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Session: Productivity and Turnover in the Veterans Health Administration

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**Liam:** My name is Liam Rose. I’m a health economist at HERC, The Health Economic Research Center here in VA Palo Alto. And we’re very excited to be hosting Aigerim Kabdiyeva who is with VA Boston at PEPReC, which is the Partner Evidence Based Policy Resource Center where Aigerim is a researcher and she is going to be telling us about productivity and turnover in VA using a very clever idea approach. So very excited for this presentation and I’m turning it over to you, Aigerim.

**Aigerim Kabdiyeva:** Thank you Liam. Hi everyone. Thank you for attending this Cyberseminar. I’d like to thank the HERC Team and Cyberseminar’s team for hosting this presentation. The research that I’m presenting analyzes the effect of productivity on turnover. This is work in progress and we welcome your comments and suggestions.

First I’d like to thank Workforce Management and Consulting at the VA for help obtaining the data.

So why are we interested in the effect of productivity and turnover? From previous literature we know that clinical workload is associated with clinicians burnout and turnover. We also know that workload is often managed through productivity standards in many healthcare organizations. And often managers in these organizations may assume that increasing productivity has only positive consequences such as better patient access to care and better patient [unintelligible 1:44]. However, higher productivity can also have negative consequences such as provider burnout and turnover. And there is little evidence on these negative consequences.

So the research question that we ask is does provider productivity have a causal impact on turnover? We couldn’t find studies analyzing the causal effect of productivity on turnover and if you are aware of such studies, please let me know. We think that there’s little research into this because the data on productivity and turnover at provider level is not easily available and also because there are unobservable variables which introduce bias and make it difficult to estimate the causal effect.

We chose psychologists and psychologists as our provider cohort for several reasons. First VHA patients have a high prevalence of mental health conditions. So these two specialties are at the top of VHA’s priority list for recruitment and retention. Second psychiatrists and psychologists make up a large group of providers working with mental health patients which gives us more statistical power to measure the effect compared to other smaller specialties. And finally, turnover among mental health providers is an important topic outside the VA as well because there is a general shortage of mental health providers in the U.S.

In our regression analysis the dependent variable on the left hand side is an indicator for whether the provider separates from the job in the current or next three month. Because the incidence of separation in the current month is very low, we defined the dependent variable as separation in the current and next three months which gives us higher incidents and more chance to detect the effect. Our main explanatory variable on the right hand side is provider productivity. We measure provider productivity as the number of RVU’s divided by FTE. RVU’s measure the amount of work performed by their provider. And FTE stands for Full Time Equivalent and it measures how much time the provider is available for work. So for example, a provider who works 40 hours a week is one FTE. And a provider who works 20 hours a week would be 0.5 FTE. When we divide RVU’s by FTE we get productivity. In other words, how much work the provider performs per unit of time that they’re available for work. We also include other individual variables which we expect to be related to turnover. Previous literature has shown that tenure, age, and weight are negatively related to turnover. So we expect that providers who are older, have been working at the VA longer, and have higher wage to be less likely to separate from the job. Next we also include financial incentives such as EDRP, retention, recruitment, and retention that the VA providers might receive. EDRP is an Educational Loan Repayment Program that helps VA providers repay their medical school loans over a five year period. And the aim of all these incentives is to increase recruitment and retention of providers at the VA. We also include medical center level variables which we expect to be related to turnover. For example, local unemployment rate measures local labor market conditions. If local unemployment rate is very low, that probably means that VA providers can more easily find a job outside the VA in the local job market. Human resources staffing at medical center is another measure that might be related to turnover. Because HR staff are responsible for managing recruitment and retention incentives for employees and they might affect employee retention in other ways. The last variable on the right hand side is the mean quit rate of nurses with up to five tenure at medical center level which we use as a proxy for unobserved medical center level factors that affect turnover.

Next we have a first poll question and I’ll turn it over to Rob.

**Rob:** Thank you, Aigerim. And that poll is up. People are making their decisions. You have about 20% to 25% of your viewing audience having answered so we’ll give people some time to go ahead and make their decisions. The question being are you familiar with instrumental variable methods for estimating causal effects? Answers are yes, no, or a little. And we have about 65% of your viewing audience having made their choices so we’ll give people just a few more moments to go ahead and choose either yes, no, or a little. And it looks like things have leveled off so I’m going to go ahead and close the poll. And I will share out the results. And I’ll let you know, Aigerim, that 29% of your viewing audience say that yes that they are familiar with instrumental variable methods. Forty seven percent, the largest number, say no. And 24% say a little. I’m sorry, I’m going to go ahead and hide the poll now and we’re back on your slides.

