On Track or Not? Projecting the Global Multidimensional Poverty Index Podcast Transcript

Natalie Naïri Quinn:
Welcome to the CSAE Research Podcasts, a series of conversations about research taking place at the Centre for the Study of African Economies at the University of Oxford. I'm Natalie Naïri Quinn, a departmental lecturer in the Department of Economics at Oxford, a tutorial fellow in economics at Lady Margaret Hall, and a member of the CSAE. Today we will be discussing the paper 'On Track or Not? Projecting the Global Multidimensional Poverty Index', published in the Journal of Development Economics.

Can we measure whether countries are on track to halve poverty incidence between 2015 and 2030? This research proposes a framework for modelling projections of multidimensional poverty. It uses recently published repeated observations of multidimensional poverty based on time-consistent indicators for 75 countries.

Joining us today to discuss the project are Ricardo Nogales and Nicolai Suppa. Ricardo is associate professor at UPB Bolivia and a research associate at the Oxford Poverty and Human Development Initiative (OPHI). Nicolai is an assistant professor in economics at the University of Barcelona and also a research associate at OPHI. Welcome.

Ricardo Nogales:
Hi everyone. Thanks for having me.

Nicolai Suppa:
Thank you very much. Great to be here.

Natalie Naïri Quinn:
We started work on this project in early 2020. We'll first explain the context in which we carried out our research and the aims of the project. The Sustainable Development Goals (SDGs) were adopted by the UN member states in 2015 as a framework for global development over the period 2015 to 2030. The first SDG is to end poverty in all its forms everywhere, and target 1.2 is to, by 2030, reduce by at least half the proportion of men, women, and children of all ages living in poverty in all its dimensions according to national definitions.

Nicolai, can you explain how OPHI has contributed to the measurement of multidimensional poverty at global and national level

Nicolai Suppa:
Sure. Thank you for the invitation. OPHI has contributed and continues to contribute to global multidimensional poverty in several ways. First, it conducted seminal research on how to measure multidimensional poverty. Moreover, it provides technical assistance to governments and statistical offices wishing to implement such measures in their countries. At the global scale, one of our current activities is the computation of the Global Multidimensional Poverty Index (MPI). Selected numbers from this index are published jointly with the United Nations Development Program. The global MPI is an international measure of acute poverty and comprises ten deprivation indicators, each capturing shortfalls in specific dimensions of human well-being.

And in constructing these indicators, we actually rely, a lot in terms of data, but also research, on the improvements that have been made during the MDG and the SDG period. And these indicators, will sound familiar to people who work in that field. For example, we consider household deprived in, and in drinking water if the household has no safe drinking water access. We consider a household deprived in drinking water if it lacks access to safe drinking water. Similarly, a household is considered deprived if it lacks improved sanitation facilities, has undernourished household members, or has school-age children not attending school. So this gives you a sense of what indicators we use in the global MPI.

There are two more things I would like to mention to give you a sense how measurement works. One thing is that we consider poverty to be actually experiencing multiple deprivation. That means a single deprivation is not sufficient for being identified as poor. Instead, you need a critical amount of deprivation before you consider to be, multidimensionally poor. we need to say something about how much poverty there is in the country. And we for this purpose, we rely usually on three aggregate indices. One is the head count ratio, which is simply the proportion of the population which is considered to be poor. The second is the average deprivation among the poor, which we call the intensity. And then we also have the so-called adjusted headcount ratio, which is the product of both intensity and the headcount ratio. What is later important for understanding of our projection framework is that these indices are bounded. So the headcount ratio and the adjusted headcount ratio have bounds of zero and one and can take any value in between. But the intensity, the average deprivation among the poor, is boundary between one third, which is the poverty cutoff of the global and Pi and one. So on average, poor people cannot have less than one third of deprivation, on average. So that’s the basic idea of how measurement of multidimensional poverty works.

Natalie Naïri Quinn:
Thank you. Before 2020, many countries were achieving substantial reductions in multidimensional poverty. However, data limitations made it difficult to monitor the extent of multidimensional poverty reduction and whether countries were on track to achieve SDG target 1.2.

Nicolai, can you explain how related work at OPHI changed that in 2020?

