage of paid house rents reported in 2012 (i.e. 5%), we equally made use of the 6% imputed rents to generate sufficient observations to derive and impute estimates of house rents for all households following the revised procedure.

Source: 123 Survey data (2005 and 2012).

Following the revised procedure (see Table 5), housing rents between 2005 and 2012 increased on average by more than factor 5, which is reasonably close, but below the increase in paid rents (29,953/4,939=6.1). This result is consistent with increasing migration, in fact, urbanisation, which exerts an effect primarily on rented houses. The increase is also much more pronounced in Kinshasa, where house rents almost rose seven-fold compared to other urban areas where an average increase of around 4.5 could be observed (with the exception of some cities located close to the Congo river, i.e. 'Urban Tropical Lowlands'). House rents in rural areas only increased by factor 3 at most. The results also highlight the magnitude of regional differences in absolute rent levels, especially between Kinshasa, other urban areas and rural areas. It is visible in the paid rents, in the imputed prices by INS and in the imputed prices estimated by our procedure – each time houses in the capital city are roughly 4 and 15 times more expensive compared to other cities and villages, respectively.

4.3 Setting poverty lines

To determine poverty lines, it is important to consider two of the core principles often put forward. On the one hand, poverty lines defined over time and across regions should be mutually consistent, which means they should refer to the same standard of living or utility level. On the other hand, poverty lines need to be sufficiently specific or relevant to the local context, implying that they should reflect locally prevailing needs and preferences (Asra and Santos-Francisco, 2003; Ravallion and Bidani, 1994).

A poverty line can be defined as the cost evaluated at local prices of 'a consumption bundle considered adequate for basic consumption needs' (Haughton and Khandker, 2009: 40), but this bundle can, in principle, be region- and time-specific in the space of commodities, as long as all these specific commodity bundles are consistently reflecting one particular level of utility (in a utilitarian tradition, e.g. Ravallion, 1998) or functionings (in a capability perspective, cf. Reddy et al., 2009). In this way, poverty lines can at least, in principle, be both consistent and specific (Asra and Santos-Francisco, 2003).

The tradition of complying to both consistency and specificity is followed quite generally for food poverty lines. Indeed, most researchers define minimum levels of food consumption by referring to particular levels of nutritional requirement (like calorie and vitamin intake). By holding these nutritional requirements constant for all regions, we can allow dietary patterns to vary with local food items while using their market value to compare food consumption between different dietary regions and over time. INS too reportedly applied this principle by defining sector-specific food baskets whose calorie content equals a minimum standard (i.e. of 2,300 kcal). There are, however, some non-trivial practical choices to be made when implementing this principle and it is unclear how INS operationalised it. We discuss the details of our practical choices in a separate subsection. Thereafter, we discuss ways to set the non-food poverty line, before combining both thresholds and deriving consumption deflators.

Metric food prices and nutrient intakes

In the DRC, as well as in many other African countries, food purchases are conducted in local measurement units (like sakombi, ekolo, etc.) as opposed to metric weights, such as kilograms and liters. In circumstances where a uniform relation exists, the conversion between local selling units and standardised measures would be straightforward. However, these local units are not necessarily the same throughout the DRC and tend to change over time, which required separate survey teams to actually weigh the food amount the household purchased. Given the cost of this operation, not every food purchase was weighed. In 2005, only 17% of all food purchases were weighed, against 52% in 2012. To convert non-weighed food outlays in their metric mass equivalent as well as to assure a consistent methodology over time, we first estimated metric prices based on the most common selling unit for the most important food items in each of the 56 and 66 price zones identified in 2005 and 2012 respectively.[8] For 2005, these price zones were obtained by crossing the three sectors of the country with the survey pools (which have been constructed to logistically organise the survey and thus reflect some degree of market integration). For the 66 price zones in 2012, the new provincial delimitation introduced in 2015 combined with the same three sectors have been used.

Although relying on prices at the household level would be more accurate to estimate each family's food purchasing power and associated level of food insecurity, the use of

8 The precise procedure to derive metric prices for each price zone is documented in Marivoet (2010).

average prices per price zone for each food item made it possible to convert 83% (in 2005) and 89% (in 2012) of all food outlays into their corresponding metric weight. These purchased food amounts were then associated to a Food Composition Table (FCT) entry, which provides the edible share of food as well as the nutrient composition of each 100-gram edible portion. Since the DRC does not have its own, we used the West African FCT developed by the Food and Agriculture Organization (FAO) (Stadlmayr et al. 2012). This FCT not only combines food composition data from nine countries, which resulted in an extensive list of food items with highly comparable data on food components, it also contains an edible conversion factor for each individual food item.[9] Despite detailed food composition data, the food labels the COICOP classification used did not always match perfectly. For example, information on the exact variety or breed, cultivar, maturity stage or fat rate of the food is generally lacking. In spite of these shortcomings, most of the other important distinctions, in terms of colour or food processing stage, could be made or indirectly retrieved. Using the associated data on edible conversion and nutrient composition, each food consumption line was then converted into its nutritional equivalent and expressed in annual terms. Apart from calories, this paper covers the following 14 micronutrients: calcium, iron, zinc, magnesium, thiamine, riboflavin, niacin, folate and vitamin A, D, E, C, B6 and B12.

Given the matching difficulties mentioned above, together with missing data on regional prices, only 80% in 2005 and 86% in 2012 of all food outlays were converted into their corresponding nutritional intakes. This still leaves a substantial share of food consumption unidentified. To address this issue, a mark-up procedure was implemented to derive household-specific prices-per-nutrient based on the identifiable part of food consumption within a set of different food groups. This information was then used to scale-up total nutrient intake for each household by relying on the corresponding monetary values of the unidentified part of food consumption. We implemented two mark-up procedures consecutively; the first relied on a categorisation of outlays into 16 food groups as identified by FAO's methodology on the Household Dietary Diversity Score. In case no price-per-nutrient could be derived for a particular food group comprising unidentified consumption, we resorted to a broader categorisation of eight food groups, taking inspiration from the World Food Programme's (WFP) (2008) procedure to construct its Food Consumption Scores.

To estimate nutrient deficiency, we also computed Adult Male Equivalence (AME) scales for each nutrient, based on the recommended intake levels by age/sex (FAO 2001; WHO/FAO 2004; WHO 2007). As a reference for these AME scales, we used a 30-year-old male and set his physical activity level equal to 1.75 while opting for a bioavailability level of 5% for dietary iron and low bioavailability for dietary zinc (15%). Accounting for differences in family size and composition, daily estimates of nutrient intakes expressed per AME could finally be obtained and compared to recommended intake levels for the adult male reference.

We then statistically estimated the relationship with per adult equivalent food expenses, and used the fitted values of the model that correspond with the minimal energy and required nutrient intakes to obtain the monetary food poverty line for each price zone.

Non-food expenditures

While with food items we can combine specificity and consistency by referring to nutritional adequacy, this is not possible with non-food items. Indeed, at least for all non-food items combined, there is nothing comparable to nutritional benchmarks to neatly determine the minimal amount and/or ideal mixture of non-food consumption. To overcome this problem, poverty analysts typically work with the assumption of 'equiproportionality' (Reddy et al., 2009) to estimate the non-food allowance. They often assume for instance that, whenever people's diet has reached the minimal nutritional benchmark, the estimated consumption of non-food items by households at the food poverty line can be considered a minimally decent level of non-food consumption.

