Courtney Kendall: Good afternoon. My name is Courtney Kendall from the National Renewable Energy Laboratory, and I'd like to welcome to you to today's webinar on the Agent-Based Model of Health Segregation and Peer Effects Influence Solar PV Adoption.

We're excited to have you with us today. We'll give folks a few more minutes to call in and log on, so while we wait I'll go over some logistics and then we'll get going with today's webinar. I want to mention that this webinar will be recorded and everyone today is on listen-only mode. You have two options for how you can hear today's webinar, so it's either use telephone or use mic and speakers. If you'd like to use telephone, use the telephone number listed when you log in or it is in the box with a specific audio pin you should use to dial in.

We will have a question and answer session at the end of the presentation. You can participate by submitting your questions electronically during the webinar. Please do this by going to the questions pane in the box showing on your screen. You can type in any of your questions at this time during the course of the webinar. Our speakers will address as many questions as time allows after the presentation.

Before we get started I would like to introduce the speakers for today. Our first speaker is Ben Sigrin. Ben is an energy analyst at the National Renewable Energy's Strategic Energy Analysis Center. He is the principal investigator of a multi-year grant from the Department of Energy, studying residential adoption of distributed solar. His research focuses on policy modeling and market analysis of distributed energy resources.

Our second speaker is Adam Henry. Adam is an associate professor in the School of Government and Public Policy at the University of Arizona. He is an affiliated faculty member with the University of Arizona's Institute of the Environment, and his primary research interest is in using social network analysis to understand how people make decisions that influence sustainability.

Also with us today is Heike Brugger. Heike is a PhD candidate in politics and public administration at the University of Konstanz in Germany. Her research interests lay in exploring the effect of social networks on energy and climate-related public policies as well as on individual sustainable consumption patterns.

Our final speaker today will be Georgia Pfeiffer. Georgia is a PhD student in public policy at the University of Arizona. She specializes in environmental policy and has worked on the SEEDS project for the last two years.

Now let's go ahead and get started with today's presentation. Ben.

Ben Sigrin: Thanks, Courtney. Hi, I'm Ben Sigrin, and as Courtney mentioned, I'm principal investigator for this project. I just want to thank everyone who is on the line right now for taking some time out of your day to join us. SEEDS has been a three-year project; we're at the very tail end of it to identify opportunities for the solar industry to increase lead generation and conversion in the residential solar market. Our findings are going to be presented in a free three-part webinar series. Our talk today discussing residential customer adoption and policy implications using agent-based modeling, which is a cutting edge simulation technique.

Our second webinar is next week, June 15th, titled "How to Get Those Considering Solar to Ultimately Make the Switch." I encourage you to register for that if you haven't already. And that talk is going to look at what predicts why some customers go solar and others because lost leads. And then our final webinar is on June 29th, it's titled "Solar Aspirations and Disinclinations: Learning from 3,600 Households." And that one will investigate customer segments – sub-segments within the residential market and what implications that has as the market starts to mature.

So again, please join me in thanking Dr. Adam Henry for his time and insight. Dr. Henry, please proceed.

Adam Henry: Okay. Thank you, Ben. Thank you, Courtney, for the nice introduction. So I think that we can move on to the next slide here.

I just wanted to give a quick introduction to our project. This is one project that is part of a larger research endeavor that's been going on centered around NREL's efforts and funded by the Department of Energy's SEEDS program. In this particular research project that we're presenting today we explore environmental consumption, theories of environmental consumption both from the using theoretical agent-based models, as well as empirically grounded agent-based models. And we'll talk a little bit about what agent-based modeling is all about and what it can contribute to the social sciences. But what we hope to do is show that through illustration, a concrete illustration.

So I'd like to start with a bit of motivation here. The graphic that you're looking at in the top-right corner is drawn from the open PV data set, which is one way of characterizing the penetration of solar photovoltaics in the United States. It's basically a heat map of solar – numbers of solar installations in different states, with lighter colors indicating more installations, which you probably noted from the color of California, for example, which is one of the states with higher levels of solar PV use.

Now solar PV adoption is one type of environmental consumption behavior that we argue we need better theories to explain. So environmental consumption can be thought of generally as how people invest in technologies that change their ecological footprint or the negative impacts that human behaviors have on ecological systems. So how people make choices about environmental consumption has very important implications for sustainability. We have good indicators of environmental consumption, although they could be better. You know, our data on how people make purchases and adopt or don't adopt is emerging.

