Informal Discussion Transcript
Concurrent Session 4B: Mortality Projections

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LEONID GAVRILOV: Leonid Gavrilov of NORC at the University Chicago. I have question for the third presentation. I'm trying to understand these heterogeneity models. They may work well when you analyze cohort life tables; when those with high mortality die off, their proportion is decreasing. But to my understanding, when you presented the data modeling mortality trajectories, some of the data were cross-sectional life tables, so I'm confused. My understanding is that if you choose models for heterogeneous populations, you should apply them to cohort life tables only.

SÉVERINE ARNOLD: We did apply the model to cohort data and to period data, so cross-section data, and in both cases, we had very good results. Here I presented only period data, but in the paper, you can find the analysis for cohort data as well.

LEONID GAVRILOV: Yes. My understanding is that you have these heterogeneity models with parameters and initial frequencies of each set population.

SÉVERINE ARNOLD: Yes.

LEONID GAVRILOV: And then when you look at this in a cohort perspective, their frequencies are changing according to their mortality trajectories.

SÉVERINE ARNOLD: Yes, right.

LEONID GAVRILOV: So in this way, I'm quite comfortable when they are used for modeling cohort life tables, but on some of the slides which you presented, the life tables were for cross-sectional data—for example, for 1900. So it was obvious that this was cross-sectional life tables.

SÉVERINE ARNOLD: Yes.

LEONID GAVRILOV: And so my question is, How is it possible to apply this ideology of cohort life tables to cross-sectional data?

SÉVERINE ARNOLD: So for cross-section tables, it will make sense if you assume that the structure of your population is not changing over time. It will then be somehow the same as looking at the cohort data. But you're perfectly right, it makes way more sense and it was developed at the beginning for cohort data. Within the paper, most of the analysis is done on cohort data, as it makes more sense. However, since you need a longer period of observation when you work with cohort data, we had to work with period data to be able to get some results. Since the results based on period data made sense and were coherent with what we observed with cohort data, we decided to keep them as well.

LEONID GAVRILOV: Okay, thank you.

SÉVERINE ARNOLD: Sure, thank you.

TOM JONES: Tom Jones from Prudential. My question's for Séverine as well. This is a more practical question than a theory question. I price pension risk transfers, and we do a lot of underwriting where we're putting a lot of capital at risk on these deals, and the data that we have at older ages tends to be very sparse sometimes and difficult to assess, and often the models that we run or the assumptions that are made at the very old ages tend to turn out to be quite conservative, because you just don't have enough data. I'm wondering if your model, and the way that you constructed it, you would be confident if you had—rather than, say, country-level data—if you had, say, some populations across various plans, if you think that a model like the one you've run would be a possible approach to being able to assess the tail risk on mortality? Thank you.

SÉVERINE ARNOLD: Sure, thank you for your question. When you work with populations that are very small, you have a high variability [volatility]. Even for Sweden, where we used national population data, we had to take the average over a few years to be able to get rid of the noise and to be able to capture the trend. So if your population or your data are too small, we can still fit the model, but I'm not so confident on the results we will get.

ROLAND RAU: Roland Rau, University of Rostock and Max Planck Institute for Demographic Research. I have a question to Andres, specifically about the figure we're seeing right here now, and please, as soon as you say no, I understand that I misunderstood something. So what you show here, I think, are those rates of improvement, and the ones are the raw ones, and the other ones are rather smooth ones, and then you showed later on—. So you still say okay, so I did not misunderstand that part. Later on, you show some kind of confidence intervals, right. Did you also look at some kind of extra aggregate measure like life expectancy? Because we played with those things and once you use some smoothed rates of mortality improvement, you get super tiny confidence intervals for life expectancy at birth, and that would rather not make too much sense, I think, if they vary only very, very narrowly.

ANDRES VILLEGAS: So no, we didn’t calculate any aggregate measure like life expectancy, but what I would expect is that at older ages, it wouldn’t matter a lot, because the variability at older ages is not that big. But if you are computing, say, life expectancies around 45 or between 20 and 40, then the impact of parameter uncertainty is going to be significant for aggregate measures such as life expectancy. I’m not sure if that is what you were asking.

JUSTIN STRUBY: Justin Struby with AIG. On the same topic with the uncertainty around the projections, I find that very interesting and something that’s very practical. I work in an environment where we are required to put boundaries around our assumptions very much, and improvement is one area in which it seems a very difficult one to come up with agreement on what future improvement will be, but then what your bounds are around your future estimates, what impacts it could have. So I want to applaud you for actually showing that, and rather than ask a question, I would like to encourage all the researchers who are working on this to spend a little more time around the practical aspects of the uncertainty around those future estimations. Thank you. [*Applause*]