Cyberseminar Transcript

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Session: The Effect of Staffing Levels on VA Reliance and Consult Wait Times

Presenter: Yevgeniy Feyman, BS, Kevin Griffith, PhD(c), MPA

**Rob:** And as it is now just at the top of the hour I’d like to introduce our presenters today. Kevin Griffith and Yevgeniy Feyman are both with the PEPReC in Boston and the Boston University School of Public Health. Yevgeniy may not make it today. He’s in transition. But without further ado, Kevin can I turn things over to you?

**Dr. Kevin Griffith:** Certainly, Rob, thank you.

**Rob:** Looks good.

**Dr. Kevin Griffith:** All right. Thanks Rob. Like you mentioned, my name’s Kevin Griffith. I’m with the Partnered Evidence Based Policy Resource Center here at the VA Boston Healthcare System, also PhD candidate at Boston University School of Public Health. Before this, I was formerly a behavioral research scientist for DoD and the Army before that. Yevgeniy is also here at the VA Boston at BU. Before this he was a Deputy Director of Health Policy at the Manhattan Institute and a research analyst at the Harvard School of Public Health. And while he’s not on the panel today, Steven Pizer, also is really important in this work. He’s the chief economist here at PEPReC and he’s associate professor of Health, Law, Policy Management at BU.

So some quick background on who we are for those who aren’t familiar. I don’t think my supervisor is on the phone so I’m not trying to shield, but I just want to give you a quick overview. So we’re here at the Boston VA and we do research with a lot of different operation partners. So we have the peer research side of things and then we have the operation side of the house and they both sort of mutually inform each other and we do a variety of different types of work.

But this work generally revolves around three core mission areas. The first which is where today’s presentation generally falls is to collaborate with operations partners to enhance planning and improve access to inefficiency or quality of care. So this could be things like helping to inform budget processes, forecasting demand for services, forecasting VA enrollment, turnover, etc., called to be identifying gaps in access, you know, facilities that may need more staff as opposed to those who perhaps are just using their staff inefficiently. And then there’s, you know, mission around collaborating with our partners in research to implementing randomized program evaluations. So we have a couple of projects ongoing. One is looking at medical scribes. So giving providers in the VA scribes to help them take notes and interact with patients more efficiently. Also projects looking at opioid misuse. So looking at, you know, can we predict people who are at high risk of opioid use. And then we have our third core mission which this project also, you know, you’ll see a little bit from this presentation today that falls under this mission. You know we serve a coordinating function with many research groups working on access trying to support research that will help inform and improve VA operations. So you’ll see a little bit of that today. Anyway, but enough about us. Let’s get into the subject of today’s presentation.

So we’re interested in the relationship between these three things primarily. So we’re looking at staffing levels. This could be the number of healthcare providers we have per, you know, some number of enrollees. We’re looking at wait times for specialty care in this case, so how long patient’s actually have to wait to see a provider. And then VA reliance which here we’re defining as, you know, what proportion of a patient’s care that you receive at the VA versus other sources in the community. And so the relationships, you know, if this was a simple relationship I could say, hey, you know, for stations that added more providers how their wait times have changed and I can take the rest of the month off. But unfortunately, it’s not quite so easy. So we traditionally think that, you know, if you want to impact your wait, like a station wants to change its wait time so it hires providers to achieve a lower wait time. But the causality can actually flow in the other direction where a high wait time can trigger a station to start hiring more providers. So if you actually just look at the relationship between wait times and staffing you could actually get sort of some odd results where it looks like where places, you know, with high staffing levels also have higher wait times or that increases in staffing cause increased wait times. But then reliance also plays a role. So if you have a high wait time or a low wait time that’s going to impact whether some Veterans use the VA for their care. Then obviously the care, the proportion of care that Veterans receive from the VA, obviously going to affect wait times. And then you have that the staffing, you know, having a large number of staff might have some direct relationship with reliance but probably the two affect each other through the pathway through wait times. So the term of art for these sort of relationships where two things cause each other is called indigeneity. And that makes estimating the effects of these relationships really difficult. You know if you’re trying to look at the effect of an intervention on the treatment, or the outcomes from the treatment, also cause whether, you know, treatment assignment or affect treatment assignment it makes the estimation quite difficult. Nonetheless, you know, we think it’s important to do.