However, the equiproportionality principle cannot be applied when relative prices between regions differ substantially. Typically, non-food items are relatively cheaper in urban areas and the same is true for food items in rural areas. In such a situation, it may be the case that rural households around the food poverty line

9 Compared to many other FCTs, the consistent coverage of edible conversion rates within the West African FCT is rather exceptional, though very important given the relatively high shares of inedible weight typically observed in fruit, vegetables, fish and meat (like pits, stones, skin, bones) – all being key to assure micronutrient adequacy. Where necessary, other sources on food composition, like the Food Composition Database for Biodiversity (FAO, 2016) and the online United States Department of Agriculture (USDA) FCT (https://ndb.nal.usda.gov), have been consulted for cross-checking or to fill out some important missing values.

spend relatively less on non-food items compared to urban households, not because they would prefer less of them but because they are relatively more expensive – or simply do not exist. Clearly, people's revealed preferences here cannot be taken as evidence of what they would opt for in the circumstances their urban counterparts face. In the extreme cases where non-food goods are simply absent, the non-food poverty line will be set to zero, as if people in such circumstances do not prefer to spend anything at all on these goods. This argument has been convincingly made by van den Boom, Halsema and Molini (2015) who argue that observed consumption does not necessarily reveal poor people's preferences, but rather reflects the poverty condition itself.[10] From a capability perspective, one could argue more specifically that what we observe reflects differences in the freedom to choose rather than differences in what people have reason to value.

Additional work is clearly needed on this subject; without further refinement one runs the risk of underestimating rural poverty, especially in remote areas. Until then, we have to rely on equiproportionality. We propose, however, to limit the potential inaccuracies resulting from the application of equiproportionality by pricing education outlays separately. Indeed, compared to other non-food needs, the local cost to cover a household's education needs directly relates to the number of school-age children. Since compulsory attendance in the DRC is limited to the primary level, we can derive a minimal school allowance based on (i) the local cost of primary schooling per pupil and (ii) the number of school-aged children without a primary school certificate.

In addition, similar to INS, we work with an austere non-food poverty line. This means that we do not quantify non-food expenses (with the exception of education expenses) at the poverty line itself, but by looking at 'how much is spent on nonfood goods by households that are able to reach their nutritional requirements but choose not to do so' (Ravallion and Bidani, 1994: 87-88). The choice for austerity is consistent with the assumption that, at lower welfare levels, the indifference curves of food and non-food dimensions become L-shaped. Austerity therefore reduces the degree of potential inconsistency comprised in poverty lines derived from areas with marked differences in relative price structures between food and non-food commodities (Marivoet and De Herdt, 2015).

Regional poverty lines

We can now present the different consecutive steps to compute a regional poverty line for each of the 122 different price zones identified in both rounds of the 123 Survey data. Given the household-specific data used to derive the school allowance, poverty lines may differ slightly between households within the same price zone. As such, our approach yields far more than 122 deflators, depending on the varying number of school-age children per household within each zone. Yet, given the small share of school allowances within the overall cost of the poverty bundles, we will broadly refer in this paper to the 122 price zones and their corresponding poverty lines and deflators.

To obtain regional poverty lines and deflators, the following procedure was followed:

1. To avoid erratic consumption behaviour to influence the computation of regional poverty lines, following (Osborne and Overbay, 2004), we discard all data from households in the first and tenth consumption decile of each of the 122 price zones. This exclusion, however, only concerns the derivation of regional poverty lines, not the subsequent analysis of welfare and poverty which intends to cover all households.

2. Using household nutritional intakes, as described above, we estimate a regression to predict the logarithm of daily food outlays per Adult Equivalent Unit (AEU)[11] as a linear combination of the logarithm of daily calorie intake per AME and the mean adequacy ratio (MAR). Whereas calories can be seen as a summary indicator of diet quantity, MAR provides

10 The same argument is used to claim that food poverty lines too may suffer from similar forms of inconsistency: when relative prices of different food items markedly differ, people will opt for different food bundles with various levels of energy density. If then only calorie thresholds are used, food poverty lines may indeed become mutually inconsistent. In this paper, however, food poverty lines are estimated based on both energy and micronutrient thresholds, and therefore this argument becomes less valid.

11 Compared to the previously defined AME, this equivalence scale controls for differences in household size and composition for *monetary consumption* as opposed to nutritional intake. Given the much higher household economies of scale within the former dimension, we define the adult equivalent unit as: AEU = $(N_A + \delta * N_C)^{\theta}$, in which N_A = number of adults, N_C = number of children (aged 6 years or younger), $\delta = 0.70$, and $\theta = 0.85$ (Drèze and Srinivasan, 1997)based on National Sample Survey data on consumer expenditure. In terms of standard poverty indices based on household per-capita expenditure, there is no evidence of widows being disproportionately concentrated in poor households, or of female-headed households being poorer than male-headed households. These findings also apply in terms of adult-equivalent consumption for any reasonable choice of equivalence scales. Poverty indices for different household types, however, are quite sensitive to the level of economies of scale. Even relatively small economies of scale imply that the incidence of poverty among single widows, widows living with unmarried children, and female household heads (all of whom tend to live in relatively small households.

information on diet quality by averaging the truncated individual nutritional adequacy ratios of the 14 micronutrients listed above (Ruel, 2002).

3 Relying on austere daily nutritional intake levels for energy set at 2250 kcal, 2500 kcal and 2750 kcal per AME (for large cities, smaller towns and villages respectively) and at 0.7 for MAR[12], the estimated regression coefficients are then used to derive a food poverty line for each of the 122 price zones. Each food poverty line then reflects the budget needed, on average, to reach the above nutritional thresholds for diet quantity and quality.

4 Furthermore, we estimate austere non-food (excluding school) allowances following the parametric method as described by Ravallion and Bidani (1994).[13] For this method, the logarithm of daily non-food consumption per AEU (including the reimputed house rents but excluding education expenditures) is linearly regressed against the logarithm of daily total consumption per AEU for each of the 122 regions, after which the coefficients, together with the previously obtained food poverty lines, are used to estimate the non-food non-school allowance. Using total consumption as the regressor, as opposed to food consumption, results in more austere non-food estimates, because it considers the non-food outlays of those having a total budget to exactly cover minimal food requirements but choosing to spend part of it on non-food goods.

5 We then compute a separate school allowance by multiplying the local primary school cost per pupil with the number of school-age children within the household. For the latter, we consider all children between 6 and 12 years of age, together with the number of children between 12 and 18 years of age who did not yet obtain their primary school certificate. The reason for the extension beyond the normal age range relates to the late school entry typically observed in the DRC: almost half of all children in their first year of primary school are older than 6 years (RDC, 2014).

6 For the unit cost of primary school, we rely on the actual education outlays of households to derive an average cost per pupil for each year and new province. As such, we collapse the price zones which belong to the same province to accommodate the difference in school quality observed between urban and rural areas (see for example DHS surveys 2007 and 2013) which in part is reflected by the higher school costs in the former compared to the latter. In the other case, when deriving a unit cost per price zone, we risk to value the difference between the urban and rural sector as purely a difference in local school costs, thus ignoring the often marked differences in quality.

7 To estimate the overall poverty lines, we add the food poverty line, as estimated under point 3, to both non-food components, as derived under points 4 and 5.