But what we really need is we really need better theories of the mechanisms that drive these indicators. And we argue that we really need to focus on what we call "models of the individual" – models of individual decision-making. Now with better theories we can design programs that exploit factors that contribute to this idea of learning, which can be broadly thought of as the adoption of more positive environmental consumption behaviors and overcome factors that inhibit these behaviors.

So in this particular research project we're really examining how social structures, macro level social structures in particular, the geography of where people live and the structure of social networks can both promote and inhibit the adoption of solar PV. Oh, next slide please. I was tapping my keyboard and nothing was happening.

Okay, so what factors influence adoption? I mentioned that where this is part of a larger endeavor of seeking out better models of the individual, what explains environmental consumption, so it's useful to talk about a couple of high-level factors that come into play. It's important to note, I think, that the world is not so simple as people making decisions based purely on monetary factors. There's a good bit of research showing that the world is more complex than this; it's not just about monetary costs and benefits.

So we consider factors that operate really at three levels. At the level of individual agents we consider individual propensity. So these might include the monetary factors, like how much does something cost, how easy is it to afford, what are going to be the payoffs over time of this technology. Also cognitive factors like concern for the environment or of values might also play an important role. Or socioeconomic factors, demographic factors.

So social influence is another important factor that's been seen to have an influence on environmental consumption behaviors. So an emerging literature – well, really a longstanding literature on social networks suggests that people are strongly influenced by others that they share connections with. And these connections might be things like friendships, it might be contact with others at work or serendipitous types of relationships that are formed, you know, wherever, at the market, on an airplane.

It also might be geographic closeness. So people who are my neighbors or people who I live geographically close to in my city.

Another set of factors operate at the level of social structure. So social influence means that these patterns of connectivity matter greatly for explaining environmental consumption.

And then at the level of external agents, of course, who we could say manipulate agents who are actually making these adoption decisions. Not manipulate necessarily in a bad way, but governments might give incentive programs that change the calculus or solar installers might use certain strategies to reach out to potential customers that change adoption decisions over time.

Next slide please, Courtney.

Okay. So I'd like to talk a little bit about the role of agent-based models in all of this. So this is a pretty complex world that we're dealing with. So individuals make decisions on the basis of much more than dollars and cents and also decisions are not independent of one another; they're highly dependent on the decisions that other agents in a complex system make. Now agent-based models we argue have a very important role to play, a very useful role to play in complementing other methods of understanding this complexity and modeling environmental consumption and solar PV adoption.

So agent-based models are essentially computational simulations where we can test out different theories of human behavior, the effectiveness of different government programs, say, or install of strategies, and view the consequences of these programs or these theories in a virtual laboratory without actually intervening in real-world systems.

Now this graphic is drawn from a recently published paper in *Nature Climate Change,* where a colleague of mine and myself outlined what we called essentially an anatomy of agent-based models. So the different uses of ABM in the literature are legion, but there are some fundamental pieces of ABMs that tie these different applications together conceptually. So pretty much any ABM has three pieces. One, we're going to specify micro-drivers of behavior. These are generally going to be drawn from theories about how individual agents make decisions. For example, if we're trying to model solar PV adoption we might have a theory that agents will adopt solar if it's economically sound. Another theory, a complementary theory perhaps, is that they adopt if others in the social network adopt, because of these peer effects.

Now in the second part of an ABM is going to be to specify the specific behavioral rules that represent these different theories. And so it might be a mathematical representation, like what we have here. So economic value of a solar system and adoption of solar by others in social network might have some linear effect, for example, on the probability of adoption. And these effects are governed by some parameter, model parameter. In this particular example it's A, where if A is close to zero it's mostly peer effects that are driving solar adoption; if it's close to one it's mostly economic effects that are driving adoption.

Now what we usually focus on in ABM is part C, is these dynamics that are generated by these behavioral rules over space and time. And what we can do is in agent-based models is we can examine what particular theories and parameters generate trends that we often observe in the real world. For example, adoption of technologies often follows this so-called S-shaped curve of diffusion of innovations, as you see in the bottom panel, which is difficult to model if you don't have this social influence perspective built into your models. And so in this way ABM can help us to understand why social influence is such an important thing to take into consideration when modeling these sorts of behaviors.