And then complicating this further is there’s this whole other batch of factors which, you know, are going to affect wait times and reliance and affect the systems. These things like unemployment rates, poverty rates, you know, the number of Veterans without health insurance, how far you live from the VA, what priority groups you’re in, household income, wealth, you know, how many options you have in the community and, obviously, like age and things like Medicare eligibility clearly are going to affect these things as well. So it’s this very complicated system of relationships that we’re trying to model here. So hopefully by the end of this presentation I will have convinced you that we have at least satisfactorily modeled these relationships and that our results are meaningful.

And we think that this is really important to do because, you know, despite these challenges, you know, gaining a better understanding of and quantifying these relationships could be hugely important for VA clinic operations. Excuse me. For instance if you want to predict how changes in your budget or staffing will affect patient wait times and patient demand, or let’s say you want to, you know, you have a standard for access that you’re trying to achieve. You know you want to have wait times below a certain threshold and you want to try and figure out, you know, well how many people do we need to hire to make that a reality. And then in health policy terms, you know, this woodwork effect is another sort of term [unintelligible 7:14], you know, increase in enrollment or utilization that may happen after you expand access. So you know, if you hire folks to reduce the wait times that could cause more people to use the VA so that might cause your wait times to go back up. So if you want to sort of understand this, you know, push and pull or what sort of woodwork effect you can expect, that’s something we’re trying to be able to model. Because you’re making the VA more attractive these are the other options in the community.

Also throughout this, I know that we have the Q&A at the end but if you have any quick clarifying questions, you know, just punch them in and, you know, Rob can interrupt me and I’ll try and get you squared away. So without further ado, for this project we have three research objectives which hopefully should flow from what I just discussed. We want to quantify the relationship between provider staffing levels at VA stations and how long folks have to wait for VA consults. We want to look at the same relationship between staffing levels and whether people choose to receive their care at the VA. And then we want to, the goal of this is do we want to be able to develop these forecasting models to allow us to predict how changes in wait times and reliance will, excuse me, predict expected changes in wait times or reliance due to changes in staffing. So if the station wants to hire more people or has some sort of budget change we want to be able to predict what’s going to happen.

But this presentation is just going to be on the first two. We’re still working on number three. This is very much a work in progress. Any feedback you folks have definitely we could roll right into development because this is not something that’s in the can and done and we’re forget about. You know, we’re still actively working on this. So one thing I want to ask is, you know, as I’m going through this I want to try and, you know, adjust what I talk about based upon your guys’s [sic] backgrounds. So if you please take a moment we’re going to open up a poll to tell me, you know, what’s your roll at the VA? Rob take it away.

**Rob:** Yes sir and that poll is up and running and we have people making their choices. We have about 40% voted and usually levels off around 70% or 80% so we’ll give people a few more moments to make their decisions. Things are ramping up quickly and I would say pretty much leveled off so I will go ahead and close the poll and share out the results. Let me make this a little bit bigger so that I can read it. And Kevin let you know that 0% of your viewing audience answered student, trainee, or fellow, 4% say they’re a clinician, 35% say researcher, 26% administrator, manager, or policy-maker, and 35% say other. And if other is your answer, audience members, you can feel free to use the questions pane as if it were a question and just let me know what that is and if you do it quickly I can let Kevin know or I can let him know at the end of the presentation. And with that, Kevin, we’re back on your slides.

**Dr. Kevin Griffith:** All right. Thank you. So I will try and adjust how much I talk or don’t talk about certain things based on that so, thank you.

So moving along I want to start talking about the data that we’re bringing the bear for this problem. So the first is some data from Milliman who is a, you know, one of those large consulting firms you may or may not be familiar with. So they created this measure of VA reliance that we’re using as one of our two primary outcomes, the other, of course, being wait times. And so this measures the percent of care that Veterans receive for different categories. So this could be, for example, cardiology is one of the categories. This is the proportion of all cardiology services and, you know, you should like CPT codes if your familiar and things that Veterans receive in the community from all other providers versus the VA. And they have certain categories they use. Unfortunately they don’t always line up with our stock code s but some of them are, you know, pretty good. They match up pretty well with the categories we traditionally bucket things in at the VA. And it’s based upon Medicare data. So they look at the, you know, over 65 population for people who are in traditional Medicare. So they exclude Medicare Advantage and they calculate based on these three years of rolling data, what’s the reliance for folks in different counties. Or they call them market areas but it’s pretty much counties. And they don’t have data directly on the under 65 population but they used this survey enrollees to adjust their population, or their estimates and extrapolate them to the under 65 population. So this is one of the data sources we use as this reliance data from Milliman.