Nicolai Suppa:
Yes, as you can imagine, the indicator construction at the country level involves massive data-cleaning work. We work with microdata sets such as DHS and MICS, which require cleaning and the construction of indicators. We have 10 global indicators in the global MPI. For each country, we have at least one. But if we have two or more, we can actually try analyse later changes over time in the aggregate. So we have at least, for 80 countries, we have already 167 data sets. So this is a massive amount of work and this has been done previously. But in 2020 the difference was first that, well, we had almost 80 countries by then for which we could compute harmonized estimates for two periods at least. But we could also foresee at that moment that, we will update this line of work more frequently on an annual basis.

Another challenge to understand the data situation is of data cleaning,

In 2020, we had harmonized estimates for nearly 80 countries, allowing us to update this data annually. We also have challenges on the workflow and the estimation, which is for this amount of point estimates, not negligible. But then also in terms of analysis, we have to keep in mind that the data is usually, for those countries, only updated every three to five years. This means we do not have annual data for each country, creating gaps that can sometimes more than five years for one country.

Natalie Naïri Quinn:
You mentioned harmonized data, which is critical for this project. Can you describe what that means in this context?

Nicolai Suppa:
Harmonized data. Service can change the underlying questions and our indicators might be affected by that. So the idea is if we want to have strictly harmonized data, we have to compare how the different questions have been asking the different service. And potentially we have in order to ensure comparability over time, we have to update the indicator construction to make it perfectly comparable.

Natalie Naïri Quinn:
Thank you. So while data is critical, we also faced methodological limitations in assessing rates of multidimensional poverty reduction and whether or not countries were on track. Could you explain the limitations of simple analyses of absolute or relative changes in multidimensional poverty, and how our main research question for this paper emerged from those limitations?

Ricardo Nogales:
Previous work largely relied on descriptive analyses of absolute and relative changes in poverty. But as I mentioned already, the data comes from different years. So one problem is that the period of observation, is sometimes three years, sometimes five or even more. To some extent this can be

addressed through analyzation of the data. So taking the average over time. But then we already assume how the average change in between was actually taking place. So we have an assumption about the trajectory.

The second observation relating to that is also that low poverty countries, for example, they cannot really reduce poverty much further in absolute terms because they're actually touching the lower bound to zero. So we realized that, in cross-country comparisons, oh, well, that the simple analysis of, absolute and relative changes is not taking into account, the upper and lower bound comprehensively. Also due to the upper and lower bound comparability across countries with simple absolute and relative change is problematic because the principal information about the level is not incorporated.

This led us very naturally to the question how to compute projections, which is very prominent in the SDG framework. In the end, this is how it emerged. So our research question came, how can we compute such projections given our data situation? ow do we how can we perform actually projection based analysis as is sometimes already done in the SDGs. And this includes questions for example, such as where the countries are on track to meet their development target. In the second step, we can also ask, how to set these targets actually in the first place. We also need projections, for example, to now cast because given the data situation, we don't have annual data. We even don't know right now how high is poverty in this or that country. So for now, casting purposes, we also need projections. And that is, how the research question of the paper emerged.

Natalie Naïri Quinn:

Thank you. As I mentioned earlier, we started this work in early 2020. Of course, another aspect of the context in which we were doing that work was the developing Covid pandemic. We'll discuss later how we extended the project to address questions related to the pandemic. As Nikolai just discussed. It was not clear that a simple analysis of absolute or relative changes would have been a meaningful way to analyse multidimensional poverty reduction or to assess whether countries are on track to have multidimensional poverty rates by 2030. So when we were working on this research, our first task was to develop an appropriate but hopefully straightforward modeling framework in which we could carry out these analyses. The simplest options would have been to model x dimensional poverty levels as a linear function, or an exponential function of time. These models embody assumptions of constant absolute changes or constant relative changes in poverty levels, respectively. Earlier research addressing similar questions had primarily assumed constant relative changes that respects the fact that multi-dimensional poverty levels are bounded below at zero, but doesn't respect the fact that they are bounded above. And in fact, constant relative change or exponential models tend to systematically suggest that the poorest countries are doing badly in their poverty reduction efforts, which might in fact be misleading.