**Aigerim Kabdiyeva**: So based on the poll results, it will be useful to go over the main idea behind instrumental variables. So I think most of us are familiar with randomized controlled trials which are a gold standard for measuring casual effects. In a randomized control trial, some participants are randomly assigned to receive the treatment while others are randomly assigned not to receive the treatment. Because treatment is assigned randomly the only difference between the two groups is that one group received the treatment while the other group didn’t receive the treatment. So if we compare some outcome for the two groups, then we obtain the clean treatment effect. On the other hand, in the case of the observational study, there’s no experiment and there’s no random assignment. So participants might have chosen to receive treatment which means that they can be very different in terms of unobserved characteristics from participants who didn’t receive the treatment. Therefore, if we compare participants who received the treatment to those who didn’t, we will obtain biased estimates of the treatment effect. And this bias is known as selection bias. Because people who receive treatment select themselves into treatment as opposed to being randomly assigned. This is where instrumental variables can help us. Instrumental variables are variables related to treatment but not related to any unobserved characteristics due to some institutional or other reasons. We can think of instruments as a source of randomization similar to randomization in the randomized control trial. So if we compare the outcomes of participants who have a high value of instrument to the outcomes of participants with a low value of instrument, we can obtain the treatment effect.

In our analysis we have two sources of selection bias. The first is time-invariant unobserved individual effect. We can think of this as all unobserved individual characteristics that don’t change over time. For instance, some providers are inherently more motivated than others. These individual characteristics can be correlated both with productivity and turnover. For instance, a provider who is more motivated is more likely to be productive and less likely to separate from the job. These individual characteristics introduce bias when we measure the effect of productivity on turnover because they’re related both productivity and to turnover. And one way to eliminate this bias is to control for physician fixed effects. So that physician fixed effects account for the individual characteristics that don’t change over time. The second source of bias that we have in our analysis is unobserved variables that change over time within a provider. For example, a provider might get sick at some point during their tenure at the VA. And when a provider is sick, they’re likely to become less productive and they’re also more likely to separate from the job because of the illness. In this case, provider’s illness biases the effect of productivity on turnover because it’s related both to productivity and turnover. And to eliminate this bias, we need an instrument for productivity within a provider over time. So we need something that affects the provider’s productivity over time but is not related to unobserved factors that also change over time. And the instrument that we propose to use in our case is total FTE of other psychiatrists and psychologists at the same medical center. The idea behind this is that when other providers at the same medical center are less available for work, I need to pick up the slack and work more as an individual provider. So the total FTE of other providers generates exogenous relation in my productivity. In other words, total efficacy of other providers is a measure of other’s availability and other’s availability affects how much work I need to do as an individual provider. When we calculate this total efficacy of other providers, we include only providers who haven’t joined or left in the current or previous two month. That’s because if other providers have low FTE because they’re leaving it could be due to unobserved factors which also affect my probability of leaving. For example, if there’s a bad manager others are more likely to leave and I’m also likely to leave and this has nothing to do with the effect of my productivity so there’s bias. To minimize this bias we include the FTE of providers who haven’t left or joined in the current, or prior, two month when we calculate the instrument.

On this slide I show descriptive statistics for our sample. We observed some individual’s in multiple month so the sample has a panel data structure. The average age in our sample is about 49-years-old. About 55% of our observations are for female employees. About 7% of observations are for employees who are also Veterans. Tenure is ten years on average. Separation from the job takes place in about 2% of cases and average productivity is about 223 RVU’s per FTE. Our instrument, the total clinical FTE of other psychiatrists and psychologists, has a value of 52 on average. So on average, 52 other FTE’s. The incidence of receiving financial incentives such as EDRP, recruitment, retention is quite low as we can see from the numbers. The average local wage is about 4.17 which corresponds to roughly $140,000.00 in annual salary for the providers. Local unemployment rate is about 5% on average. Private wage trend is an estimate and it’s actually estimated trend differential so I’ll skip over explaining the size of this number. The mean quit rate of nurses which we use as a proxy for unobserved factors if 4% on average. The ratio of HR manager FTE’s to medical FTE’s is about 2 to 100 and 1 to 100 for HR assistance. And the mean tenure of HR managers and assistants is 15 years and 11 years respectively.