The next is we had to come up with a measure of wait times. Which, so we developed this algorithm to pull data from the VA corporate data warehouse to calculate how long folks actually had to wait to see for further specialist. So for the VA side, you know, we included, and it’s important because we included not only just completed appointments but also appointments that were cancelled and discontinued. The reason why we did this was because we felt that if we excluded appointments that were cancelled or discontinued we might be putting a downward bias on the wait times. Because you could think that, you know, for stations that had a really long wait time, patients might be more likely to cancel their appointment. So by including them, you know, we think we’re getting a better estimate of the wait times that Veterans actually faced. Unfortunately for community care, community care was a giant pain. I don’t know if anybody’s worked with that data to actually calculate these wait times. For a couple reasons; one is that the specialty like a stock code, isn’t traditionally listed in many of the community care visits, or data, so we had to actually develop this algorithm to identify what sort of specialty people we’re seeing. And then we had to limit it to completed appointments because if you have a cancelled, or if the appointment is incomplete for any reason, we actually don’t have an appointment date listed in the CDW so we don’t know how long your wait time would have been. So you know for our primary outcome here we’re looking at VA wait times but we do include the community care wait times as a control variable so that’s why I bring that up.

And then we have a large number of other data sources so our, you know, you can take pity on some of our research analysts and folks that had to help us with this. So we have, obviously, the Health Resources & Services Administration Area Health Resources File. This is a great county level dataset that has all kinds of information from the census and American Community. All of these different government data sources pulled together. So we’ve used this to get data on median household income, you know the percentage of adults under 65 without health insurance, you know Medicare eligibility, the number of specialists that are available in the community, and some other variables. We used the American Community Survey. This is primarily to get a measure of Veterans unemployment. Then we have the Bureau of Labor Statistics which gives us the larger unemployment picture. We have data from Housing & Urban Development which gives us, you know, housing price index for most counties. We have data from NBER, the National Bureau of Economic Research which helps gives us distances from different zip codes so we can sort of, you know, estimate how far, you know, the nearest VA medical center is from different zip codes. Then we pull a variety of things from the CDW as well. Whether that’s, you know, the proportion of Veterans in a county that fall into each priority group, you know where the clinics are located, the number of enrollees in each county month. So is a large number of sources brought to bear for this project.

So we have a, I would say, what is a complicated study design. I know this is not a methods Cyberseminar so I’m going to try my best to do this at a very high level. But I am happy to go into, you know, intricate, painful detail either in the Q&A session or if you want to follow up with me separately because I think there’s actually some really cool stuff we did. But I will do my best to explain it at a very high level because I know this is not a statistics class.

**Rob:** Kevin I do have one clarifying question that just came in on the last slide. This person asks by not having the cancelled/discontinued appointment data in CC wouldn’t you be creating inherent bias?

**Dr. Kevin Griffith:** Yes. So that’s, so absolutely, I think that there is, if we are looking at the

wait times that we have for community care I think there is absolutely some level of downward bias there on the estimates Because you know, we’re excluding people that might have looked at the wait time and be like oh my gosh this is too long I’m going to go to the VA or whatever. Absolutely. Fortunately for this, that sense is not one of our main out comes. We’re a little less concerned about it because it’s just something that we’re including as a control variable in our models but, absolutely, that’s a great point.

All right so getting back to the study design. We have our key predictor of interest here is obviously staffing levels and we’re measuring that by the number of FTE’s per, you know, here we used 100,000 enrollees for five specialties. So we initially looked at, you know, these first four so cardiology, gastroenterology, urology, and orthopedics. And we chose these because these are high volume purchased care that include two surgical and two non-surgical specialties. These were chosen in consultation with Office of Veterans Office Care (OVAC). And then ophthalmology we added very recently. So we’re trying to, we want to eventually expand this beyond the initial four and that was one of the easiest ones to just grab. So we’re looking at changes over time. So we have data from FY14, FY16. That’s the latest data that’s available for the reliance. We have wait times, obviously, more sooner than that but we don’t have reliance data going beyond that yet. Hopefully get some updates soon. This is at the county level. So we’re looking at, you know, changes in each of the 3,000 some odd counties in the U.S. We’re looking at changes within counties because there’s, we suspect there’s certain characteristics of counties that are going to be associated with wait times. And to control for that as best we can we’re looking at changes within counties as opposed to differences in counties that have high and low wait times.