So, as Nikolai mentioned, by 2020 we had two harmonized observations available for 80 countries. In fact, for the research in this paper, we used the data for 75 of those countries, which was also, well comparable across countries, but with only two harmonized observations available for each of those countries we were limited in how much we could learn about the shape of individual countries. Multidimensional poverty trajectories. So what we did when we were developing our modelling framework was to effectively combine data from countries at different poverty levels and at different stages along a poverty reduction trajectory. A simpler graphical analysis, which we report in figure seven in our paper, suggested that modelling multidimensional poverty instance as a logistic or S-shaped function of time makes a lot of sense. Logistic functions also respect the theoretical bounds at zero and one. So we carried out more formal cross-country model selection analyses as well, they are reported in the paper in tables three, four and five and those more formal and analyses the model selection analyses that we did supported this choice of model. So the logistic function provided us with a really good model for the incidence of multidimensional poverty. For the intensity of most dimension of poverty, as Nikolai mentioned, we have a lower bound of one third and again an upper bound of one. We modelled the intensity of multidimensional poverty in a similar way to the incidence, but with a modified logistic function that respect the lower bound of one third. Now, multidimensional poverty levels themselves, which are decomposable as the product of incidence and intensity, we modelled exactly like that as the product of the model of the instance, the model of the intensity.

So having developed this modelling framework and having calibrated our preferred models for 75 countries, we were then able to assess whether these countries were on track to halve multidimensional poverty between 2015 and 2030. Ricardo, would you be able to describe our results and explain how these results relate to SDG target 1.2?

Ricardo Nogales:
So first of all, I would like to emphasize that our results are based on logistic trajectories are not typical constant relative change models. This is important because we're able to pick up if there is any acceleration, for example, along the trajectories that we have, especially for the poorer countries which are starting at a very high level of poverty in the first place. So that the upper bound is respected but we're able to pick up this acceleration. In a nutshell, we find that out of the 75 countries that we analysed, for which we have two data points that are strictly harmonized, as Nicolai explained, 51 are well on track to half poverty between 2015 and 2030 meeting the SDG target. But we find that 24 are not. So the heterogeneity among the countries, say across world regions is actually very important. And in the paper, we don't omit to describe this entity that we find. For example, in the case of East Asia and the Pacific, we are able to include eight countries in our analysis, and all of them are set to meet the target by our projections. It's a relatively similar result in Europe and Central Asia, where we able to include 11 countries and 91% of them are set to meet the target by our analysis. However, we are able to include 35 countries in sub-Saharan Africa, and only half of them are set to meet the target. So half of the countries that we include in sub-Saharan Africa are set to not have poverty between 2015 and 2030.

Now, one important thing that we also find is that we focused on the incidence of poverty, meaning the proportion of people that live in that situation in each country and we project that as a preferred index. However, as Nicolai explained, the MPI, the Multidimensional Poverty Index can be adjusted to take into account intensity as well. Meaning the extent or the depth at which people experience the condition of poverty. If we actually take into account the NPI, meaning the headcount ratio adjusted by intensity, then some important results emerge. For example, if we take into account the projection of the MPI, Guinea and Ghana would actually meet the target by the

MPI, meaning that they would have poverty as measured by the adjusted headcount ratio, and that only the headcount ratio. This is important because it casts a little bit of conversation around how poverty should be defined and what aspects of poverty need to be assessed when we think about a poverty evaluation over time. This result means that even though people in Ghana and Guinea, the proportion of people living in poverty in those countries, are not necessarily going to be cut by half in the 15 years of the SDGs. The intensity at which they experience this poverty condition can actually be reduced substantially. And that's important because Guinea and Ghana are some of the countries, in sub-Saharan Africa, that if we don't think about how to extend this notion of poverty, can actually have a very dark result. But in our case, if we change the measure and adjust the index to take into account intensity, probably the result can give a little bit more hope for policymaking.

Natalie Naïri Quinn:

Thanks, Ricardo. So as well as assessing whether countries are on track to halve poverty by 2030 based on their observed progress, we were also able to implement counterfactual analyses to address what if type of questions. Nikolai, could you describe some of these analyses and discuss the implications of this work for setting development goals?

Nicolai Suppa:

So one of the nice features of this modelling framework is that we actually can have a single parameter which describes the full trajectory for a country, meaning like including the part of the acceleration and the slowdown subsequently. And in our analysis, we have this, this data, all these parameters for the for the set of almost 80 countries. So in the end, we observe a distribution of that parameter around the globe in terms of how multidimensional poverty has been reduced. And this information we use for a counterfactual analysis informed by empirical performance, which actually took place. So we ask the question, what if countries perform slightly better or slightly worse? Would they reach or miss their targets? What we find in that kind of analysis is, for example, that 12 out of 24 countries, which are not achieving the target, if they were to deliver instead, median performance, according to our observation, they would actually meet the target. So that sounds very much like feasible targets. On the other hand, we also find several countries which would fail to meet the target if they would deliver slightly weaker performance, of the lower quartile empirically. But then we look at the entire distribution and we find in the end that for many countries, it turns out that the, targets set in this way are actually way too ambitious or too unambitious. For example, in the case of Ethiopia, we find Ethiopia has, according to our evidence, a median performer in poverty, multidimensional poverty reduction. But it turns out that even if you would deliver a poverty reduction performance similar to the upper quartile of what we observe in our data around the world, Ethiopia would still miss the target. So this suggests that the target has been set in a unrealistic way in the first place.

