# Getting Started with TVEM

with Stephanie Lanza & Sara Vasilenko

(Time-varying effect modeling)

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This podcast will introduce interested scientists to time-varying effect modeling (TVEM). Host Aaron Wagner talks with Methodology Center Investigators Stephanie Lanza and Sara Vasilenko about the new types of questions scientists can answer by applying TVEM to existing data or to new studies. Sara and Stephanie have been at the forefront of both applying TVEM and training scientists to use TVEM. Multiple participants from their TVEM workshop in June already have submitted TVEM manuscripts to journals. In this 25-minute podcast, they provide the introduction needed to determine whether could be useful in your work.

Speaker 1: The Methodology Center Perspective podcast is brought to you by The Methodology Center at Penn State, your source for cutting edge research methodology in the social, behavioral, and health sciences.

Aaron: Hello, and welcome to methodology Minutes. My name is Aaron Wagner, and with me today are Methodology Center Scientific Director and Professor of Biobehavioral Health Stephanie Lanza, and Methodology Center Research Associate and Research Assistant Professor of Health and Human Development Sara Vasilenko. They're here to talk to us about time-varying effect modeling, or TVEM. Stephanie and Sara, welcome, and thanks for being here.

Stephanie: Thanks for having us, Aaron.

Sara: Hi, Aaron.

Aaron: So, to get started, what is a time varying effect model?

Stephanie: The time-varying effect model is a very intuitive extension to regression analysis. So, most of our listeners have used regression analysis many times in their research, and the point of regression is to estimate the association between predictors and an outcome. It's as simple as that. So for example, you might want to know how somebody's mood is related to their craving to smoke. What you're assuming when you fit regression is that that effect that you're estimating is a universal truth, or a constant with time. What TVEM allows you to do is estimate those associations dynamically with time. So if you were studying a sample of people who were going through a smoking cessation attempt, that link between mood and craving might actually vary with time. And in fact, we know, theoretically, that it should, that once you get through withdrawal, that link will be decoupled.

Aaron: And you actually did that research, is that right?

Stephanie: That's right. We worked on an empirical study to do just that.

Aaron: Yeah. We'll talk about that in a little bit. But, it's a time-varying effect model. What's the difference between a time-varying effect and a time-invariant effect? I think we were just kinda getting at that, but to make that explicit.

Stephanie: Well, let's take one step back, and let's go back to this example in how mood and craving to smoke might be associated. Your mood is a snapshot in time. You can capture what one's mood is at one point in time, but their mood is actually dynamic. Their mood can be changing over time. So if that's the predictor in our regression analysis, we would call that a time-varying covariant, or a time-varying predictor. Typically, we would estimate that association between mood and craving to smoke as a time-invariant effect, and so the association would be a single estimate that says, basically, on average, this is how these two things are associated. Or, you could say that regardless of what their momentary mood is, its link to urge to smoke is fixed, regardless of what their mood is at that moment.

Sara: Yeah. So when I'm grumpy, I want to smoke, and that's the way it is for me all time.

Stephanie: Right, it's a universal association.

Sara: Yeah.

Aaron: Got it.

Sara: Yes.

Stephanie: Even if your mood is changing with time, which we know it does. So the time-varying effect allows you to go one step further and say, take the hypothetical example that you quit smoking today, and you're a heavy smoker. Your mood may be very tightly linked to your craving throughout that first day of quitting smoking. But maybe if you're successful, maybe two weeks down the road or a month down the road, that link between your mood and your craving for a cigarette weakens. Maybe it's no longer driving that urge. And so that's an effect of a variable changing with time. And so TVEM allows us to look at that empirically.

Aaron: So this is the association that it allows us to see. What sort of novel questions can TVEM help us answer?

Sara: Well, it can help you understand really any kinds of associations or processes that you think differ over time, differ over a person's development. So there's really unlimited, almost, questions you can ask. Some things I think you could look at is how are two different risk behaviors, how are they differentially associated over time? Those things can help you figure out questions like when would be the best time to intervene on a particular behavior, based on when it's more likely to occur, and also what kind of things would make sense to target. So if, say, your substance use and your sexual risk behavior are very tightly associated early in adolescence, it might make sense to do some kind of intervention that targets them together. If that association is weaker at later ages, you might need to approach those kinds of things separately. So you can both understand how this process changes over development and use that to inform interventions.