Okay. Next slide, Courtney.

Okay, so I don't want to spend a lot of time on this slide, but I'm prone to do so. I get a bit professorial here with the teaching illustration. So one of the advantages of ABM is that it's a nice complement to more traditional methods of social science research that we're usually trained in, like statistics. So in statistical analysis we can think of ourselves as being engaged in this deductive inference, where we make observations about the world and then we have some functional form that we assume to be true and we fit parameters in order to maximize the fit between our model and the real world. And so one can imagine ways in which this will get us into trouble if we have very strongly held theories about what generated the observed phenomenon.

So, you know, one example is we can imagine that we're the Ancient Greeks who dig up a fossilized skull of a dwarf elephant, and we have a theory about what generated this fossil, and it might have been the Cyclops, for example the Cyclops Polyphemus, who had Odysseus and his men trapped in his cave. And that story would be perfectly consistent with the data that we had observed. But in fact there are other processes that might have generated this fossil, this evidence. And ABM is a way of examining these different states of the world that might have given us what our observations of the world today in what we might call "inductive simulation."

Next slide, please.

Okay, so let's bring this back into the topics that we're going to focus on today. So that was a bit of high-level discussion of agent-based modeling and environmental consumption. So what we're going to focus on in the models that follow is how programs that are meant to enhance PV adoption may have unintended consequences. Those unintended consequences are going to come from the great complexity that in which adoption curves adoption dynamics are created or generated.

So the common wisdom, at least one common wisdom about how to enhance PV adoption is that peer effects or this notion that people in – adopters create other adopters in their social networks will create social multipliers that magnify the benefits of programs. So adoption might spread through networks and over space. But many social systems are segregated systems in the sense that people with high propensities to adopt tend to influence others with high propensity to adopt and vice versa. So programs that benefit high-propensity agents may not necessarily spread evenly throughout a social system and create potentially negative consequences for access to solar PV and ultimately environmental justice.

So we can explore these dynamics in a theoretical ABM, which Heike is going to talk about next. Next slide, please. Thanks, Heike.

Heike Brugger: Okay. Thanks. I will talk about the incentives model. So what we'll look at is how this structures that are embedded in the social networks will influence the diffusion of solar photovoltaics. And as Adam already mentioned this, what we think is that network structure very strongly influences how the diffusion process will take place. And we have different forms of network characteristics and what we will look at here is specifically network segregation, so how does the segregation of networks, meaning, yeah, high-propensity actors talking to high-propensity actors and influencing them will have an effect on how solar or other environmental sustainability patterns will diffuse over the network.

So what we will have a closer look at is the success of incentives programs so far is mostly measured as the overall adoption rate of renewable energies. So a program or an incentive is called success – successful if the adoption rates are high or if the adoption rates increase and if we have an increase in the adoption speed. What we want to suggest here or what we want to show with agent-based model is that the intended side effects are not really well covered with the measure of adoption speed. So if we look at different – if we look at a different outcome, this will be the quality of an incentive. How will the quality of an incentive – how will the incentive, yeah, be passed on in terms of equality measures.

Okay, sorry. Next slide, please.

Okay, so we have three specific policy incentives that we're having a closer look at, and those are the feed-in tariff, leasing options, and seeding to poorer communities. So the feed-in tariff was initially first implemented in Germany in '91, and what the feed-in tariff does is it guarantees adopters a long-term fixed rate to their solar that they feed into the grid – the energy that they feed into the grid, and therefore highly reduces financial risk as well as amortization times for PV. But as well we have a high upfront investment that is necessary, so the incentive speaks to people who already have high – who have a higher income, who are able to make the upfront investment and then will have the gain in the long-run. So we can see that this feed-in tariff or the policy of the feed-in tariff diffused widely worldwide. In 2007 we had 46 jurisdictions, so countries as well as regions who implemented the feed-in tariff.

Another option for policy incentives would be to have leasing options, to have it based on a third-party ownership we would eliminate the upfront cost for installing solar. So this would be also available for households which don't have that much money to invest in the first place. And studies have shown that this actually increases the demand and widens the range of potential adopters. So we have more adopters, we have a wider range of people that can adopt because the upfront costs are reduced. And leasing options are, for example, widely present in California; they are not as present in Europe up to this stage.