In a related exercise, which is not counterfactual but gives us a sense of the magnitude, how far countries can be off, we computed the years that the countries would need in order to meet the target and for a good amount of countries we find actually that the target is met five years before. So already in 2020. And for another large amount of countries, we find that they need ten more years. So this again, makes clear that for some countries, it's completely unambitious. And for other it's overly ambitious and both comes with costs as we this as we explained in the paper.

And one conclusion is that this kind of analysis casts obviously doubt on a one size fits all approach to a set poverty reduction targets in relative terms, like cutting poverty by half. Maybe what I should add in terms of feasibility of the targets and just very briefly, the literature already discussed previously that in initial conditions meta, because there was a prominent debate, in relation to the MDGs already. And what has been emphasized is that in principle, levels where the countries are meta, but the previous trends that the previously observed trajectory matters too, and also, the appropriate model choice as we explore in our paper. And together with these things, we can actually arrive at more appropriate projections for the case, of business as usual, as, as it is sometimes called. But then if we have, which is the case in our model, we have coefficients that are comparable across the countries. We can actually use this empirical information to ensure that the ambitious targets are also feasible so that we're not demanding, outlandish high, reduction targets. And in principle, this information can also be used, in our exercise, we only use national data, but in principle, one could of course explore subnational performance of countries as well and see what is feasible and what not.

Natalie Naïri Quinn:

Thanks, Nikolai. That's a really important and interesting point, I feel, and I'm certainly concerned about the way that the SDG target has been stated as really setting up very poor countries that are actually making remarkable progress in poverty reduction, kind of setting them up to fail in terms of what can they achieved by 2030. So maybe on the basis of this work, there can be some rethinking of the way that these targets are set. Like all research projects, we face some challenges along the way. Riccardo, might you be able to summarize some of these challenges and explain how we were able to address some of them, at least?

Ricardo Nogales:

Yes. I would like to start with at least three clear challenges that emerged during our research.

So the first one is the data limitation that we have. So we are working in a world where the question that we ask is actually very important for policymaking at the international and national levels, but we have very, very limited data to do that. So, as Nikolai explained, we need strictly harmonised data to be comparing things that are meaningful to be compared, and, if we can, we need to do that for several countries in the world. So, the frequency at which we can update this information, these observations is actually quite limited, and it amounts to the granularity of the data that we can have across time for each country. So the first challenge is, of course, the limitation of information that we have to perform this exercise. And I think that one of the salient points in our paper is precisely to do the best that we can with this data limitation and to overcome that in a meaningful way.

The second one is that when it comes to projection of, say other development indicators such as monetary poverty, there are well-established methods and there is a growing trend of literature in that direction. But, we can hardly borrow from this kind of literature to inform our exercise. The reason is that the determinants of multidimensional poverty are not as well understood, for example, as monetary poverty. For example, there is a wealth of literature in terms of the relationship between economic growth and monetary poverty, or how growth determines poverty through trickle down approaches. But, there is very, very limited evidence about how exactly growth, for example, has an impact on multidimensional poverty or other determinants. So, we are not able to necessarily have, traditional, say, covariate space model, to inform projections of multidimensional poverty because not only the data limitations that we have, but also because of theoretical restrictions that are not necessarily clear about suggestions in terms of what determinants or explanatory variables to include in such exercises.

And maybe one third challenge, I would say, and maybe a lesson learned, is that, of course as you mentioned Natalie, we want this paper to be influential at the policy level. So we want this to be as academically rigorous as we can, of course, but also to be useful outside of academia and policymakers. But then, as Nikolai mentioned, one key parameter that we have is, what we call the paper. The beta parameter is very much, logistic rate of change. But it's not as intuitive, for example, as a constant relative change rate. So in this case, it's difficult to convey the importance of not only taking into account, the recent progress, but also the starting point, which is kind of summarised in that parameter. So how to use that parameter for, say, for example, target setting is also one challenge that we have going forward.