To summarise, we calculate the poverty line Z as:

$$Z_{p,y}|k = Z^{\text{food}}_{p,y} + Z^{\text{education}}_{p,y,k} + Z^{\text{non food}}_{p,y}$$

Where:

p and *y* represent different price zones and years;

$Z^{\text{food}}_{p,y}$ is defined in function of both calories and micronutrient needs;

$Z^{\text{education}}_{p,y,k}$ cover the need to pay for quality education for all k children aged 6-18 without primary school diploma;

$Z^{\text{non food}}_{p,y}$ is calculated as the non-food items (except education) consumed by people who could attain the food poverty line but choose not to.

Compared to the poverty line approach followed by INS, the methodology outlined here is different in that it (i) also includes recommended nutritional intakes for micronutrients, (ii) separately adds a school allowance based on the number of school-age children, and (iii) defines an austere non-food poverty line.

12 The energy thresholds chosen respectively correspond to physical activity levels (PAL) of 1.45, 1.60 and 1.75. They reflect the structural difference in energy requirements from more sedentary to more physically active working populations, while being conservative overall to respond to the need for austerity (FAO, 2001). In a similar vein, we decided to set the MAR threshold at 0.7, which empirically corresponds to a daily energy intake of 2,500 kcal per AME, to reflect more-or-less the same level of austerity for diet quantity and quality.

13 Alternatively, one could derive the non-food allowance in a non-parametric way to avoid, among other things, imposing a functional form. For example, one could estimate the mean non-food consumption level of households whose total consumption fits within increasingly bigger intervals around the food poverty line. Given its computational complexity, this procedure has not been adopted in this paper.

The most significant deviation from the official approach, however, concerns the level of spatial precision. Indeed, we do not work with just 2+2 poverty lines but we defined 56+66 poverty lines (i.e. one for every price zone and year[14]), thus making our approach much more sensitive to the specificity requirement.

Figure 2 displays the minimal daily amount of Francs Congolais (expressed in AEU) needed to avoid poverty for each province, sector and year. The figure shows that there is substantial spatial heterogeneity. Within the urban sector in 2005, for instance, this amount varies between 636 FC in Kinshasa to 186 FC for the smaller towns in Haut-Katanga; and between approximately 474 FC for the villages in Kasai compared to 107 FC for the villages in Tanganyika. An equally pronounced variation in living conditions seemed to prevail in 2012. Indeed, for the urban sector, poverty lines range from 2,165 FC in Kinshasa to 632 FC in the smaller towns of Tshopo. Within the rural sector, poverty lines vary from 1,445 FC in Sud-Kivu to 572 FC in Tanganyika. In other words, the same consumption or income level in nominal terms may result in completely different real welfare levels, depending on prevailing prices and needs at a certain time and location. These cross-sectional differences are more or less comparable to the price differences between the two survey rounds (reflecting inflation over a seven-year period).

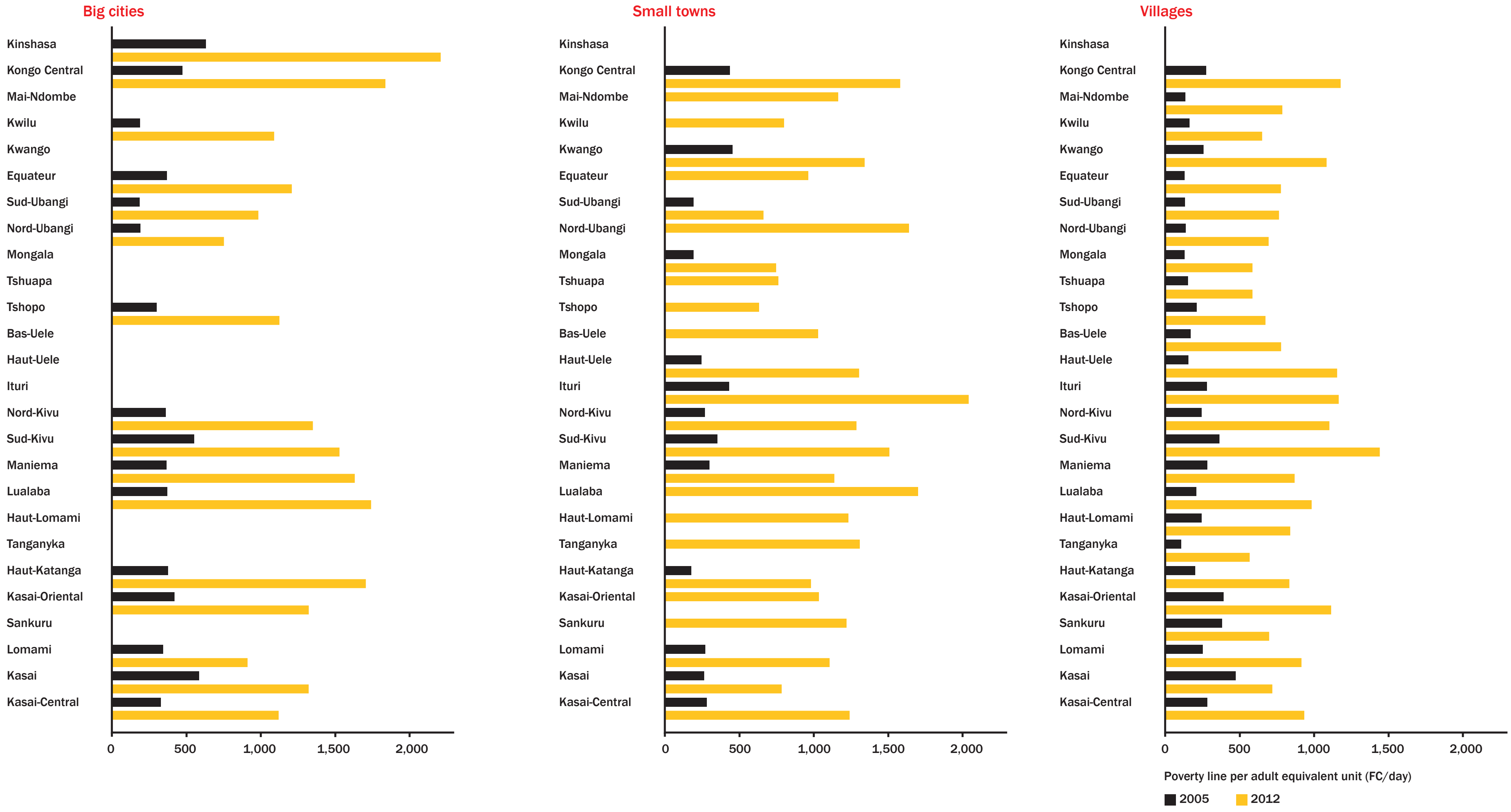
To assess to what extent the INS-based methodology that distinguishes only between urban and rural areas captures this variety, we used a Theil decomposition. It showed that the official poverty line methodology based on the valuation of two area-based poverty baskets appeared to capture only 36.7% of total variation of regional poverty lines in 2005 and 46.8% in 2012. In other words, compared to the methodology developed in this paper, the INS method only captured one third to less than half of the variation in living conditions across space.

Further, while the poverty lines on average have increased by 21% per year following our methodology and by 29% according to the INS approach[15] (these inflation rates correspond to an increase by factor 4.0 to 5.8), significant variation also exists across price zones: whereas prices climbed sharply by more than 33% (or by factor 7.5) in the villages of Haut-Uele, they increased at a more moderate pace of only 6% (or by factor 1.5) in the rural sector of Kasai. In sum, inflation between 2005 and 2012 has been an important factor affecting the wellbeing of many Congolese; however, as expected, the effect is different across locations.

