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Employment Type and Length of Stay in Substance Abuse Treatment: Economic Factors and Gender Specific Effects

Quinn A.W. Keefer

Department of Economics, Claremont Graduate University, Claremont, CA, USA

Department of Economics, Whittier College, Whittier, CA, USA

Correspondence: Quinn Keefer, Department of Economics, Whittier College, 13406 East Philadelphia Street, Whittier, CA 90608, USA. E-mail: quinn.keefer@cgu.edu

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Abstract

We present an economic argument for the effect of employment on length of stay in substance abuse treatment, which is documented to contribute to positive post-treatment outcomes. We begin by presenting a theoretical model which predicts longer lengths of stay for employed versus unemployed individuals, as is observed empirically. The model shows that along with its psychological benefits, employment increases length of stay by increasing the opportunity costs of substance use. As labor market outcomes and experiences are different between men and women we empirically examine the gender specific effects of employment on length of stay. Furthermore, we consider that there are different types of employment. We conduct an econometric analysis of the Treatment and Episode Data Set for discharges (TEDS-D) examining the effect of being full time, part time and unemployed. The results agree with previous research and the economic model presented, any employment increases length of stay. However, men receive greater benefits from both types of employment. Also, men receive the greatest increase from full time employment, whereas women from part time employment. The results further suggest the need for gender specific treatment policies.

Keywords: substance abuse treatment, employment, gender, length of stay

1. Introduction

Policymakers have a long history of enacting policies to reduce drug use and drug related crime. There are two basic options available to policymakers, attempt to reduce supply or attempt to reduce demand. To date the United States government has employed many resources to reduce the supply of illicit drugs. According to the *Los Angeles Times* the United States has spent a total of $2.5 trillion on drug prohibition (Fleming, 2008). These policies include increased border patrol and law enforcement. However, policies attempting to reduce the supply of illicit drugs may have unintended consequences. While decreasing supply will reduce the quantity of drugs consumed it will inevitably increase prices. As many scholars have noted, increases in price may bring increases in drug related crime as users commit crime to finance drug habits (Fuji, 1974 for example). Therefore, many people advocate alternate policies that decrease demand. Drug treatment has been shown to be an effective method of reducing drug use and improving the economic situation, including employment, of drug users (DeLeon, 1984; Hall, 1984; Hubbard, Rachal, Craddock, & Cavanaugh, 1984; Platt, 1995; Simpson, 1984). Therefore, the success of drug treatment has relevant policy implications.

Not only is there an effect of drug treatment on post-treatment employment, but many studies have identified a positive effect of employment on drug treatment completion and success (Bausch, Weber, & Wolkstein, 2000; Butzin, Saum, & Scarpitti, 2002; Logan, Williams, Leukefeld, & Minton, 2000; Peters, Haas, & Murrin, 1999). One benefit in particular is employment has been identified as increasing retention, or length of stay in treatment (DeLeon, 1984; McLellan, 1983; Platt, 1995). Research has identified length of stay in drug treatment as an important predictor of drug treatment success (Simpson & Brown, 1997; Zhang, Friedman, & Gerstein, 2003). Individuals who remain in drug treatment longer have more beneficial outcomes. For example, French, Zarkin, Hubbard and Rachal (1993) show that length of stay significantly reduces post-treatment drug use and criminal activity.

Researchers have attempted to capitalize on the benefits of employment by implementing new treatment programs and interventions (Bausch et al., 2000). Many of these new policies have the goal of either gaining employment for individuals or upgrading employment (Leukefeld, Webster, Staton-Tindall, & Duvall, 2007). Correctly designing such policies is of great importance. On an individual level it will improve the effectiveness of drug treatment. On a macro level it will more effectively reduce the demand for illicit drugs, reducing consumption and drug related crime.

However, labor market outcomes and their effects often vary with gender. For example, the participation of women in the labor force is much different than men, most likely for child-bearing and care purposes. Also, the reaction of men and women to labor market changes is many times different. For example, women typically exhibit larger labor supply elasticities (Kimmel & Kniesner, 1998). Furthermore, the experiences of men and women in labor markets are different. One situation is the prevalence of gender discrimination, with women earning significantly lower compensation than men (Hersch, 2006).

Since the experiences and outcomes of labor markets tend to be gender specific, it is pertinent to know if the benefits of employment on drug treatment length of stay apply equally to men and women. Furthermore, employment is a broad classification. There are many types, or categories, of work. For example, workers may be full time or part time. They may be unemployed or not in the labor force for a particular reason. This raises important questions. For example, if a person is employed part time is intervention resulting in them being employed full time beneficial or harmful?

The contributions of this paper are (i) to present evidence that the discrepancy in length of stay between employed and unemployed individuals can be explained using a simple economic model and (ii) to look further at the different employment statuses and identify their gender specific effects on length of stay, something called for in Platt (1995). As previous interventions and treatment programs have recognized the need for gender specific options, the evidence presented here can be used to design more effective substance abuse policy and treatment programs (Prendergast, Wellisch, & Falkin, 1995; Reed, 1987 for example).

2. An Economic Model of Employment and Length of Stay

Employment has been linked to self-esteem, self-worth and independence (Bausch et al., 2000; Comerford, 1999; Leukefeld et al., 2007). In turn these characteristics have been shown to reduce substance abuse. Also, employment has been correlated with less depression and psychological problems (Bausch et al., 2000; Leukefeldet al., 2007; Zanis, Metzger, & McLellan, 1994).