Natalie Naïri Quinn:

Thanks, Ricardo. Yes indeed. The beta parameter. It's the key thing that we calibrate for each country. And it kind of summarizes everything, everything that we can say about that country's poverty reduction trajectory, but quite how we communicate it in an accessible way in a policy context, we haven't yet figured out, suggestions from listeners are very welcome indeed.

Ricardo, could you explain the potential value of our work for policymakers at national and international level?

Ricardo Nogales:

Yes, of course. So building of what I was saying. So we aim, for a work to actually inform policy making against poverty. But, for that we need to make this accessible for policymakers and make it a habit that whenever they analyse multinational poverty, at least they try to use whatever updates they have in their national multidimensional poverty indices to inform how the trajectory has changed, whether or not something some events can be positive or negative. It can be a program, a widespread program, or it can be say, negative environmental conditions have actually shifted the trajectory as they had it before the update. So I think that keeping track that this can be routinely, included in multi-dimensional poverty analysis, country wise, is something that we could actually do, countries can actually do. And we hope that this paper ignites the curiosity towards that direction.

And also one thing that is very important, and you already mentioned it, is that our work in the present paper has been inspired in SDG 1.2. Because 1.2 mandates that we, track poverty according to national definitions. Our work, of course, is intended to be one that informs an international audience about what happens with a set of countries across the world. But actually, when it comes to policy making against poverty, a lot of countries have actually adopted national versions of the index that we analysed in this paper to fine tune it to their context and the realities. Meaning that they have what we call national multidimensional power indices, which are stable, permanent and, official measures of poverty within their country. So how does our method, for example, behave and how does it inform trajectories of national multinational poverty indices is certainly a question that we need to find out. But that, of course, could lead to a lot of very important literature on this, since our aim is to have a first started the mythological aspect to do that, I guess that I phrase it as a challenge, because we do want this to be applied in those context as well.

Natalie Naïri Quinn:

Thanks, Ricardo. I think my understanding is that most of those national mPIs are kind of built using the Alkire-Foster framework, just like the global MPI. So I'm hopeful at least that the framework that we've developed in this paper, which was developed specifically for the global MPI, may well be useful also for the national MPIs. So far, our discussion has focused on applications of the framework to multidimensional poverty projections. Nikolai, do you anticipate that it could be useful for monitoring other development indicators?

Nicolai Suppa:

Yeah, definitely. One of our focuses in this paper was on the bounded nature of our sub-indices, in particular the headcount ratio and the adjusted headcount ratio, which bounded zero one, but also the intensity which has a lower bound of one third. So explicitly we're looking for a model that takes this into account. And the logistic model that what the modified logistic. Now it actually is potentially relevant for most of the other indicators, because most of them are have also bounded nature. So we often have zero one bounds for the proportion of literate adults, for example.

Now the question is, what are the other models that are often used in the literature in many cases, as mentioned previously, it's the constant relative change model. This in principle respects the lower bound. When we are approaching the lower bounds, the absolute changes become smaller and it's so we have this period of slowdown, but we don't this model does not account for the period of acceleration. So in principle, it's convex over the entire period. So we are lacking the concave part that the logistic actually can provide. Now, it seems that some of the literature is not focusing too heavily on this aspect, which might be simply due to relevance in the particular field, because in many cases, the constant relative change is a good approximation for the logistic model. So if we are, in terms of a poverty measure, for example, below levels of 0.5, well, one can discuss where it's a good approximation, but in that area they are not, not too far away. But if it's in particular for the poorer countries that this could make a big difference, because in the end, you would assume, like a very steep reduction. Now, what happens sometimes also in the literature is that the actually the model is used implicitly, for example, in the calculation of the average annual reduction rates of indicators. And if we set targets based on that, if we compute and compare performance based on average annual reduction rates, we actually implicitly assume, constant relative change model. So using the logistic model or the insights we have from the analysis in this paper could be useful for other not for other bounded indicators in the development, other development indicators as well, which are many of the non-monetary indicators obviously.

Natalie Naïri Quinn:

Thanks, Nikolai. As we mentioned earlier, we started this project in early 2020 just as the Covid pandemic was taking hold globally. Nikolai, can you explain how the frameworks that we developed in this paper for modelling projections of multidimensional poverty also turned out to be a useful framework for assessing the potential impact of the pandemic on multidimensional poverty.