We’re also using, it’s called instrumental variables which I’ll give, if not familiar, I’ll give a very high level explanation of what that is. And this is a method that’s used to control for that indigenated [sic] I mentioned earlier. When your treatment, in this case staffing and your outcome, both effect each other you have to do, use some more complicated statistics to account for that relationship. And then we do something called double LASSO which, you know, we have a large number of control variables. So this helps us to wade through the thousands of potential control variables and pick which ones we want. And I’ll also give a high level of overview of how that works and I think that’s a pretty cool thing we did here.

So instrumental variables at the 10,000 foot level. So this is used really common in Econometrics which is a fancy word of saying statistics and economics. And it affects, you know, it’s really useful when you think about this issue of indigeneity. So here’s where outcomes affect treatment assignment. Perhaps the most famously in the healthcare space this is used for the big Oregon Health Insurance Experiment. When you offer people Medicaid, you know, obviously not everyone’s going to sign up for it. This is a famous Medicaid Expansion in Oregon. You know if you just look at the effects of insurance for people who signed up, you’re getting potentially a biased affect. But if you use an instrumental variable approach, you can actually control for that bias. And so here, you know, our treatment is staffing levels. But instead of using that in our models we use what’s called an instrument which is another third variable that I’ll talk about in the next slide. And this allows us to see the true relationship between treatment or staffing and our outcomes. So it’s pretty cool. A couple of rules for this to work. So when you’re thinking of this third variable can’t just be anything. It’s got to be something that is, you know, preferably really strongly correlated with treatment assignments and so this is something that has to be really correlated with staffing levels. But it can’t have any direct effect on the outcome, or it shouldn’t. So it should only affect the outcome through your treatment. And so the term of our here is complete mediation. So here, you know, we tried a few different things and, you know, one that we landed on it seems to work pretty darn well. So as opposed to VA specialists we used the county level number of non-federal specialists. So this, obviously, you know, the number of specialists in the community is not going to have any direct effect on the VA wait times but it affects the supply of potential VA specialists, you know, it’s the pool from which you hire from and so on. But the effect of the VA hiring on this supply is trivial because there’s many, many more non-federal specialists than there are VA specialists. So even though there’s a little bit of, you know, perhaps relationship going the other way, you know, it’s enough that it’s not a concern.

So this is how we actually control for that complicated relationship that I showed you earlier in the presentation as [unintelligible 22:30]. I’m happy to go into painful detail on how this works in another forum. And we also used, it’s called double LASSO which LASSO, it stands for Least Absolute Shrinkage and Selection Operator. So we have a large number of variables that we could include in here. So we have, and when I count them there are 3,335 potential variables for our regressions. All of those demand shifters I mentioned earlier like unemployment rates and so on. But then there’s a whole ton of, you know, dummy variables for calendar month, calendar year that account for changes. You know we want to account for just natural sort of change over time. Then we have dummy variables for each county of which there are like 3,142. And then we want those in there because then we’re controlling for all these sort of time and variant local characteristics that could cause problems if you don’t control for them. Obviously when you have this many variables, you can cause some issues with the estimation. So double LASSO is pretty cool. It’s a very new, machine-learning technique that Seminole paper only came out in like 2012 which is, like yesterday in statistics terms. And it provides various advantages over traditional data driven ways to select variables for like step-wise regression which has a lot of problems or just subjectively choosing them. So it works by automatically removing variables that are not associated with either the treatment, in this case staffing levels, or the outcome, so either reliance or wait times. So in this case, you know, if you have variables that either aren’t related with your treatment or your outcome, there removed from the regression. It also, you know, handles another [unintelligible 24:27] or problem when you have, especially many, many variables and regression [unintelligible 24:35]. It’s where you have the very strong, [unintelligible 24:34], two or more variables that are very highly correlated that can cause problems for statistics. So double LASSO will pick one and remove the others so you get a much more parsimonious model, one that’s easier to estimate and to understand and it’s independent of the researcher’s decision making. So you know, the opportunity for me to sort of cherry pick what gets included in the model is removed because this is all done automatically. So it was super helpful for this.