There's also Stephanie was talking about looking at time since quitting smoking, and so you can look at how processes change over time from and event. You could look at how the effect of an intervention might weaken or get stronger over time, to see when you might need to provide some kind of booster intervention, and those sorts of things. So lots of potential applications, both in more developmental observational research and in examining the effects of interventions and designing interventions, those sorts of things.

Stephanie: Yeah, Sara really hit it on the head there. The two big thrusts of applications of TVEM today that we see, that we've been working on ourselves, and that we're seeing real quick uptake in in the field of behavioral sciences, is developmental changes of associations between variables and time-varying associations that are typically examined using intensive longitudinal data such as ecological momentary assessments or momentary assessments. One thing that we haven't really made explicit yet today is something about how these associations might vary with time or age, and a really important key with TVEM is that the change in associations is not assumed to be linear or quadratic or any kind of parametric form. So we're talking about allowing estimates of our outcome and estimates of the associations between predictors in our outcome to be completely freeform as a function of continuous time. And so we're not making any a priori assumptions about shapes, trajectories, having any kind of parametric functional form, like a quadratic curve.

Aaron: Thank you. Now that we've kind of got a handle on what TVEM is, we're recording this podcast as part of the Year Of TVEM here at The Methodology Center. What makes this the right time to have a Year Of TVEM?

Stephanie: That's a great question. So this is our first Year Of at The Methodology Center, and so this whole idea of really punching up one interesting development in methodology today for hosting a Year Of was really motivated by where we are at in research using TVEM. TVEM is only beginning to be disseminated from our Center. We did our Summer Institute on Innovative Methods this summer on TVEM, and last year Sara and I gave a pre-conference workshop at the Society For Prevention Research on TVEM. I also did a pre-conference workshop with a colleague, Mike Russell, this summer at the Society For Ambulatory Assessments. So those are the first three TVEM workshops ever. TVEM is now accessible to behavioral scientists everywhere as a SAS Macro. It's extremely easy to use. You can download the free software, put it on your computer, and fit these models, and you can be up and running in a matter of minutes or hours for fitting your first model. And so now the trainings are happening, the software is available, and the uptake that we've seen already has been just remarkable. So it's at its infancy, and we see the potential for applications of TVEM as really, really huge.

Aaron: It was pretty impressive at the Summer Institute to see people just kind of sit down in the workshop, and as soon as the Macro was introduced, to 30 minutes later have them looking at results. Fewer than 30 minutes later, actually.

Stephanie: It was impressive to see how far the participants could go in the time of the workshop, and at the time of this recording, which is just two months since Sara and I taught the Summer Institute, we know of one participant who already had a paper accepted at Drug and Alcohol Dependence, using TVEM.

Aaron: And yeah, I was in touch with another participant just this week who said that she had a paper that she was submitting this week.

Stephanie: That's great. We are all sitting around smiling.

Sara: Yeah, and a related reason I think this is a good time for the Year Of TVEM is now that it's become more available to substantive researchers, and we're starting to get more publications, I think research using this method is really growing exponentially and expanding, and it's really exciting to see, and a good time for people to get involved and try using this method if they have questions that it could answer.

Aaron: So this method is out there now, and who should be using it? Basically, what type of data is TVEM good for? Where should it be applied?

Sara: Well, the most important thing is it should be applied in a case where you have a research question where you want to look at time-varying effects. So if you are interested in how associations differ over some sort of time, whether it's by age, by time from an event, those sorts of questions, that's the first thing that you really need to think about in terms of is TVEM right for me. You need that kind of time-varying research question. And then you need to have enough data over the entire time period you're interested in. But you can use TVEM with cross-sectional data, with more traditional longitudinal data, and with intensive longitudinal data, like EMA data. So it can be used with all kinds of different data, if you have a time-varying research question and you have sufficient data that's looking at the time period you're interested in.

Aaron: So speaking of these different types of data, can you give us an example of how TVEM has been useful for EMA data?