On this slide I show the results of the naive fixed affects regression. This regression is naïve because we investigate only the association between productivity and turnover, not the causal effect of productivity and turnover. This regression does control for provider fixed effects but doesn’t control for within provider unobserved factors that change over time such as if provider gets sick during their work at the VA. The estimated coefficient on productivity is we can see is negative which means that higher productivity is associated with lower turnover. If we interpret this coefficient as a causal effect, we would conclude that making providers work harder would result in lower turnover which would be, of course, a win-win situation, but we know it’s not likely to be true. And this estimate is likely biased by unobserved factors which are related both with productivity and turnover within a physician over time.

So now we reached our second poll question and I’ll turn it over to Rob.

**Rob:** Thank you and that poll is now up. Question being, if we want to measure a causal effect, which one is desirable? Covariate balance, covariate imbalance, or I don’t know. Aigerim, we have about 20% of your viewing audience having made their choices so we’ll have to give them a little bit more time. I think this one is a little bit more complicated than the first poll so I guess we’ll probably have to be a little bit more liberal with how much time we give people. And it looks like about 50% have made a decision. And it’s going up rapidly from there so we’ll give people maybe another 10 or 15 seconds to go ahead and make their choices. And things have leveled off so I’m going to go ahead and close the poll and share the results. And Aigerim, 40% of your viewing audience say that covariate balance is desirable. Only 14% say covariate imbalance is desirable. But 46% don’t know. So we’re going to go ahead and hide the poll and we’re back on your slides.

**Aigerim Kabdiyeva**: Thank you Rob. So covariate balance is related to the idea of randomization. If treatment is random, we expect the treated group and the untreated group to be the same except for the treatment. So we expect all variables other than treatment to be the same on average in the treated and untreated group and that’s what we mean when we say covariate balance. So in the table on this slide, in the first two columns I show average values of variables when I divide the sample based on productivity. The first column is for below medium productivity subsample and the second column is for above median productivity subsample. We can see that above median productivity sample has a higher age, higher tenure, and higher wage. So this means that the providers with higher than median productivity have a higher age, wage, and tenure than lower productivity providers. And if that’s true, there also more likely to be different in an unobserved way as well. So that’s why we want to use an instrument and in columns three and four I divide the sample based on the instrument instead of the productivity. Column three is for subsample with above median value of instrument which corresponds to lower individual productivity because they’re negatively related. And column four is for the subsample with below median instrument which will correspond to higher individual productivity. And when we compare columns three and four covariate balance is much better than for columns one and two. Tenure is slightly lower instead of being higher. Wage is almost the same. And the difference in age is smaller. So there’s more covariate balance when we divide the sample based on the instrument which means we should have less bias when we use the instrument rather than productivity itself.

On this slide I show the first stage fixed effects result. So for this regression, we regress individual productivity on the instrument to see if they’re related and we do find the negative relationship as we would expect. When other providers are more available to work, I don’t need to work as hard as an individual provider. Individual productivity is individuals work performed divided by the time that the individual is available to work. Ideally when other providers are more available we would want your individual work to decrease, but we would want your time available to work to stay the same for this to be a good instrument. When we regress the two components separately on the instrument we find that the individuals work performed is correlated with the instrument and individuals time available is also correlated with the instrument which is other’s availability. And we think one of the reason is that providers tend to take vacations at the same time so time available to work is correlated to work among providers. If you have other insights into why individual providers availability is correlated with other providers availability in the same specialty please let me know. That would be very helpful.

Now we will go over the two-stage least squares result. So two-stage least squares is a method that uses the instrument to estimate the causal effect. Previously we looked at the naïve fixed effects regression which looked just at the association. Now we’re using the instrument and these are the results with the instrument. We find that the coefficient on productivity is positive unlike in the naïve fixed effects regression. So using an instrumental variable method makes a big difference in this case and it implies that making providers work harder would result in more provider turnover, not less.

We can use the estimates to predict an effect of a hypothetical increase in productivity. So let's consider a VHA policy that proposes to cut appointment times from 30 minutes to 20 minutes increasing productivity roughly 50% which is about 111 RVUs per FTE on average in our sample. Using our estimates this implies about a three percentage point increase in the probability of separation which is quite sizable relative to 2.3 percentage point baseline probability of separation in the sample. And one caveat here is that the coefficient that we estimate applies to the small local changes in productivity, so when we apply it to a large change in productivity this is somewhat problematic.