But again, happy to go into more detail. But I don’t want to bore you with, you know, a bunch of [unintelligible 25:23] statistic details for an hour. So let’s starting getting into some results. So first I want to show a few charts about our outcome data. So this is, you know, sort of looking at what sort of geographic variation we have. You know this is important because if we don’t have much variation in our outcomes or our predictor than we don’t really have a research study. So here are two maps of stations with average consult wait times for cardiology. The VA is on the left. The community care is on the right. So the darts are different stations. And fortunately, at least for us, for our research purposes, we see substantial variation. Perhaps some of that variation is not beneficial to Veterans but it’s good for us at least. You know simple we see wait time ranges from 15 to 157 days for the VA with an average of 50 days for cardiology. This is from March 2019 which has been the ones I pulled for this. Community care which, again, is in our models as control variables only. This ranges from nine to 110 days with an average of 51 days. So that’s just something, that’s our first outcome, that’s good, there’s plenty of variation there.

Next we looked at VA reliance. So one challenge with the Milliman data is this VA reliance is not available for all specialties. So if you noticed there are only three specialties listed here. These are the three of the five that we actually have reliance data for; so it’s cardiology, orthopedics, and ophthalmology. So this figure is called a violin plot. It’s similar to a box plot which you’re probably more familiar. But it sort of shows the distribution. So as, for example for cardiology, you know the scale on the left is the, you know, the proportion of care that folks get from the VA so it goes from zero to one. For cardiology most counties have reliance between about 15% and 35%, but some as high as about 55%, others as low as 5%. Orthopedics has a much tighter spread with an average around 35%. And ophthalmology has a similar average to orthopedics but it’s spread all over the place. So a lot of variation here which is good for us to study.

And then next looking at variation in staffing levels. So again we see this wide variation which, perhaps, isn’t great for accessing some areas of it but its super easy for our models because it gives us something to study. You know we see the largest amount of variation in staffing is for cardio. You know there are some stations that just don’t have any or don’t do these services at all or at least they have no staff reported for it. And you see, you know, less variation for urology and, perhaps, orthopedics as well. But we get a lot of variation across the country.

But one thing with staff we also wanted to check and make sure there is variation within counties because, again, we’re looking at changes within counties over time. If counties are sort of have steady in their staffing levels over time then that’s not helpful. So we also looked at changes over time within a county. So this histogram is the difference between the minimum and maximum FTEs for cardiology [unintelligible 28:51] the difference in the maximum minus the min for cardiology over this study period. And we see that it’s only, you know, a small number of counties that have like no change. Most counties do have some, some cases very large changes in staffing levels over the study period. So again, that’s really good for us. Gives us something to study.

But now enough with the appetizers. Let’s go on to the main course. So one of the big take-aways is, shocker I know, but increased staffing is associated with lower consult wait times. So in here, you know, we have specialties. We have the second column is the nationwide average for FTEs per 100,000 enrollees. And then the third is the nationwide average for wait times in days. And then we, excuse me, the results here, so the beta is our estimated changes in wait times if you add in FTE. So for example, again, to put this in perspective of one FTE change, you see, is a very large change in staffing. So for cardiology if you have an average of 4.76 if you bump that up by one that’s a very large change. But we see that it would lower wait times for cardiology, actually, at the smallest effect it would lower wait times by two days. GI, endoscopy, urology were more measured then, you know, say that if you add in FTE per 100,000 enrollees you’ll lower wait times by seven days. Orthopedics had a very large change and I’ll show you and it’ll become a little clearer on the next slide. This suggests that orthopedics has less pent up demand and also that, perhaps, reliance would change less for orthopedics and that’s why you get such a large estimate for it. Ophthalmology didn’t get a significant effect here. So ophthalmology, you see, the beta’s actually positive, we have this super wide competence where it goes from like negative 31 to 37. So really inconclusive result for ophthalmology. But in general, you see lower consult wait times due to increased staffing levels.