14 As previously stated, the outlined methodology in this paper in fact yielded more than 122 poverty lines, which is due to the inclusion of household-specific information to determine school allowances.

15 These yearly inflation rates have been obtained using a population weighted average of the increase in poverty lines observed for both sectors and each price zone, following our methodology and the INS method respectively.

Figure 2: Regional poverty lines by province and sector, DRC (2005-2012)



Notes: To facilitate comparison with the official poverty lines, the set of austere regional poverty lines has been linearly inflated by factor 1.321, which is the ratio of Kinshasa's non-austere over its austere poverty line in 2012.

Source: 123 Survey data (2005 and 2012).

4.4 Using poverty line-based deflators to account for differences in cost of living

Given the country's size and its sheer variation in living conditions and economic opportunities (Marivoet, 2016) this paper provides a descriptive but detailed geographical overview of Congo's food markets as well as the nutritional status of its population. To do so, this paper will mainly rely on the 1-2-3 budget survey data, conducted in 2004–2005. Along both dimensions, access to food and nutrition, a good deal of spatial variation exists. First, overall efficiency of domestic food markets seems extremely poor. The capital city of Kinshasa is a good example of this; it is food deficient and poorly connected to its own hinterland and therefore highly dependent on foreign food imports. Markets in the former provinces of Kasaï, in the center of the country, and the conflict-prone northeastern part of the country are two minor exceptions, as food prices are slightly more equal. Furthermore, the most competitive food producers are found in Équateur and North Kivu. Notwithstanding these differences in food access, about five diet types can be identified. The most energy-rich diet is based on cassava and palm oil, typically consumed in Maniema, Orientale, Équateur, and rural Bas-Congo. As a result, these provinces on average display higher calorie intakes. Apart from diet composition, income levels and prevailing nonfood needs also determine energy sufficiency. For these reasons households in Katanga and North Kivu are relatively well nourished too, while urban dwellers in Bas-Congo and Orientale (contrary to their corresponding rural sector, which is manifested in the heterogeneity of regional poverty lines, a common denominator needs to be established to make nominal consumption levels comparable across time and space. As already stated, the same income level would give people in different locations a different status in terms of, for example, food security, shelter and education, depending on the prevailing level of food prices, weather conditions and quality of public service delivery.

To account for observed contextual diversity, standard economic theory prescribes using price indices to convert nominal consumption into purchasing power equivalents. Apart from well-known index number issues (Deaton and Heston, 2010), however, price indices also do not account for differences in local needs, which may in turn arise from variations in biophysical characteristics, prevailing social norms or public goods. In the words of Deaton and Heston, 'if all prices were identical in Moscow and in Ouagadougou, it seems meaningful to say that the price level is the same in both, even if the cost of living is higher in the colder, northern city' (2010: 6). Even though they acknowledge that ignoring cost of living 'leaves the welfare basis of the calculations unclear' (2010: 6), they 'do not know how to do better, and therefore endorse a statistical rather than a welfare interpretation of [...] price indexes' (2010: 6).

Yet, given our poverty lines are specific to different price zones and years, they can serve as a basis for a cost-of-living approach. Indeed, the whole idea of a poverty line is that – making abstraction of a number of practical problems, as discussed above – households living on this line do achieve the same level of wellbeing (or ill-being) irrespective of where they live or when they have been surveyed. In other words, we can use differences in poverty lines between regions and years as deflators to express all households' wellbeing levels, wherever and whenever surveyed, in one common metric. More specifically, in what follows, we will express all households' consumption in terms of Kinshasa's prices in 2012.

4.5 Discarding suspicious calorie consumption and attenuating final impact on sample size

While addressing the above methodological issues, several households had to be removed from the sample as they had either insufficient or unreliable data to implement the repairs. Table 6 lists three areas of concern.

First, nutrient intake levels per AME are inaccurate for households where the mark-up procedure for unidentified consumption, as discussed above, could not be executed. This occurs when none of the outlays in a particular food group could be assigned an equivalent in nutrient intakes. If this conversion was not feasible for more than 10% of all food outlays or when one or more family members had missing information on age or gender, the corresponding household was removed from the sample. In our dataset, we could not accurately compute nutrient consumption for 1,267 households.

The second area of concern involves the calculation of imputed house rents. As it appeared, some house attributes found among homeowners were not found among renters. As a result, no house rent was imputed for 342 households.

Third, we dropped households with very unrealistic levels of calorie intake. In nutrition research (Lovon

Table 6: Sample size after various methodological accommodations, DRC (2005-2012)

Number of households	2005	2012	Total
Initial datasets	12,087	21,403	33,490
After removal of households with:			
Insufficient data to estimate nutrient consumption	11,597	20,626	32,223
Inaccurate imputed house rents	11,594	20,287	31,881
Unrealistic levels of calorie consumption	9,784	17,011	26,795
% loss of initial sample size	19.1%	20.5%	20.0%
Final dataset after welfare imputation	11,636	20,119	31,755
% loss of initial sample size	3.7%	6.0%	5.2%

Source: 123 Survey data (2005 and 2012).

and Mathiassen, 2014), a daily calorie intake per AME below 500 kcal and above 5,000 kcal is considered to be impossible. Therefore, we discarded households consuming less than 500 kcal per AME but decided to drop only the households consuming more than 7,500 kcal, because in the case of the 123 surveys, the information on food consumption is sometimes ambiguous; the questionnaire at times refers to 'consumption', yet some questions also particularly mention 'purchase' (Smith et al., 2014). So, it may well be possible that households purchased food to keep as stock. Apart from absolute calorie criteria, we also removed households with suspicious data identified by relative criteria. Inspired by Alfani et al. (2012), we labelled observations as 'highly suspicious' either when households consume less than 1,431 calories per AME (which corresponds with the 20th calorie intake percentile) while having more wealth than the 80th asset-index[16] percentile; or when households consume more than 4,868 kcal per AME (i.e. more than the 80th calorie intake percentile) while having less wealth than the 20th asset-index percentile. Following this double criterion, an additional 5,086 households were removed given their unrealistic recording of food consumption.

As a result, the sample shrunk to only 26,795 households, which represents a total 'loss' of 20% of the initial sample size. In itself this is not a problem, as long as the surveys' representativity is not affected. However, the three areas of concern focus on aspects which may disproportionately affect the 'tail' and the 'head' of the welfare distribution. This is certainly the case for identifying unrealistic calorie consumption. As such, this reduction in sample size is deemed to have direct implications for computing various measures of poverty and dispersion as well as for analysing welfare changes in general.

To address this issue and restore sample representativity, we opted to fit a consumption model on the reduced sample of 26,795 observations and apply its coefficients to impute an estimate of consumption for the households previously removed. More specifically, we estimated the log-linear relationship between consumption, deflated through the method outlined above, and a set of covariates based on household demography, asset ownership, quality of the dwelling, schooling, employment and location. Appendix B presents a summary of household variables used together with model results. After imputing the fitted consumption values for the removed households, the overall loss of sample size is reduced to 5.2% for both surveys combined, leaving a dataset of 31,755 households in total.