Another possible _____ _____ seeds solar PV to poorer communities, and what is behind that means that free PVs would be given out to selected agents in poorer communities to increase visibility of solar within these communities and to increase the peer effect also in poorer communities, yeah, and increase, for example, information provision. One way for PV to diffuse would be that people learn about all the benefits that they can have with PV. So positive effects of this seeding of poorer communities are already shown in pilot and experimental studies, but so far they are not widely applied anywhere.

Okay. Next slide, please.

Okay, so we have different incentives that actually speak to different groups of people and what we want to have a closer look at is how these incentives actually influence the diffusion curves within the networks. So what we would say that any of the three incentives will fasten diffusion within the network. So no matter whether we have a segregated or an integrated network, we expect diffusion to be faster when an incentive is present.

And then also for the speed of adoption we expect that the feed-in tariff will lead to faster uptake of installations in segregated as well as integrated networks. And so are the other two incentives; will have a faster speed of adoption—that is what we think. Then we have a second dependent variable, and this would be the difference in adoption dynamics. So if we have a closer look at low and high-propensity actors, we actually think that the feed-in tariff will lead to an increase in inequality while other measures, like the seeding policy, would lead to a decrease in inequality. So yeah, to make the adoption course more equal between low and high-propensity actors.

Okay. Next slide, please.

So to have a closer look at how to get a better picture of how this looks like, what we want to model, we have the tale of two communities here. So we have two hypothetical communities, Community A and Community B, and Community A will have agents with a higher propensity to adopt.

Next slide, please.

So this higher propensity to adopt can be, as Adam mentioned earlier, based on socioeconomic variable, so we have higher incomes; or based on values that are standing behind. And what we see in the real world is that communities are class _____ along this line. So for example, we'll have communities where the income is higher than in other communities. I think this is obvious. So we have Community A and they already have a higher propensity to adopt than the agents in Community B.

Next slide please.

So this leads obviously to more adopters in Community A than in Community B. So in this case we will have three actors in Community A, for example, and one actor in Community B. And as the next slide shows, this interim will increase the social multiplier effect within Community A. So now we don't only have – now the agents in Community A don't only have higher propensity to adopt, but they also have a higher social influence from other actors because they're so close to actors that have already adopted solar. So they have a higher propensity in the first place and they have a higher social influence as compared to actors in Community B. And as shown in the next slide, this will lead to overall adoption rates that are higher in Community A, based on those two effects.

Okay. Next slide, please.

So this was the first diffusion process, how it would look like without incentives. So now I will come to you how we set up the model. What we did is that we did repeated random simulations in a program called R and we had about 30,000 simulations to get our results. And what the model does first is it populates with 100 agents. So we have 100 agents within the system, and as shown, in the next slide those 100 agents have – will be randomly assigned to one of two groups, so either the high or the low-propensity group. So in this case we have the high-propensity group, the white agents, and the low-propensity group, the green agents. And those two groups, they simulate what we observe in the real world, that we have groups with different conditions, different socioeconomic values and so forth. So this is represented by the two colors and the two different kind of agencies.

Okay. Next slide, please.

Okay, so what we see here is what we talked about earlier, how does the network look like. We have a random network here that is governed by a segregation parameter S. So what this parameter does is, as you see in the left network, if we have a segregation parameter of zero this means that all the actors have the same probability to be linked, no matter whether we have two green actors or a white and a green actor or two white actors, they all have the same probability to be linked. And as the segregation parameter increases, as in the network on the right side, the probability increases that the actor solving more to actors that are like themselves. So the higher the segregation parameter the higher probability that actor selection and solve to actors that are kind of themselves. So what we can govern here with this parameter is to see how we have different network structures in the real world and how this affects diffusion processes within the model.

Okay. Next slide, please.

Okay, so Adam was talking earlier about the point that we need models that are actually starting from an individual perspective. So what our model does is we look at one specific agent within the network, so each time step one specific agent is randomly chosen, and then this agent has a probability to adopt or not. And as mentioned earlier, the probability is governed by different parameters. So one parameter that is very important, as Adam stated, is the social influence parameter. So am I influenced by the actors around me? And the higher the social influence parameter the higher the probability that I care about what my neighbors do. So in this case the agent has six neighbors and three of them have adopted already. So you will have a higher probability to adopt than if none of his neighbors would have adopted already.