**Rob:** Kevin another qualifying question.

**Dr. Kevin Griffith:** Yeah go for it.

**Rob:** By staff do you mean providers, not support staff?

**Dr. Kevin Griffith:** Yes. Yes. Providers.

**Rob:** Okay, thank you.

**Dr. Kevin Griffith:** And then for reliance, again we have, you know, three of the five categories we have reliance data for. So this shows the mean column here, the average reliance. Again, about 25% of cardiology care for Veterans is provided by the VA versus the community. You see the estimated change in VA reliance due to added staff. And again, these are large changes in reliance but that’s because this would represent a fairly large change in staffing. And so you can sort of see why cardiology, or ophthalmology, might not have much change in wait times because if you lower the wait times, you know, you’re going to end up increasing reliance which is going to cause wait times to, perhaps, go back up. And then orthopedics sort of, you know, as expected, orthopedics had a, at least from the wait time results there was a change in reliance so, you know, if you add staff you’re going to improve, or increase, orthopedics reliance but it’s small. Which again, this comports with this thing on the data from the previous slide that, you know, that’s why you could get such a large change in orthopedics wait times because you wouldn’t be attracting that many new patients or new enrollees. You’d mostly be lowering wait times for existing enrollees. But ortho is a very small change so a one FTE add would only increase ortho reliance by like 1.24 percent, so pretty small change there.

And we did a number of, you know, we’re still doing a number of sensitivity analyses to make sure that our results are robust to various changes in our assumptions and I’m not going to drag you through the remaining 30 minutes of all these different ones but, you know, [unintelligible 33:26] just sort of show some of the changes. So for example, you know, the data I showed you previously were contemporaneous. This is looking at staffing levels in a given month and wait times, or reliance, in a given month. But we’re thinking, you know, appointments are generally made, you know, one or two months in advance so perhaps we should be using the staffing at the time the appointment is made. Like that’s going to be more relevant. So we tried using one month lags. We also tried using two month lags but this is the results for reliance using one month lags. You see the results are still consistent and pretty significant. Orthopedics the estimate is basically unchanged. Cardiology and ophthalmology the estimates are slightly lower but were still, you know, strongly positive and significant results. So so far, you know, in our [unintelligible 34:18] analyses our results have been pretty robust to changes in our assumptions but, you know, we continue to play around and trying to break our models. You know, if anyone has suggestions for other things we should check, you know, happy to find other ways to try and prove ourselves wrong.

So there’s some, in my mind, some pretty clear implications for, you know, the work that we’re doing. The first is that, you know, not all specialties are created equal. So these, you know, if you add staff the responses in one specialty are going to be different then if you added staff in a different specialty, right? So when we saw this, you know, the changes in wait times, oh I’m sorry, the changes in reliance were much larger for cardiology and ophthalmology as compared to orthopedics. But if you wanted to lower wait time you get a much better bang for your buck by adding staff for orthopedics. And this sort of makes sense because orthopedics is going to have that lower, sort of woodwork effect. You’re going to attract fewer people to use the VA instead of community by adding staff there. At least that’s what our model suggests. And you know you could use something like, you know, our goal here is to eventually put this in a tool that folks could use or simulate. You know, if had changes in staff whether that’s, you know, plus or minus due to, you know, some budget changes, you know, how do you think that’s going to affect utilization, right? So what proportion of care Veterans are receiving from the VA. Or you know, if you want to meet some new access standard how many folks do you need to add to sort of, not only lower your wait times, but to offset the increase in reliance that you might expect. And so the data that I’m showing here are for national but, you know, we could certainly plan to and you can already use this to sort of predict local effects. So if you want to know, okay this is great, you’re telling me how what on average would happen. I want to know for my particular station what would happen. We can absolutely do that. So our models allow us to account for local characteristics and different, you know, idiosencratic [sic] things about your community for us to tell you, you know, how this might affect your wait times and your reliance.