16 This asset index has been derived by applying the polychoric extension of principal component analysis as developed by Kolenikov and Angeles (2009) to 24 common asset ownership variables to obtain a measure of permanent income. These asset items include: car, truck, motorcycle, bicycle, non-motorised and motorised canoe, radio, television, Hi-Fi/VHS/DVD, fridge, freezer, stove, cooker, air-conditioning, fan, sewing machine, telephone, computer, chair, table, bed/mattress, lamp, writing machine and wardrobe.

5 Impact of methodological choices on poverty estimates

To quantify the importance of each of the incremental repairs proposed in this paper, Table 7 presents the level and change in poverty incidence between 2005 and 2012 for sector and province following slightly different specifications. Starting from our replication of INS poverty estimates (re-copied in column (a)), each of the subsequent specifications then reflects our response to a particular problem identified in the survey data and official poverty analysis. We discuss each of them in turn.

Effect of spatially disaggregated poverty lines

First of all, applying 122 poverty lines (see column (b)) has a substantial effect on the level and change in poverty. In general, for both years, poverty headcounts are revised downwards, which points to the fact that the true cost of living in many regions is substantially lower than assumed by the four aggregate poverty lines, as defined by the INS. This is especially the case for the rural sector, in general, as well as for the more rural provinces, such as Bandundu, Equateur, Orientale and Katanga. In contrast, Kinshasa becomes much poorer when using the specific and relatively higher poverty line for the capital city as compared to the aggregate poverty lines used for the urban sector, in general. This effect is most salient for the 2005 survey round. When evaluated against the conservative poverty line of 420 FC, which reflects the cost of living of all urban areas combined, less than 47% of the Kinshasa population would be poor. Yet, when applying a separate and higher poverty line for Kinshasa as proposed by our method, the poverty headcount would be as high as 72%. The effect of these revisions on the poverty trend depends on their relative magnitude observed in both years. For the country in general, the increase in poverty becomes less pronounced, dropping from 9.3 to 5.1 percentage points. This positive effect is even far more important in Kinshasa, Maniema and Kasai-Occidental, as opposed to Equateur, which is the only province where the poverty trend substantially worsens when applying the 122 poverty lines. In sum, moving from 4 to 122 location-specific poverty lines very much underscores the high degree of spatial heterogeneity in the DRC, which is important for policy design and better targeting.

Separate introduction of a minimal schooling allowance

Given the relatively small share of education outlays in the total budget, the addition of a separate schooling allowance to the location-specific poverty lines has only a minor effect for both the level and change of poverty (see column (c)). In Kinshasa however, poverty reduction drops from 5.3 to 2.9 percentage points and is no longer significant, mainly the result of an increased poverty headcount in 2012. This may be due to either a higher proportion of children not having a primary school certificate in 2012 or the relatively higher primary schooling costs observed in 2012 compared to 2005.

Stabilising the sampling frame

Equally, stabilising the sampling frame has further improved the accuracy of our poverty estimates. However, the effect of this methodological revision is very moderate (see column (d)), except perhaps for Nord-Kivu where the increase in poverty became significant and sharper after correcting for sampling weights, going up from 0.9 to 5.4 percent points. This is in line with the fact that this particular province has become much more urbanised over time, which methodologically means evaluating more household budgets to a relatively higher urban poverty line. The limited impact among the other provinces with a strongly biased sampling frame (such as Bandundu, Equateur, Maniema and both Kasai provinces) can be explained by the relatively minor difference in overall consumption between the urban and rural areas.

Complete rent imputation

The effect of rent imputation on poverty is straightforward. Given the very incomplete imputation of house rents in 2012, poverty headcounts for that year are consistently lower after adding a housing consumer value to all households (see column (e)). The effect on the 2005 poverty estimates, in contrast, is rather negligible, because (i) the initial rent imputation was already fairly complete, and (ii) the re-estimation procedure has produced largely similar house rent values. As a result, poverty trends for each of the regions look more positive following this methodological revision. This is especially the case for the urban sector, in general, and Kinshasa, in particular, given the higher house rents typically observed in these areas. In the capital city, a full imputation of house rents to all households results in a large and significant decrease of poverty by 16.3 percentage points, while the poverty increase for the country as a whole becomes insignificant.

Recalculating the end and tail of the distribution

Finally, the effect of removing and reintroducing households with a suspicious calorie intake level (see columns (f) and (g)) has been fairly limited for most regions in both level and change of poverty. In addition, it is difficult to identify the main drivers of these methodological effects. Indeed, suspicious calorie intakes not only occur to a different degree at either end of the welfare distribution, they were also flagged using the dimension of household wealth, which, together with other predictors, led to the estimation of an alternative welfare level. However, for the urban sector, one can observe lower poverty headcounts for 2005 and 2012, which perhaps relates to an inadequate recording of food consumed away from home, being an important food source in urban settings. This underreporting may have become more pronounced in 2012 compared to 2005, thus yielding a more significant poverty reduction of 3.3%. In Nord-Kivu, this methodological correction has the opposite effect, resulting in a higher incidence level for 2012 and a significant and more pronounced increase in poverty (5.3%) between both survey years.

Table 7: Evolution in poverty headcount (%) following different methodologies, DRC (2005-2012)

	(a)			(b)			(c)			(d)			(e)			(f)			(g)		
Poverty lines	4			122			122			122			122			122			122		
Separate schooling	No			No			Yes			Yes			Yes			Yes			Yes		
Sampling weights	Initial			Initial			Initial			Corrected			Corrected			Corrected			Corrected		
Rent imputation	Incomplete			Incomplete			Incomplete			Incomplete			Complete			Complete			Complete		
Suspicious calories	Maintained			Maintained			Maintained			Maintained			Maintained			Removed			Removed		
Welfare imputation	Non applicable			Incomplete			Incomplete			Incomplete			Incomplete			Incomplete			Complete		
N sample	33,490			32,223			32,223			32,223			31,881			26,795			31,755		
	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.	2005	2012	diff.
Urban	64.4	75.5	11.1***	61.8	66.2	4.5***	62.8	68.1	5.2***	61.7	67.8	6.1***	63.3	61.8	-1.5	61.1	57.5	-3.5*	61.9	58.6	-3.3**
Rural	75.2	84.7	9.6***	61.9	67.4	5.5***	63.5	68.9	5.5***	63.3	67.6	4.3***	63.8	66.2	2.5**	67.8	68.4	0.7	66.8	69.5	2.6**
Kinshasa	46.6	56.1	9.5***	71.9	66.6	-5.3*	72.6	69.7	-2.9	72.6	69.7	-2.9	76.0	59.7	-16.3***	70.4	53.8	-16.6***	73.7	55.7	-18.0***
Bas-Congo	69.3	79.3	10.0***	62.1	73.5	11.4***	64.4	74.8	10.3***	64.9	75.2	10.4***	66.2	73.0	6.8**	66.6	72.0	5.3+	67.5	72.5	5.0+
Bandundu	90.2	91.1	0.9	68.0	61.1	-6.9**	68.8	62.0	-6.8**	68.1	62.5	-5.6**	69.8	61.7	-8.1***	72.1	64.0	-8.0***	72.1	63.6	-8.5***
Equateur	91.1	90.4	-0.6	49.7	59.9	10.2***	51.5	61.7	10.2***	51.5	61.3	9.9***	51.0	58.7	7.7***	56.7	60.6	3.9	53.3	59.9	6.5**
Orientale	71.9	79.4	7.4***	57.9	61.7	3.7	59.7	63.1	3.5	60.0	63.1	3.1	60.5	59.8	-0.7	65.2	62.0	-3.1	63.9	62.0	-2.0
Nord-Kivu	75.6	75.4	-0.2	59.4	60.3	1.0	61.9	62.9	0.9	60.0	65.4	5.4*	61.0	62.8	1.8	60.9	66.8	5.8*	60.5	65.8	5.3*
Maniema	57.8	86.4	28.6***	50.4	62.5	12.2**	51.1	63.9	12.9**	50.1	63.8	13.6***	50.7	62.3	11.6**	55.6	62.3	6.7	53.1	65.2	12.1**
Sud-Kivu	82.8	84.6	1.7	90.7	83.2	-7.5***	90.6	83.5	-7.1***	90.3	83.3	-6.9***	90.3	82.1	-8.2***	89.5	79.8	-9.7***	90.5	84.9	-5.6**
Katanga	70.0	82.7	12.7***	51.0	64.9	13.8***	53.0	67.3	14.2***	52.6	66.7	14.1***	52.8	64.3	11.4***	56.3	60.6	4.3+	54.7	63.3	8.6***
Kasai-Oriental	62.1	89.9	27.8***	61.8	80.2	18.4***	63.1	80.9	17.8***	64.6	80.5	15.9***	65.5	79.2	13.7***	67.1	78.2	11.1***	66.9	80.1	13.1***
Kasai-Occidental	59.1	87.6	28.5***	63.3	60.4	-2.9	63.7	61.3	-2.4	63.3	62.9	-0.4	64.1	61.5	-2.6	66.6	64.5	-2.1	68.0	63.5	-4.5+
DRC	72.1	81.4	9.3***	61.9	67.0	5.1***	63.3	68.6	5.3***	62.7	67.7	4.9***	63.6	64.6	1.0	65.5	64.6	-0.9	65.1	65.6	0.5