Stephanie: Sure. Let's think again about this idea of predictors of craving to smoke a cigarette. We used TVEM to analyze data from over 1000 adults who were addicted to nicotine, and all of them agreed to and successfully quit smoking, as planned. And they were followed for the first two weeks intensively after they quit smoking. So they were all going through withdrawal symptoms during this time and had varying degrees of success with quitting smoking. So we were able to use TVEM to reanalyze these clinical trial data to look dynamically at what is really driving or predicting their craving to smoke at a moment in time during the two week window. We were able to discover that different nicotine replacement therapies and different treatments for smoking cessation worked in different ways as a function of time.

So specifically, treatments to smoking cessation were effective at reducing that link between negative mood and urge to smoke, but only during the first two days after they quit. So right upon quitting, the treatments were effective in operating that way. But a week later, the successful quitters, who were still struggling with withdrawal symptoms, treatments really were effective at reducing the effect of their baseline nicotine dependence on their craving to smoke. So taken together, this kind of information that TVEM revealed can tell tobacco researchers a little bit more about how those smoking cessation treatments are operating. And down the road, these kinds of results could actually inform what treatments might be best given to what types of patients.

Aaron: Sara, you also said that TVEM was useful for panel data.

Sara: Mm-hmm (affirmative).

Aaron: Can we talk about that a little bit? Do you have any example?

Sara: Yes. That's something I've been very interested in looking at, because I'm very interested in studying development from adolescence into adulthood. Most studies don't have very intensive data where they follow people up for years and years, because that's just very expensive and difficult to do. So I have done work using data from the Add Health study, which has four waves of data where adolescents are followed up, two times in adolescence and then two times in adulthood. And because people enter the study at different ages, I had decent coverage of time from ages 14 to ages 32, where there were measurement occasions in all those different ages. So we could use TVEM to look at associations over that adolescent into adult period.

So an example of what I've done with this is looked at how different predictors of sexual risk behavior changed across different ages. And some examples of what I've found in that were the association between substance use and having multiple sexual partners were very strong earlier in adolescence, and that association became much weaker over time. So this suggests some developmental changes that are occurring related to this association, and that perhaps intervening on multiple risk behaviors might be more effective earlier in adolescence compared to in early adulthood. It also looked at the effect of depression on multiple sexual partners and found association lasts a lot longer for women compared to men, suggesting that for men, sexual risk behaviors might be seen as more acceptable and less associated with depression. And for women there's less of a developmental change, it's always perhaps perceived more negatively for women.

So those are some of the sorts of questions that I've been interested in, but there's many more questions that could be addressed with all of the different panel studies there are out there. I'm excited about some of the implications for studying human development that can be done with existing data that is already collected.

Aaron: Are there any types of data, or any situations, at least, where a researcher really shouldn't use TVEM?

Sara: I think there are many different types of data you could use, so I wouldn't say it's necessarily restricted by the type of data, but there are definitely situations where TVEM might not be the most appropriate. And it's really situations where you don't have a time-varying question, and more practically when you can't think of a way to sort of center your data at a meaningful zero point. So what I mean is, in Stephanie's EMA example, the data was centered at the quit date. So even if people were in the study at different dates, they all had this meaningful zero point where you could look at time from that period, and structure your data accordingly. But in other EMA studies, you might try to, say, sample just a typical two weeks in a person's life, and a lot of times when that kind of data is collected, you don't really have a time-varying research question. There's no event you can center your data around. So in that case, TVEM might not be the most appropriate method for your data, though there certainly may be creative ways you could use it, depending on your question. But if your question is just about, as we were saying earlier, whether you crave smoking more on days you're grumpy, and you don't have a time interlaid over that, then maybe you'd wanna use a multi-level model or some other kind of analysis.

Stephanie: I think TVEM can allow a lot of researchers to think more creatively about the questions they might be able to answer with their data. So for example, if you were using an ambulatory device to measure physical activity for individuals over, say, a two week period, and you have this basically streaming data, you wouldn't necessarily think that the drivers of physical activity would change in some systematic way over the two week period. These 14 days are meant to be a sample in time of their lives. However, you could think about, because you have that density of data, you could think about how drivers of physical activity might change throughout the course of a day. And in this case, you could take a sample day and look across all the participants in your study. Maybe the link between mood and physical activity is weaker right when you wake up, but toward the end of the day, your mood might really dictate how physically active you're willing to be.

Aaron: Right. And is that an actual result, or is that just a hypothetical?