So here we will look into robustness of the instrument. When we introduce the instrument I explained that we include the FTE of providers who haven’t left or joined in the current or past two month because providers leaving could be related to unobserved factors. Now we analyze the robustness of this definition by increasing the lookback period to three month from previous two month. And we find that the first stage regression here is significant as before. And just to remind you the first stage is the relationship between productivity and the instrument to see whether the instrument is really related to productivity.

Next we look at the two-stage least squares results where we use this more conservative instrument and we find that the estimated coefficient is a little smaller in size and its significance is lower.

Next we run some analysis to check sensitivity by year. So we split the sample by year and run the analysis for each year separately. And what we find that the first stage is significant in all year subsamples but the results of the two-stage least squares model are significant at 5% in 2015 and 2016 and significant at 10% in 2014. So they are significant for most years but not in 2017.

We also ran this analysis for other specialties to see whether we would find a similar result. We chose primary care physicians as one group and optometrist and ophthalmologists as a second group because we expected these groups to have a large number of providers. And what we find is that in the first stage the results are not significant for PCPs. So for PCPs other providers availability is not related to my productivity. And we think that this might be related to how PCPs work is structured and how the structure of the work compares to psychologists and psychiatrists. Because PCPs are responsible for a panel of patients and this seems to imply that they are less likely to pick up the work of other PCP’s. When in the case of psychiatrists and psychologists they don’t have a panel. Next when we run this analysis for optometrists and ophthalmologists, and this is a preliminary analysis for them because we don’t have all the covariates for optometrists and ophthalmologists, but what we find is that the first stage is significant. So the razor relationship, negative relationship between others availability and my productivity, but the full two-stage least squares instrument is not significant. And one reason for this could be that the sample size is much smaller. The sample size for optometrists and ophthalmologists is about three times smaller than for psychiatrists and psychologists.

In summary, instrumental variable analysis shows that higher productivity leads to higher turnover unlike naïve fixed affects regressions. The estimate is significant for most subsamples by year and loses some significance when we extend the lookback period to three month for the instrument. When we conduct the analysis for PCP’s and optometrists and ophthalmologists we don’t find significant effects.

So one limitation of this analysis is, and I mentioned this when we looked at the first stage relationship between individual productivity and the instrument others availability, and the limitation is that so my work performed and my availability are correlated with others availability. And this could be because providers take vacation at the same time. So one thing that we plan to do is to remove the correlation between individuals availability and other’s availability and then see if individual availability still correlated if we removed the correlation due to vacations. Another thing that we plan to do is to run the analysis for optometrists and ophthalmologists with the full set of covariates which we need to work on because for now we have only the key variables. And finally, we’re looking for other specialties with the large number of providers who tend to pick up each other’s work when others are not available. And if you have suggestions about such specialties, please let us know.

So this concludes my presentation. I include my contact info in case you have questions or comments and I include the link to PEPReC website. Thank you and I’ll turn it over to Rob for questions.

**Rob:** Thank you, Aigerim. We have a couple of questions queued up. But audience members if you’d like to ask a question you can go ahead and enter it in the questions section of the GoToWebinar dashboard. It’s that white piece of software that came up on your right hand side of your screen when you joined and I will read it. This question Liam actually answered by typing but I’ll ask it to you anyway. This person asks what level is this at, VISN? And Liam’s answer was that they should be individual physician level statistics.

**Aigerim Kabdiyeva:**  Yes. That’s true. So it’s individual month level observations.

**Rob:** Thank you. And the other question that we have right now, this person asks, please what is your source of data for FTE and RVU for VA Physicians?

**Aigerim Kabdiyeva:** So for FTE, we get FTE from OPUS. There’s a cube, a pyramid cube by OPUS which has individual level FTE data. And for RVU’s, we look, so we pull data on the visits for these providers and then we know the CPT codes, the type of procedures they provide at0020the visits, and we match them to a Medicare spreadsheet which has RVU’s for each CPT. And then once we have for all the procedures that the provider has we know [unintelligible 33:08] then we can aggregate and find the total RVU’s that they provided in a month.

**Rob:** Thank you. This next person, a couple more came in while you were answering. This next person asks what was the data source for termination?