Notes: The poverty lines used behind the estimates of column (a) are those summarised in Table 3; the one used to compute our estimates amounts to 2,061 FC per day per adult equivalent unit, which is the non-austere poverty line (calorie threshold=2.750 kcal, MAR=0.9, and an ordinary non-food allowance) derived for the full sample after having deflated nominal consumption using the 122 austere poverty lines.
+ = significant at .10, * = significant at .05, ** = significant at .01, *** = significant at .001.
Source: 123 Survey data (2005 and 2012).

Comparing our replication of the official INS results (column (a)) with the estimates following the full method outlined in this paper (column (g)), we note that the poverty outlook is completely different, both at the bottom line of Table 7 and in the details.

Looking in depth, only the provinces of Bas-Congo and Katanga show some consistency in the changes in the magnitude and direction of poverty: both the official approach and the one proposed in this paper point to a significant increase of poverty between 2005 and 2012, though our method produces more conservative trend estimates. In all other regions, either the direction of poverty or its magnitude is very dissimilar. For example, the steep increase of poverty by 11.1 percentage points in the urban sector as derived using the official approach is in fact contradicted by a slight, but significant, decrease of 3.3 percentage points using our method. The same conflicting trend between the official and revised poverty methodology applies to Kinshasa and Kasai-Occidental, where the difference amounts to more than 27 percentage points.

In the remaining cases, there is no real difference regarding the direction in which poverty evolved over time, but the magnitude is very different. The most noticeable change is observed in Maniema and Kasai-Oriental, where poverty unequivocally increased, by around 28 percentage points following the official method as opposed to 12-13 percentage points with our approach. For the whole country, (our replication of) the official method yields a poverty increase of almost 10 percentage points, whereas the approach presented in the paper points to a situation of almost complete stagnation around an incidence level of 66%. In line with these dissimilar poverty dynamics, poverty levels and rankings of 2005 and 2012 will inevitably be very different too when comparing the official and revised results. For 2012, both methods yield similar results for Kinshasa and Kasai-Oriental, with poverty being much more pervasive in Kasai-Oriental compared to the capital city. On the other hand, we can observe large discrepancies for Bandundu, Equateur, Nord-Kivu and Kasai-Occidental, where the INS methodology systematically yields much higher poverty headcounts.

At the bottom line of Table 7, our improved methodology estimates poverty at significantly lower levels than the poverty figures either replicated in column (a) or published by the INS and the World Bank. Still, around two-thirds of the population in the DRC can be qualified as 'poor' according our standards. But most importantly, in between 2005 and 2012, poverty did not decline substantially (as reported by INS and the World Bank), nor increase substantially (the result of our replicating the INS methodology) – it basically remained the same. This result is, in itself, quite surprising, given that the significant increase in per capita GDP over the same period would suggest otherwise.

6 Growth incidence curves

In this section, we use growth incidence curves (GIC) to describe how the gains from growth – or its absence – are distributed over different quantiles of the income range (Ravallion and Chen, 2003).

Figure 3 presents the GIC for the DRC by displaying the average daily consumption level per AEU (expressed in Poverty Line Units) for each of the ventiles identified in both years on the left Y-axis, while summarising the annual growth rates between 2005 and 2012 on the right Y-axis. The poverty headcount of 66% is now visible in that per AEU income surpasses the poverty line between ventiles 13 and 14. The GIC remains negative until ventile 17, which implies that the income of the poorest 80% of people has (slightly) declined. Only the two richest deciles saw their income increase. Overall, there was no change in household consumption (or only an insignificant decline from 0.950 to 0.948 PLUs), so there was just some redistribution from poor to rich, as also testified by a 3% rise in the GINI coëfficient from 0.300 to 0.309.