Stephanie: That's a hypothetical.

Aaron: Yeah, okay. Great, thanks.

Sara: Yeah. It's just kind of an example of how there's probably some sort of application of TVEM we can think of for almost any kind of data, so it's really not about the type of data but really about the type of question.

Stephanie: Question, absolutely.

Aaron: Great. Thank you very much. So you've been talking about risky sex and substance use, smoking, and a little bit about physical activity. In what other fields could TVEM be applied?

Stephanie: TVEM is relevant to any field, truly any field. Again, it all comes down, as Sara said, it all comes down to the research question. If you think that the association between variables may change over time in some meaningful way, then assuming that you have the data to support that question, you should try TVEM. So it's really relevant to any. I mean, certainly in our areas we've focused on smoking and substance use and sexual risk behaviors, any health behavior I think lends itself really naturally to TVEM. But if you had the right data, you might be able to look at how policy changes may be related to certain outcomes in government data. Or maybe you have daily diary data, and you randomly assign individuals to some sort of weight loss treatment, and others are in the placebo group, then that kind of data would naturally fit as well. So really anything could potentially be relevant for TVEM.

Aaron: Thanks. So, if we have a listener out there who has become convinced, "This sounds compelling, I would like to try this," what are the next steps?

Sara: Well I know I've said this a lot, but I think the first thing is really just to think about your potential questions, and if they are time-varying, how you would set up your data to have a time metric that's centered in some meaningful way. And then I think one next step is just to look at your data, see if you have sufficient data to cover the time period you're interested in, to look at things in continuous time over this time period. I think those are some preliminary steps, just to make sure you can use TVEM, and your questions are compelling for this method.

And then I think the biggest thing that ... Well, apart from interpretation, which can be complex, probably the most time-consuming thing is to get your data ready for analysis. You want it in a long format with multiple measurement occasions per person. You want to recode your variables that are time-varying to make sure they're coded in a consistent way across the entire time period you're interested in, which can be a bit challenging in longitudinal studies where they change how things are measured. And then, once you have all the preliminary stages, you've thought about your question, you have looked at your data carefully, and you've set it up appropriately, then you would download the TVEM SAS Macro from The Methodology Center, look at the user's guide, figure out how to do the coding, and then just start trying it. It's kind of exciting, because you can get these nice graphical results, these figures that show how the association changes over time. You can get them pretty easily by running the Macro, and then I think it's a little addictive to kind of want to see more. I think it's very compelling to be able to see these things changing over time, that's automatically generated by the Macro.

Stephanie: Yeah, I think what I would say to all the public health researchers out there is if you are compelled to do some additional analyses or secondary data analyses of public use data or of your own data that you've already analyzed to address your specific aims, you can delve deeper into your data very often using TVEM and find some amazing new results that are relevant to developmental time or real time. The learning curve for using this particular new technique is not very steep compared to other approaches. You don't have all of the intricate decisions that you might have to make, say, when you're doing latent variable modeling. I think the learning curve is not that steep, the investment is low, and the payoff can be quite, quite large.

Aaron: You mentioned the SAS TVEM Macro. Talk to us a little bit about the capabilities of the software, please.

Stephanie: The SAS Macro for TVEM can handle outcomes that are normally distributed, that are binary, that are count variables, and even zero-inflated count variables. So it's quite general in that way. Coming in the fall of 2015, so the semester that we're just beginning, we're gonna be releasing a new version of the Macro, and this version will have random effects, which is going to really open up even further possibilities for using TVEM to analyze existing data.

Aaron: What's next for your work on TVEM?

Stephanie: Well, as far as the software itself, more capabilities will be added down the road. Certainly the ability to include complex survey weights is on the agenda for a future release. For our research, one of the big things that Sara and I will be focusing on this year is a new R01 grant that the National Institute on Drug Abuse awarded us. We're gonna be looking very closely at the etiology of drug use and abuse among adolescents and adults, so we'll be relying on TVEM to understand the role of risk factors from a more developmental perspective.

Sara: So we're very excited to start some of that work, and so you can look out for some of those results in the future hopefully.

Aaron: Great, we really look forward to seeing them. Sara and Stephanie, thank you very much.

Stephanie: Thank you for your time.

Sara: Thank you.

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