Then we have the propensity difference. So this is what the colors were stating earlier, the green and the white agents. So we'll have agents that are more affluent or agents that are less affluent, agents that have higher values towards sustainability than others. So this is governed within the propensity difference parameter.

And then we have the incentive parameter that comes into place here. So what the incentive parameter does is it will describe whether an incentive is targeting a specific actor type. So as I stated earlier, we have, for example, the feed-in tariff that is targeting more affluent actors while seeding or leasing options would be benefiting less affluent actors. So this is governed by the incentives parameter.

Next slide, please.

Okay, so this is just a quick overview of what I just said, that the feed-in tariff, the incentive parameter will be higher for high-propensity actors, while seeding with 1.5 would higher the chance of adopting by 50-percent for low-propensity agents.

Okay. Next slide, please.

So we come to the results of the study. What we did is, as I said before, we had a simulation run about 30,000 times and this is how the adoption dynamics look without incentives. So we see that, as expected, high-propensity groups have generally more higher rates of adoption than low-propensity groups but they follow a similar dynamic.

Next slide, please.

Okay, what we see here is we have the integrated as well as the segregated network and now we can see substantial important differences between those two network types. So in the upper-left corner you see integrated networks over all actors at the same probability to be connected to each other. We don't see segregation here. And if we have the feed-in tariff – if the feed-in tariff is in place within those networks it looks quite similar to the dynamic that we saw before. So it doesn't really change the pattern of the dynamic within integrated networks. But if we look to the right side, the right up corner, we'll see how the feed-in tariff plays out in segregated networks. And now we see as compared to the left side a huge difference. So it would suggest that the feed-in tariff, so an incentive that is benefiting high-propensity actors more than less-propensity actors actually needs to increase in the differences of adoption dynamics, which means that actors that are less affluent are even less likely to adopt solar or are less influenced by the positive incentive if we have segregated networks. It doesn't decrease their probability, but it won't increase their probability while it highly benefits high propensity actors.

And on the seeding problem we have tried another effect. So what we see here on the left down corner is how it plays out in integrated networks. And what we can see here is that it highers the propensity of less-affluent actors. And this is the case in the integrated networks as well as in the segregated networks. So the seeding actually has the opportunity to bring the two curves closer together, meaning it decreases in equality between the two groups.

Okay. Next slide, please.

Okay, so this is what I just explained in raw numbers basically and what those numbers mean. We have here as a dependent variable the average wait time. So basically representing how fast adoption diffuses through the network, and again, the process within integrated networks and within segregated networks. And what we can see here, so smaller values are better, right, in decreasing waiting time. It means that all of those three incentives that we studied, the feed-in tariffs, leasing programs, and the seeding program, will decrease wait time, so they increase adoption speed and are thus good for overall adoption rates.

And we can see here that the feed-in tariff is doing very good in integrated networks while seeding program does not do as good in speeding up adoption. In segregated networks, however, leasing programs that benefit less affluent as well as high affluent actors in the same _____ will have the fastest or the fastening effect.

Next slide, please.

So now is the question how this looks like not for the average wait time, so not for the speed of adoption, but for the difference between the two groups, between the white and the green group. And here we see that only the seeding program – within the segregated network only the seeding program has an effect that has the intended effect that we would want to have, basically decreasing in equality between the two groups. So the seeding program as suggested by the graphs earlier is able to decrease the inequality, while feed-in tariffs actually increase inequality between the two groups through only benefiting the high propensity actors and not forwarding the positive effect to groups that are segregated from this group.

Next slide, please.

Okay, so this is, again, basically what the tables just showed us, but I want to have a closer look on the right side, on the segregated network. And what we can see here on the right side, the seeding, that only actually the seeding has a positive effect on equity, meaning you can see this by the yellow box being above the zero. So only the seeding has the positive effect within segregated networks and the feed-in tariff as clearly shown here has a negative effect. You can see that the speed of adoption increases more with the feed-in tariff, but only the seeding leads to an increase in adoption as well as an increase in adoption rates.

Okay. I think this is it for me and I will give back to Adam.