Nicolai Suppa:

Yeah. That was actually a companion paper of the projections of work. Because if you can imagine, if you start working on projections and then the Covid crisis is unfolding, then who cares about the projection bit beyond 21? So the question is, put it the other way, is how can we contribute to, to the to the then unfolding, Covid crisis? What we try to do is to assess the potential disruption due to Covid. Technically, we could rely on simulations because the Unesco for example, provided information about school closures and we have a, school attendance, indicator in the global MPIs. So we could use, relatively easy access depending on the, data of the Unesco, what a school closure of a certain period would mean for the global MPI. The problem, however, was, as we mentioned, our data situation because much of the data has been outdated with respect to the Covid shock. So because if the data is only updated every three to five years, many countries had pre-Covid data from 2015 and earlier even. And then if we run the simulation on that kind of data set, it obviously ignores the poverty reduction, the change in poverty more generally that it probably has taken a place in the meantime. And this is what this is where projections actually come into place. And in that paper, we combine simulation and projection techniques in order to integrate the poverty reduction that took place between the last survey data set collected up to the moment of 2020, the unfolding Covid crisis, and we also take into account that the shock might have been different given that new level, of poverty we would expect, according to our projection framework. So this is essentially a standalone paper where we use projections. And one of the results there is that depending on the different, simulation exercises that we did, we estimate that there might be a setback between three and 10 years in terms of recently achieved, poverty reduction at the global level. The paper is entitled Global Multidimensional Poverty and Covid 19: Decade of Progress at Risk and has been published in Social Science and Medicine.

Natalie Naïri Quinn:

Thanks, Nikolai. It was a really, really interesting exercise working on developing the projections framework and at the same time immediately applying it to kind of very much live research questions at the time.

In the paper that we've been discussing here, our main application was a country level assessment of whether countries were on track to halve multidimensional poverty between 2015 and 2030. Ricardo, can you explain how the framework that we developed is also proving useful for within country analysis?

Ricardo Nogales:

Yes. So again, coming back to the idea that we want this paper to be as mythologically solid, but also as useful as we can for policymakers. So far analysis has focused on what happens with indicators at the national level. And we do find interesting results, especially when we try to see what happens across nationally. But when it comes to actual policy for ending poverty at the national level, we need to understand country heterogeneity as well. And one important thing about the method that underlies the MPI is an action that is called, subgroup, the composability, which allows the index to be broken down and to inform about the situation of poverty for different population subgroups within the country, data permitting, of course.

So in this case, if we actually perform the same framework, but not of the country level, but for the indices that correspond to each of the subnational groups that are of interest, then we can see to what extent our heterogeneity is in the trajectories within the country as well. So in that sense we can detect, for example, whether some provinces or states or regions within the country are lagging behind as opposed to others that are perhaps thriving when it comes to reducing multidimensional poverty. That allows us to see if, according to the pledge that we know about whether some people are actually being left behind in this process of development. That other country level may look promising, but when you dig a little bit further down, you see that there within country differences, the need policy, attention. But not only in terms of geographical differences, we can also perform this analysis if data permits, for different population subgroups according to socio economic, conditions. So for example, we can do age wise decompositions, we can do an analysis of what happens with, for example, female headed households. And essentially we can understand a little bit better what lies within this trajectory that we have, for a country, but also for different subgroups within the country.

Natalie Naïri Quinn:

Thanks Ricardo. Meanwhile, since we finished this paper, data availability has improved again. Nikolai, can you update us on this and describe the research that we're currently working on that makes use of the improved data?

Nicolai Suppa:

Yeah. As we explained previously, the current work in this paper relies on two observations for each country and each of this information already comes with a certain error which comes from, we call it as a sampling error or measurement error. And all of our point estimates are already produced with, standard errors and confidence intervals for each country year observation. Now based on this information, we already compute also error margins for the entire trajectory. And we use this information also in the inferential exercises within the paper. So when we want to test, for example, whether the target is met or not. But the limitation of the current paper is because we only have to infer, two observations per country, we actually ignore projection error, we calibrate, but we don't see. We cannot estimate due to data constraints, the trajectories. And this is what we are currently exploring. So if we are estimate, for example, at the country level or country specific models, we would need at least technically three observations. And at the moment we're exploring different options on how to include such projection errors. Which one option is to work with specifically with cross country models. And another one is to work with country level models which have more than, say, five or 10 observations. And that's something currently ongoing. We are exploring in order to get more accurate error margins for the different, analytical exercises.

Natalie Naïri Quinn:

Thank you. So thank you, Ricardo and Nicolai, for joining me for this interesting discussion today. And thank you to all of the listeners for listening to the CSAE Research Podcast. We hope you'll join us again next time. To listen to more episodes from the series, please go to the CSAE website.