But with any research product there’s, you know, a number of important limitations. So our methods have some clear strengths that I outlined earlier but also some limitations here. I’ll go few of the ones that jumped out to me. First is with the Milliman reliance data and also the FTE data at the VA. They don’t always line up, you know, very cleanly with stock codes which, you know, are what we used for looking at appointment wait times and so on. So we tried to rectify this by we chose, you know, those reliance categories that do match pretty well. You know, for example, the Milliman data has gastroenterology. But their gastroenterology sort of combines gastroenterology and GI endoscopy which are broken out separately in the VA system for stop goods. So we combined it on the VA side to try and make this as much of a apples to apples as possible. Some of our data is monthly. So if you’re looking for our wait time data, priority groups, unemployment, etc.. But some are annual, for example, the Milliman reliance data or our instrument that we used as a non-federalist specialist that this data’s provided annually. So we had to do a number of adjustments to make this work so we had to like [unintelligible 38:04]. And as any VA data Veterans knows there’s miscellaneous warts in the data. For example when we were looking at these community care consults I mentioned we developed this algorithm to classify them by service. Found that about 13% of the consults we just, basically there’s not enough in there for us to tell what the heck they did. And then, you know, with the double LASSO, you know, this is a neat approach that allows us to do the selection on what variables to include in the model but also still may cause [unintelligible 38:40] on the effects of staffing. But one limitations is all the other variables in the model are just sort of treated like their nuisance parameters so you can’t really interpret their effects. So the double LASSO tells us the effects of staffing but if we wanted to look at, you know, all the other variables in the model and what they mean we’d have to do something else. And this just tells us the effects of staffing, not the effects of like unemployment and community care wait times, etc. We have to do more to get those results.

But we have a number of extensions we’re, as I mentioned, again, this is ongoing work and so I’d love your feedback on what else you might like to see, especially if you’re researchers. You know if you want to sharp shoot the method or tell us what sensitivity analysis we should do. You know if your operations or managers apprise me how to make it more impactful and useful to you. But we already plan to obviously include additional specialties. We want to, you know, do a bunch of additional robustness checks, these are changing all those [unintelligible 39:43] statistics things to see, you know, how much it affects our results. You know I mentioned in the instrumental variables, you know, we sort of landed on this instrument that we used, this number of non-federal specialists. But there’s others we want to try to see, hopefully, the results are similar. And then eventually we do want to extend this to sort of look at the effects of the, we think the effects of the other variables of the model are interesting even though they’re not the primary focus here. So we want to, you know, one that we are particularly interested in sort of this, the community care wait time as sort of a substitution for, you know, VA wait times so we’re interested in that effect. We plan to look at that. Then we actually want to develop and hopefully deploy this station level forecasting model that allows us to quickly look at the effects of staffing changes on wait times and reliance.

And Yevgeniy, who looks like got caught in transit today, you know, we’re not independently wealthy so this work would not be possible without some generous support from QUERI and OVAC so we are thankful to them for that. We are also thankful to, we got some guidance and support for our efforts and important background from the Office of Policy and Planning. So we’re also grateful for their contribution. And with that, you know, I will take questions if you want to, if you have questions afterwards, you know, feel free to shoot me an email. I’m also on twitter as an assume normality because I’m a giant stats nerd. If you’re a statistician you’ll understand what that is. Thank you for calling in and listening.

**Rob:** Well thanks, Kevin. We don’t have any further questions at this time. You did have me ask you clarifying questions during the session but let me just take the opportunity to remind attendees that if you have any question at all that you’d like to have Kevin answer you can go ahead and use the questions section of the GoToWebinar dashboard, that white piece of software, white window, that pops up on the right hand side of your screen when you join the Webinar. Again Kevin, at this time we don’t have any pending questions. I don’t know if you have any closing comments that you’d like to make while we wait for people to type those in if they’re going to. Oh, one just popped up so why don’t I just go ahead and ask you. Will a more detailed statistical analysis be made into a presentation?

**Dr. Kevin Griffith:** Oh absolutely. You know at some point, you know, we have to do that both within PEPReC as we, you know, we have our own murder boards where we try, you know, sharp shoot methods. Also I’m probably going to present this at the American Society of Health Economists next year so they’ll definitely be versions of this probably for VA and then also for external. But if it’s something you’re interested in, you know, I think these methods are really cool so I’m happy to talk agnosium about them. Definitely shoot me an email and as soon as something becomes available, I can send it your way.