Adam Henry: Okay. Thank you, Heike. Let that sink in for a couple of seconds. So as a theoretical model what this is is it's a model – what Heike has just presented is a model that isn't calibrated based on data observed from the real world, however, it does bring real-world phenomenon into the model that we observe. For instance, we observe segregation in the real world. Now we're going to come to this in a moment, where we're actually trying to measure these sort of phenomenon. But the basic idea of this model is a fairly powerful one, which is that the structure of social systems can dramatically change the effect of strategies that we want to use to enhance PV adoption or any other sort of technology adoption. So we should try to model these dynamics in order to get a better sense of whether or not programs that want to try to enhance adoption are going to work or not.

Okay, so these models, as I note here, are useful for showing the importance of certain factors in producing outcomes, but how do these dynamics play out in the real world? So in order to try to apply these ideas to a real-world solar PV adoption we've spent the last several years developing an empirical, geographically constrained agent-based model, which we call the "Golden Solar" model.

Next slide, please.

And what does the model seek to explain? If we could go to – oh yes, thank you. What does the model seek to explain? Well, the model works at the level of metropolitan regions of the United States, so could in theory be applied to areas outside of the U.S., however, the model is built on data with a particular structure that's available in the United States in particular. And it aims to model what these solar adoption curves, these observed solar adoption curves, in different metropolitan regions. So we have applied this model in some preliminary applications to four metro regions across four states: California, Arizona, New Jersey, and New York. And we observe – so apologies for the labels on the horizontal access; this is going from the year 2003 to 2013, and so you can read the tick marks as years after 2003. And this is the proportion of adopters that we have observed in each of these metro regions over time.

Next slide.

Okay, so as before, we need a model the individual to explain adoption. Now we assumed that these decisions happened at the level of a house. Not a household, but a house. So households live in houses, but our agents are essentially these structures on which solar PV is put. And the decision to do this, we can talk about that, but it's not terribly important at the moment. Agents are assumed to make binary decisions, either adopt solar or do not adopt solar in every year that they're a non-adopter. And adopters are assumed to never become non-adopters in the sense that they get rid of their solar PV.

So as with our theoretical models, our decisions are assumed to be a function of three factors. Number one is economic propensity, what are the monetary motivations for solar? Number two is cognitive propensity, so what are the non-monetary motivations for solar? Like environmental concern or becoming more energy-independent and so on. The third factor is social closeness to other adopters. Now unlike in the theoretical model where we were talking in terms of social networks, now social closeness is viewed as geographic proximity, which we view as a network, as Georgia will note in a few moments.

These factors are not so easy to measure and much of our effort has been to work on actually trying to estimate these different variables that are thought to produce adoption curve over time.

So we can go to the next slide and I'm going to hand it over to Georgia to talk a little bit about estimation and the model runs. Thank you.

Georgia Pfeiffer: Thanks for that introduction to the empirical model. So as Adam said, we're looking at three inputs into the decision to adopt solar. The first one is the economic propensity of each house to adopt solar. So the economic propensity includes any kind of monetary benefit and cost to installing PV. This includes not only the cost directly out of pocket to buy the PV, but also the subsidies that come from the states. There are frequently grant programs and such that allow households to subsidize the installation cost of solar.

On the bottom right of the screen you can see a graph of the average economic propensity over time, and this really illustrates the importance of the incentive programs to the economic propensity to adopt solar. The peak in the middle of this graph is actually where the incentive programs are at their strongest. And as economic propensity drops off this is due to incentive programs kind of wrapping up and expiring in different states.

On the lower left-hand side of the slide you can see the functional form of the economic propensity. So I'll just explain this really fast. The capital *I* in the first part is the income of the house. The income of the household is transformed with the function *g* in order to fit it over a -1 to 1 range. And this just kind of places everybody on a continuum to show how able they will be to pay for the installation of PV. After the addition sign we have the benefit minus cost. We have the net benefits of installing solar. These terms take care of the cost of installing solar in each region as well as the state incentives that are offered in each region. This net benefit is transformed by the function *f* so it also fits into the range of -1 to 1. And then using the factors *a* and *1-a* we weight these two pieces, the income and the net benefits in order to combine them to create the economic propensity.

Next slide.

So once we have the economic propensity assigned to each house we also assign each house a cognitive propensity for adopting solar. And this just includes everything that's non-monetarily related to the adoption of PV. So we estimated from a survey that spanned all sort of states that we have involved in this model, and cognitive propensity is estimated in a different _____. So what _____ here? We _____ _____ model that used just economic and spatial independent variables, and then we focused a second model that involves economic, spatial, and cognitive independent variables. The difference in the residuals between these two models are what we defined with a cognitive propensity of the actors in the survey.