**Aigerim Kabdiyeva:** So we obtained data from Workforce Management and Consulting Office and I just want to clarify that this is all cause separation. So we included all separations which could be due to quitting or they could be due to retirement because some people when they want to leave, they might retire earlier. And also the incidents of leaving, any kind of leaving, in the data is very low so the way we define separation is all cause separation from Workforce Management and Consulting data.

**Rob:** Thank you. This is a follow up I think to an earlier question about what level the statistics were at. This person comments, 52 FTE’s seems high for other mental health providers.

**Aigerim Kabdiyeva:** Maybe, maybe it’s, we have a lot of observations from stations which are large so those observations probably dominate the average. But in general, psychiatrists and psychologists, because we have such a high prevalence of mental health diagnosis in VHA we have a lot of psychologists and psychiatrists. And we often see that for specialties where there are fewer diagnoses such as cardiology or so on, but we have much fewer providers and much fewer FTE’s. But this is the number that we get for mental health providers. And another reason for this number being different from what you would expect is that the sample that we have is a panel data sample so individual observations, we have multiple observations for some individuals. So it’s not an average across individuals, it’s an average across individual month sample.

**Rob:** Thank you. I apologize ahead of time for my mangling of a term that’s going to come up. Did the review consider providers documentation workload with, and this person writes s c i b e and/or without s r i b e, it’s that both scribe? I’m not sure.

**Aigerim Kabdiyeva:** I’m not familiar with these terms. It would be great if maybe you could, if the audience could write more information about.

**Rob:** The questioner says that it is scribe, yes, but is really asking and says that scribe completes documentation or notes for the provider. So the question is, did the review consider providers documentation workload with this thing that completes documentation or notes for the providers?

**Aigerim Kabdiyeva:** So I think what the question is asking if, when we measure the workload, we include the time that they spent doing documentation? And I’m not sure whether this is included. So the FTE that we get from OPUS is a clinical FTE and I’m not sure whether documentation would be included in the FTE or not.

**Rob:** Thank you. If you’re conclusion is that cutting office visits to 20 minutes from 30 minutes means that provider turnover will increase, have you calculated how many more Veterans would be treated? Perhaps the trade-off is worth it.

**Aigerim Kabdiyeva:** Yes we haven’t calculated the trade-off. Maybe that’s something that we need to do so that we can compare the two numbers. Yeah that’s something that we can do in the future. But also, overall, we know that there’s a shortage of mental health providers in the VA and in the U.S. in general so that’s something that we need to keep in mind. And any kind of increase in, I guess visits, so if we decrease the appointment time and we serviced more patients in the subsequent periods we would have fewer providers. So I guess we would also need to compare future, the trade-off in the future visits to be able to see what’s the net effect.

**Rob:** Thank you. This next person asks, is there a manuscript under review or published?

**Aigerim Kabdiyeva:** This is a work in progress. We haven’t submitted it for review yet.

**Rob:** Thank you. Currently this is the last question that we have. What is the nurse quit rate considered a proxy for?

**Aigerim Kabdiyeva:** So it’s a proxy for unobserved medical center level factors. So let’s say a medical center has a bad manager, a manager who manages both nurses over all, all the clinical staff. So nurses would be affected and psychiatrists would be affected and psychologists would be affected. So if we look at the quit rate of nurses we can capture these unobserved factors which likely affect psychiatrists and psychologists as well. And we chose nurses because there are usually a lot of nurses at medical center level. So we can measure this variable quite well for nurses but we couldn’t measure it well if we, let’s say, chose cardiologists or other kinds of specialties.

**Rob:** Thank you. I’m not sure if this is the same questioner but somebody writes in, can nurses quit rate negatively affect physicians even if the reason is not related?

**Aigerim Kabdiyeva:** Yes. I think so because nurses support the psychiatrists and psychologists so that could directly affect the turnover among psychiatrists and psychologists, yes, that’s true. So I think when we include the nurse quit rate we control for sort of net, we control for a bucket of all of these factors which are worse conditions because there are fewer support staff or worse conditions because of other unobserved factors.

**Rob:**  Thank you. That is the last question that we had queued up at this time. I don’t know if anybody has anything else that they want to ask but perhaps this is a good opportunity, Aigerim, for you to make closing comments.

**Aigerim Kabdiyeva:** Thank you, Rob. So I would like to thank the audience for attending the Cyberseminar. Thank you for all your questions and comments. If you have further questions please contact me. And a big thank you to HERC and Cyberseminar teams for hosting this presentation.