**Rob:** Thanks, Kevin. This person writes back that they are looking forward to seeing it. And that is your email address currently displayed on people’s screens. [Kevin.griffith@va.gov](mailto:Kevin.griffith@va.gov). Again at this time this person, here they come, great. I missed the first part of the presentation, so apologies. But I wonder if you’ve done some similar analyses in primary care? Can you describe how you determine staffing? A challenge with VA specialists is many provide care to Veterans as WOC’s. Oh wait a minute. Yeah, there’s two different questions. I apologize, everybody. This person says I missed the first part of the presentation, so apologies. But I wonder if you’ve done some similar analyses in primary care?

**Dr. Kevin Griffith:** Yeah. So we do have a couple folks within PEPReC that are looking at productivity and turn over. So it’s a similar sort of looking at staffing levels and wait times is actually one of the options they use. So that’s not something I am doing but, you know, we do share notes. So probably at some future Cyberseminar you’ll see a PEPReC presentation. It’s Siva Palani and Kyle Barr are my colleagues that are doing that, and Taeko Minegishi. But I will definitely mention that to them. I’m not sure if they‘ve thought of that but at least for this part, you know, so far we’ve focused on specialty care.

**Rob:** Thank you. That person writes that they are looking forward to that. And we have on here, can you describe how you determine staffing? A challenge with VA specialists is many provide care to Veterans as WOC’s, or without compensation, or through contracts so they don’t have an actual FTE, full time employee. Also many MPP’s, and I don’t know what that stands for, are used as well for specialty care. We’re you able to account for these issues?

**Dr. Kevin Griffith:** For the staffing, gosh, I am thinking of the orders. We didn’t calculate that ourselves. There’s a different agency within the VA. If you shoot me an email I could find that information it’s escaping me at the moment. But there’s another acronym at the VA that calculates FTEs for station months for different specialties. And they don’t do it for all specialties but they do it for some. I think the ones that are easier for them to do. And that’s what we used so I’d have to check and see exactly how they handled it. But that’s what we’ve used. That’s not something that we developed in house. But again, if you shoot me an email I’m happy to share more information on that.

**Rob:** Thank you. Another person writes in, I believe this is a helpful comment, staffing data equals OPES, Office of Productivity, Efficiency, and Staffing.

**Dr. Kevin Griffith:** And that does ring a bell. Thank you.

**Rob:** Well thank you for that. For forecasting changes in wait times will you use a linear regression framework with a LASSO penalty, or are you thinking of a different method?

**Dr. Kevin Griffith:** Yeah with this, we did use a linear regression for this. With the double LASSO and the instrumental variables so, you know, if you’re doing a normal like LASSO regression, you know, it’s all sort of done in the same step. With double LASSO it’s a little different that you run, you actually run [unintelligible 47:17] in essence, three regressions. So you run a LASSO regression with your treatment variable as the outcome. And you get a list of all the variables that are associated with your treatment. And then you run another LASSO regression with your outcome as the dependent variable. And you get a list of all the variables that are associated with your outcome. And then you take the union of those two sets. So you get the list of all the variables that are included or associated with either treatment or outcome. And then you put those in a third regression which is the instrumental variables which also was a linear regression. So with the double LASSO you’re using it to select the variables for inclusion into a later regression. And so that’s the 10,000 foot view of how that works, but yeah.

**Rob:** Thank you, Kevin. It looks Yevgeniy never did make it. He’s probably still in transition. But that was the final question that we have at this time. I don’t know if you have any closing comments that you’d like to make. But if you do, now would be a good time.

**Dr. Kevin Griffith:** Okay, no. I cannot think of anything else, again, you know, thank you, Rob, for helping to put this together and thank you everyone for attending. You know, if you’re in the shower in the morning and you know something, ah, I can’t stop thinking about that awesome presentation Kevin gave and I have this burning question that I just can’t, then shoot me an email, or whatever, and I’ll do my best to answer it.

**Rob:** Great. Well thank you once again, Kevin Griffith and I’m sure I’m going to mangle his name but Yevgeniy Feyman and also Steve Pizer for his mentorship in this project. Audience members when I close the webinar momentarily you’re going to be presented with a short survey. Please do take a few moments and give us those answers. We definitely count on your answers to continue to bring you high quality Cyberseminars such as this one. And with that, I will just wish everyone a good day and thank you once again, Kevin, for a great webinar.