Once we have these cognitive propensities we model the cognitive propensity as a dependent variable with the data available from the census as the independent variables. This gives us a functional form for the cognitive propensity that can then be applied to the agents and the agent-based models in order to predict they are cognitive.

Next slide.

So the third factor influencing solar adoption, as Adam said, is the spatial closeness. So for most regions we don't actually have data on adopter locations, so what we did instead is to randomly assign the agents to locations within the zip codes where we knew we had gathered the data, and then to represent the spatial proximity of the network. As we did some simulations using this model we reassigned agents solar solutions, so we sampled across a very wide variety of spatial proximity networks.

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So this relates back to the theoretical model, because we can see segregation happening in these empirical models. The economic and the cognitive propensities do wind up being clustered within the simulations that we're doing with the actual data. And I believe, Adam, you're going to step in and talk about _____?

Adam Henry: Yeah. Thanks, Georgia. So we just have a few minutes, so I wanted to try to go through the rest of this pretty quickly. This slide is just meant to illustrate that in our metro regions – this represents Tucson – you really do have segregation in terms of agent types, cognitive propensity and economic propensity. So in general they follow this sort of S-shaped curve, but you really do see a high propensity and a low propensity group, so that assumption from the theoretical model seems to hold up empirically. Thanks, Georgia.

Georgia Pfeiffer: Okay. Next slide.

So we're going to jump to the alpha simulations. So just to briefly explain, this adoption decision is modeled on a logistic function, just like it was in the theoretical model. And then we ran this, calibrating the parameters and the logistic functions and fitting the simulations for historical data so we can try to figure out those parameters. So the first graph shows the results for Arizona. The red line which you can see on the first half of the graph is the historic adoption trends. The black dots are the calibrated and predicted trends over time. So they're calibrated – the calibrated time steps are the ones where we had core data. And this is where we were putting our parameters. And then branching out from that, this is predicting in the future time steps and where we might be, given the drivers that we're measuring for adoption terms.

The average calibrated perimeters are in the left-hand side of the graph as well as the observed segregation that we see in the spatial network.

Next slide.

So this graph is the same layout except these are the results for New York. So we see a much shallower adoption curve in this one, which we saw historic adoption _____ much slower pickup here. But then again, we see the predicted adoption expanding over time.

Next slide.

Same setup for New Jersey. I know that we're a little bit short on time, so I'll just go through these pretty quickly.

Next slide.

And the results for California, where we see much faster adoption.

And the next slide.

So the Golden Solar model, this data-driven agent-based model, enables us to apply these theoretical models to the overall thesis. But there are lots of data constraints. The data management for this model was a little bit difficult; we don't have data, especially on the spatial considerations, readily available. So the preliminary results, even though we're a little bit constrained on data, show the importance of the non-economic factors. So we see even though the incentives are _____ _____ _____, so the spatial proximity and common _____ factors are still driving adoption forward.

So this model shows us that segregation is not just of theoretical importance, but it also seems to be a real phenomenon that models suggest that they can transform the effectiveness of programs to enhance solar adoption.

Okay, I think that that is it for the presentation.

Courtney Kendall: Thank you very much, Georgia. Thank you, Ben, Adam, Heike, and Georgia, for that great presentation. Now we'll go ahead and get started with the Q&A session.

We will get to as many questions as time allows. And if you are interested in asking a question please go to your questions pane showing on your toolbar and we'll go ahead and answer those questions.

Okay. Well, we have a question here, "How did you determine your probabilities? Did you use any expert opinion or data?"

Ben Sigrin: Adam, do you want to answer that one?

Adam Henry: Courtney, so how did we estimate the probabilities? Did we use expert opinion or data? Was that the question?

Ben Sigrin: Yeah, I think this question is targeted towards calibrating the empirical model. So can you speak more about how that model was calibrated?