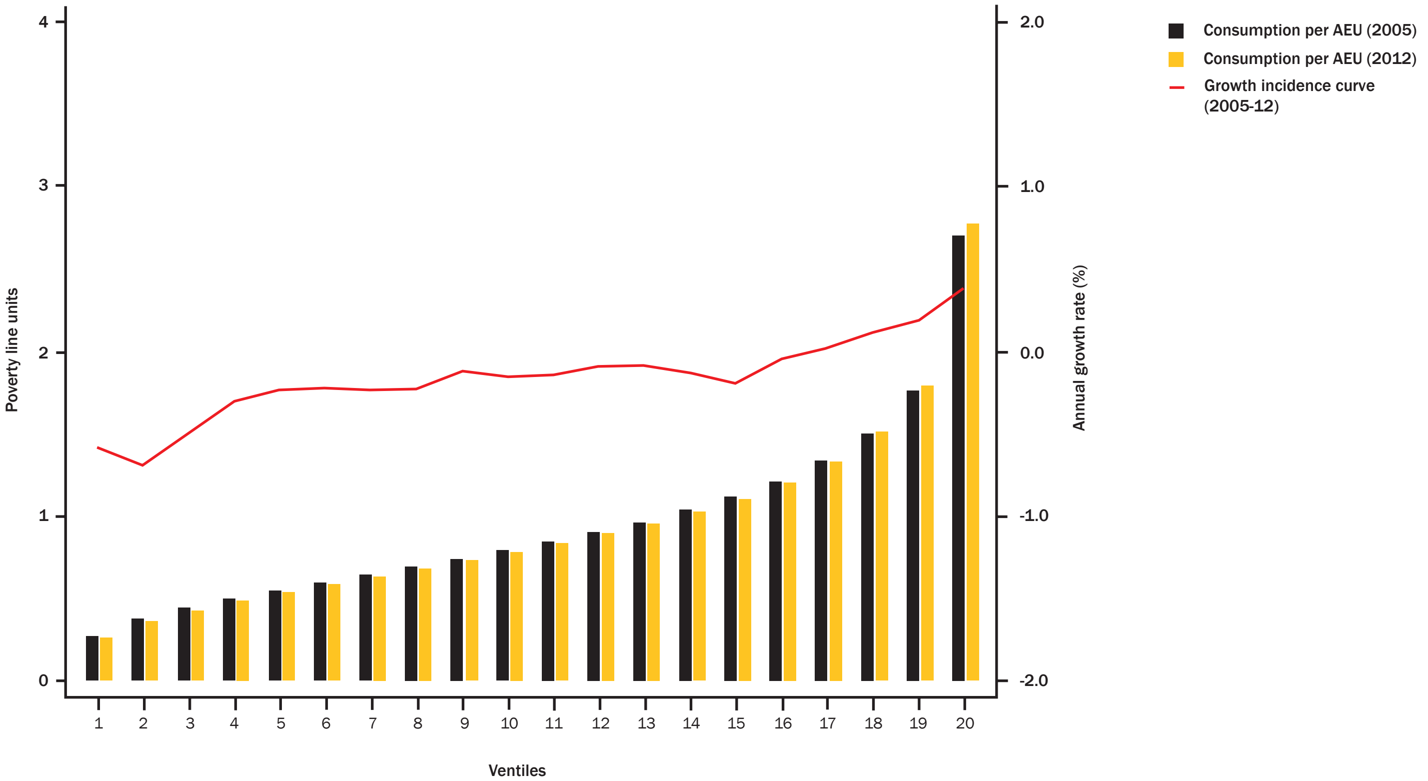
We only compare two cross-sections, so there is no guarantee that the households situated in, say, ventile X in 2005 would still live in the same ventile in 2012. We can, however, test whether the above presentation is robust to the presence of such mobility by making use of quasi-nonanonymous GICs, i.e. by first partitioning all households in particular groups and then regressing the quantile consumption growth of these particular categories against their rank in the initial distribution (Lakner and Milanovic, 2016).

In Figure 4, we display the estimated quasi-non-anonymous growth incidence curve through a kernel-weighted local polynomial regression[17] after first having subdivided the DRC in different territorial categories. The estimate does not completely reproduce the shape of the anonymous GIC (see Figure 3 above) but it confirms the inequalising character of the predominantly negative growth scenario. The more interesting observation is, however, the divergent ways in which this scenario was experienced in different areas.

Clearly, Kinshasa's inhabitants (approximately 10% of the population) can be identified as the winners of this period of zero growth, as almost all percentiles of Kinois experienced positive consumption growth at rates between 2% to 4% (and even higher precisely at the bottom decile). This scenario of fairly equitable, and

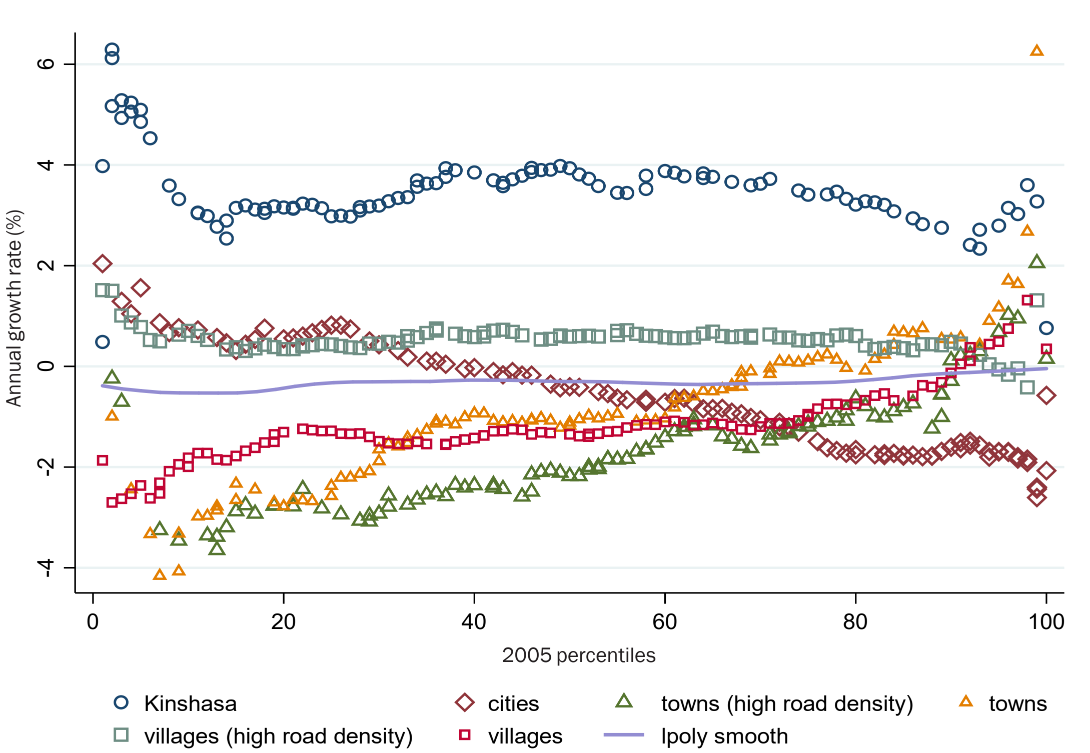
17 Kernel=epanechnikov, degree=0, bandwith=6.19

Figure 3: Growth incidence curve, DRC (2005-2012)



Source: 123 Survey data (2005 and 2012).

Figure 4: Quasi-nonanonymous growth incidence curves, DRC (2005-2012)



Source: 123 Survey data (2005 and 2012).

positive growth, is not at all shared by the other territorial categories, however. Other cities (approximately 15% of the population) present a much more ambivalent evolution, with the poorest layers experiencing positive growth while the top half of the distribution experiences net decline. We subdivided the remainder of the sample (representing 75% of the population) into towns and villages and according to whether they were located in areas with high or low road density (defined here as less than 50 kms of medium to good quality road per 100,000 inhabitants). The high road density variable seems to play an important role in distinguishing between villages (65% of the population) that exhibit a slightly positive growth performance (located in the high road density areas) and those (two-thirds) that exhibit a negative performance except for the top decile. The negative and regressive pattern is even stronger for (the two types of) towns. If, on the whole, inequality has increased, this is driven by phenomena that can be located both in towns and in regions with sparsely connected villages.

Taken together, what stands out is the quite exceptional situation of Kinshasa's inhabitants. While well-connected villages (approximately one-third of the countryside) still realise a slightly positive growth, the other regions have mostly experienced negative growth. Almost all the growth went to Kinshasa, to the disadvantage of Congolese living in cities, towns and villages located in provinces with low road density.

7 Conclusion

In this paper, we first demonstrated that the poverty figures produced by both the INS (2014) and the World Bank (2016, 2018) are not reliable. Indeed, neither of the sources provides convincing or transparent methodological detail to link original datasets with published results.

Moreover, our replication of INS estimates using its own 2005 methodology resulted in estimates that diverged substantially from the reported figures; we found an increase in poverty, not a decrease as the INS reported.