Adam Henry: Oh, I see. Yeah. Okay. So that's a good question. We have a basic functional form which we didn't put on the slides, but it's very similar to the incentives model that Heike had presented. It's basically a low git function, where the probability of adoption is a logistic function of the economic propensity with a parameter, the cognitive with a parameter, social influence with a parameter. Now these parameters were estimated from the data, so we took the observed adoption curves, those four red to yellow adoption curves in one of the slides in the regions. And then we adjusted the parameters computationally and went through thousands and thousands of possible combinations of parameters and then we chose the ones that created the best fit with the observed adoption curve over time. So that's just a long way of saying that they were estimated by the data.

Courtney Kendall: Great. Thank you. And your slide with the adoptions over time, I noticed that the adoption curves actually go down in some cases. Why is this?

Adam Henry: Well, that's an excellent question, Courtney. Or maybe that was from a participant. Let's see now. This was slide 28. Would it be possible…

Courtney Kendall: Do you want me to go back to 28?

Adam Henry: Yeah, would it be possible to show us slide 28? Thank you.

Courtney Kendall: Yeah, I can do that.

Adam Henry: Oh, I'm sorry. You know, it's slide 28 on my – yeah, if you'd just move forward another two slides, or one slide.

Courtney Kendall: This one?

Adam Henry: No, the – in two more. Two more forward. Four more forward.

Courtney Kendall: Okay. I was like, "Which one?"

Adam Henry: Okay. Yeah, so it should be slide 29, I believe.

Courtney Kendall: Oh, okay. Forward, not backward. Okay. Sorry.

Adam Henry: Hey, there we go. Okay. So these are the observed adoption curves, the data that were used to choose the best-fitting model parameters. Yeah, and so Tucson, for example, does show this decrease over time of proportion of solar adopters, which actually violates the assumptions of our model, which is a solar adopter will never become a non-adopter. But actually that's not why it's decreasing. It should be decreasing because the number of installations doesn't grow as fast as the housing stock, as the number of houses. And so I believe that that's why the proportion is going down. In our model actually we have a simplifying assumption that the housing stock remains fixed over time, and so this is actually something that we're not able to model yet.

Courtney Kendall: Okay, great. Thank you for that. You said that the cognitive variable was based on survey data. What kinds of questions did you use?

Adam Henry: Let's see. Another good question. So I had to just refer quickly to a document that we have that explains this in detail. There's some complexity to the answer, but it's a good opportunity to make a plug, I think, for our survey team. So concurrently with the agent-based modeling we've had survey folks working on a survey of solar PV adopters, non-adopter considers, and the general public. And they'll also be doing a webinar in the coming weeks, which I would encourage people to attend.

So we use survey data to get at this cognitive propensity idea. In the survey we ask questions like the degree to which individuals are concerned about environmental issues. We ask questions about their education, we ask questions about their knowledge of other people who have adopted solar. And all of these questions are used in this difference of residuals method, where we take out all of the explicitly economic factors and then everything that's left over is considered cognitive. So the cognitive factors are just a great big soup, essentially, of everything that seems to be significant from the survey, like environmental concern or degree of innovativeness of the agents, that's not economic.

Courtney Kendall: Great. Thank you so much, Adam. We have time for one more question. And how is census data used to measure cognitive propensity?

Adam Henry: I'm sorry, could you repeat the question, Courtney, please?

Courtney Kendall: Sorry. How is census data used to measure the cognitive propensity?

Adam Henry: Oh, yes. Okay. So right. A central problem with the estimation of these attributes of agents is that it's well and good to use a survey data to get at things like environmental concern, that we will know if we ask a person directly. But it's another thing to apply this in a region where we don't have survey data like that for specific agents. And so what we have to do is we have to come up with imperfect measures of these theoretical concepts. And so what we did is we used data that are available on census to predict survey respondent's measured cognitive propensity, so to predict all of these things like environmental concern and innovativeness. And this was done mainly by using data on education, age, income, and we also included dummy variables for states in order to capture the state variation.

Courtney Kendall: Great. Thank you so much. Well that is all the time we have today for the question and answer session. I would like to thank our speakers, Ben Sigrin, Adam Henry, Heike Brugger, Georgia Pfeiffer for their time today. You guys did a great job. And I have a webinar sign-up showing the next webinar in the SEEDS webinar series, the link listed there, I was just informed that you cannot register there, but I will send out a link to everybody that was registered and attended with that link if you are – would like to attend those two webinars.

So with that I'd like to thank everybody again for attending, and this concludes today's webinar. Thank you so much and goodbye.