Our proposed methodology to estimate wellbeing and poverty using household budget data includes several steps. First of all, we corrected the INS methodology for sampling errors and for incomplete imputation of rents to homeowners in 2012. The latter correction particularly had a substantial effect on the poverty estimates. Further, we improved the INS methodology by applying a spatially disaggregated poverty line approach which allowed for more sensitivity to local specificity in both consumption (including dietary) patterns and prices and by introducing a separate allowance for household-specific education needs. We also used the 122 different poverty lines to generate consumption deflators. This disaggregated approach also had a major effect on the poverty estimates. As a result of the improved methodology, poverty dynamics in all provinces (except perhaps Bas-Congo and Katanga) either change direction or magnitude in a way that is different to the replicated INS results.

Overall, we estimate that, between 2005 and 2012 there was essentially no change in the (very high) level of poverty nor in the average growth per adult equivalent consumption, while inequality slightly increased. A further disaggregation of growth per quantile and per region indicates that growth was highly concentrated in Kinshasa and, to a lesser extent, in villages located in provinces with a higher road density, to all other regions' disadvantage.

The methodology outlined in this paper as well as the associated poverty revisions do have shortcomings. In fact, this paper's main purpose is to highlight the need for more in-depth research to improve the accuracy of estimations of wellbeing and poverty using household survey data. We see three possible areas for further work.

First, given the impact of the proposed methodology on final estimates of growth, inequality and poverty, further research on the methodology itself is necessary to develop better alternatives. While the repairs proposed in this paper for all methodological issues are open to critical scrutiny, we think that most value addition will come from further work on dealing with contextual diversity in space and time. In particular, the way in which inter-contextual differences in public service provisioning is taken into account (or rather: not taken into account) might be one important way forward.

Second, the proposed methodology requires further validation and qualification through triangulation with other data on livelihoods, such as assets, schooling, health, etc. Some of this data may already be available in the 123 Surveys, while some would have to come from other sources. Evidently, each of these alternative indicators measure a different dimension of wellbeing or livelihoods, yet any rough correspondence may be useful both as a validity check on monetary welfare and to enrich our understanding how wellbeing evolved across space and time.

Third, various types of distributive analysis and decomposition tools could be employed to study the welfare and nutrition distributions in more detail. Who precisely won and who lost between 2005 and 2012, and why? While our results suggest that almost all the growth benefits went to Kinshasa, to the disadvantage of Congolese living in cities, towns and villages located in provinces with low road density, a more systematic analysis is needed to make sense of the observed patterns of ‘winners’ and ‘losers’.

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Annexes

Annex 1: Log-linear regression results for rent imputation

ln(rent)	Coef.	Std. Err.	t-statistic	p-value
Quality of wall (modern)				
rudimentary	0.027	0.055	0.490	0.623
natural	-0.222	0.062	-3.560	0.000
other	0.203	0.104	1.950	0.052
Quality of floor (modern)				
rudimentary	-0.258	0.103	-2.510	0.012
natural	-0.522	0.112	-4.680	0.000
other	-0.460	0.186	-2.480	0.013
Quality of roof (modern)				
rudimentary	0.005	0.081	0.070	0.948
natural	-0.280	0.098	-2.840	0.004
other	-0.139	0.338	-0.410	0.680
Number of rooms	0.177	0.024	7.270	0.000
Number of sleeping rooms	-0.015	0.026	-0.580	0.562
Energy used for cooking (modern)				
rudimentary	-0.421	0.057	-7.340	0.000
natural	-0.754	0.073	-10.360	0.000
other	-0.776	0.283	-2.740	0.006
Type of water (tap)				
improved	-0.492	0.049	-10.010	0.000
rudimentary	-0.447	0.068	-6.570	0.000
other	-0.033	0.261	-0.130	0.900
Type of sanitation (flush)				
improved	-0.125	0.054	-2.300	0.022
rudimentary	-0.312	0.056	-5.520	0.000
other	0.201	0.160	1.250	0.210
Type of garbage collection (service)				
rudimentary	-0.131	0.082	-1.590	0.111
none	-0.086	0.079	-1.090	0.275
other	-0.175	0.125	-1.400	0.161
Year (2005)				
2012	1.847	0.073	25.360	0.000
Sector (Kinshasa)				
other urban	-0.502	0.074	-6.820	0.000
rural	-0.784	0.108	-7.260	0.000

Year * Sector (2005*Kinshasa)				
2012 * other urban	-0.267	0.085	-3.140	0.002
2012 * rural	-0.865	0.114	-7.580	0.000
Biozone (Savanna highland)				
Savanna lowland	-0.026	0.051	-0.510	0.613
Tropical highland	0.211	0.079	2.670	0.008
Tropical lowland	0.293	0.069	4.250	0.000
Constant	11.555	0.144	80.310	0.000
R2	0.665			
Adj-R2	0.662			
F-statistics (31,3886)	191.51			
Observations	3,918			

Source: 123 Survey data (2005 and 2012).

Annex 2: Log-linear regression results for welfare imputation

ln(deflated consumption)	Coef.	Std. Err.	t-statistic	p-value
asset index (see Section 4.5.)	0.183	0.008	23.160	0.000
quality of wall				
rudimentary	0.021	0.014	1.490	0.136
modern	0.038	0.015	2.490	0.013
quality of floor				
rudimentary	0.076	0.015	5.170	0.000
modern	0.117	0.035	3.360	0.001
quality of roof				
rudimentary	0.072	0.012	5.910	0.000
modern	0.035	0.028	1.240	0.213
number of sleeping rooms per person	0.146	0.013	11.460	0.000
energy used for cooking				
rudimentary	0.111	0.012	9.070	0.000
modern	0.147	0.027	5.360	0.000
type of water				
unprotected well or spring	-0.015	0.012	-1.320	0.186
protected well or spring	0.050	0.014	3.540	0.000
public tap	0.051	0.019	2.660	0.008
outside private tap	0.096	0.024	4.010	0.000
inside private tap	0.123	0.041	2.980	0.003
type of sanitation				
hole	-0.024	0.013	-1.860	0.063
public latrine	0.025	0.025	1.030	0.303
private latrine	-0.007	0.017	-0.400	0.690
public toilet	0.066	0.024	2.710	0.007
outside private toilet	0.071	0.031	2.280	0.023
inside private toilet	0.089	0.046	1.940	0.052
type of garbage collection				
rudimentary	-0.019	0.017	-1.170	0.242
services	0.086	0.031	2.750	0.006
household size	-0.072	0.002	-30.860	0.000
age of household head	-0.011	0.002	-5.460	0.000
(age of household head)^2	0.000	0.000	4.660	0.000
female household head	-0.029	0.014	-2.060	0.039

widow household head	0.020	0.019	1.070	0.286
polygamous household head	0.082	0.014	5.810	0.000
average age of adults	0.003	0.001	3.490	0.000
dependency ratio	0.000	0.000	-9.680	0.000
unemployment ratio	-0.001	0.000	-3.470	0.001
years of schooling of household head	0.000	0.002	0.170	0.868
average years of schooling of adults	0.022	0.002	9.620	0.000
price zone (1-122)				
_cons	7.108	0.055	128.400	0.000
R2	0.401			
Adj-R2	0.397			
F-statistics (155, 21679)	68.46			
Observations	21,835			

Notes: Dummies for 121 price zones are not reported, but all except three have coefficients significant at p<0.05.
Source: 123 Survey data (2005 and 2012).

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Cover photo: Members of a local local volunteer organization plant trees in a school yard as part of activities for International Volunteer Day in Goma, eastern Democratic Republic of the Congo (DRC).
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