While the psychological benefits of employment are very real and influential, this paper presents an economic argument for the effect of employment on substance abuse treatment. To do so we present a simple static model of the length of stay decision. The intuition of the model is that employment increases the opportunity costs of using substances. If an individual has a job, substance abuse has a much higher opportunity cost since the employee can be terminated. As a result, employed individuals take action, choosing longer lengths of stay, to prevent them from realizing the greater opportunity costs.

First, we assume people have utility over consumption of non-substances (goods), C, and substances, S, $U(C, S)$. Examining the direct effects we have.

$$\frac{\partial U}{\partial C} > 0 \quad \text{and} \quad \frac{\partial^2 U}{\partial C^2} < 0$$

$$if \begin{cases} 0 \leq S < \bar{S}; \dfrac{\partial U}{\partial S} > 0 \\ S = \bar{S}; \dfrac{\partial U}{\partial S} = 0 \\ S > \bar{S}; \dfrac{\partial U}{\partial S} < 0 \end{cases} \quad \text{and} \quad \frac{\partial^2 U}{\partial S^2} < 0$$

The quantity $\bar{S}$ may be incredibly small, depending on the substance. For example, if we examine alcohol, many people consume it and receive positive utility. However, many people over-consume alcohol at which point they are receiving negative utility.

Let w denote an individual's wage, h labor supply and Y non-labor income. Consumption in goods is $C = wh + Y$ .We follow previous research by modeling the effect of length of stay in treatment, T, on substance consumption as a linear relationship where time in treatment reduces substance consumption $S = S_0 - \alpha T$ (Grella, Hser, Joshi, &Anglin, 1999; Simpson, Savage and Lloyd, 1979; Zhang, Friedmann, & Gerstein, 2003). The implicit assumption is that S_0 is a natural level of substance consumption. That is to say, in the absence of treatment an individual will consume substances at some level determined by factors outside of the model. We can now rewrite the utility function given the above definitions.

$$U = U[C(w,h,Y), S(T)] \tag{1}$$

Furthermore, every employee faces a probability of being terminated, $q \in [0.1]$. The probability of being terminated is dependent on productivity, with increased productivity being associated with a lower probability, $q(p)$ and $\partial q/\partial p \leq 0$. We make the very simple assumption that substance abuse weakly reduces job performance, $p(S)$ and $\partial p/\partial S \leq 0$. From above we have the complete expression for the probability of being terminated, $q[p(S(T))]$.

To determine the optimal choice of length of stay individuals maximize their utility. We then compare the solutions for employed versus unemployed individuals. If an individual is employed their utility is as presented above in (1). However, if they are unemployed their utility simplifies.

$$U_U = U[C(Y), S(T)] \tag{2}$$

For an employed individual, since they face a probability of being terminated, they maximize expected utility.

$$\max_{T_E} (1-q) * U_E + q * U_U$$
$$\max_{T_E} [1 - q[p(S_E(T_E))]] * U[C(w,h,Y), S_E(T_E)] + q[p(S_E(T_E))] * U[C(Y), S_E(T_E)]$$

The first order condition (FOC) is

$$\frac{\partial U}{\partial S_E} = \frac{\partial q}{\partial p}\frac{\partial p}{\partial S_E}\left[U^E - U^U\right] \tag{3}$$

For an unemployed person they simply maximize their utility by choosing length of stay.

$$\max_{T_U} U_U$$
$$\max_{T_U} U[C(Y), S_U(T_U)]$$

The FOC is

$$\frac{\partial U}{\partial S_U} = 0 \tag{4}$$

2.1 Prediction 1

From the FOCs we know that $T_E \geq T_U$ (See Appendix A1). This shows that a simple economic model predicts the length of time in treatment for employed individuals will be greater than unemployed individuals. The model's key assumptions are that substances weakly decrease productivity, the probability of termination is dependent on productivity and that there is a level of consumption of substances at which users no longer derive any benefit. These assumptions are very weak and show that the effect of employment on length of stay in drug treatment can be understood using a simple economic model of decision making.

2.2 Prediction 2

In the model individuals do not always choose treatment. At low enough levels of substance consumption both employed and unemployed individuals will choose zero time in treatment (See Appendix A2). This captures people who use substances, such as alcohol, and do not need or choose treatment.

2.3 Prediction 3

The model predicts that the threshold of substance consumption, the level of substance use where an individual chooses treatment, is less for employed individuals (See Figure 1 &Appendix A2). That is to say, at certain levels of substance use an employed individual will choose time in treatment, but an unemployed person will not. This is very important because it shows that not only do employed people have longer lengths of stay, but they are more likely to engage in treatment.

<table>
<tr><td></td><td colspan="3">0 Natural Level of Substance Use Max</td></tr>
<tr><td>Employed</td><td>No Treatment</td><td colspan="2">Treatment</td></tr>
<tr><td>Unemployed</td><td colspan="2">No Treatment</td><td>Treatment</td></tr>
</table>

Figure 1.Depiction of Prediction 3.

Description: Comparison of thresholds of natural level of substance use for employed and unemployed individuals. The top bar represents the amount of natural substance use, increasing right to left. The Treatment and No Treatment bars for employed and unemployed represent the range of natural substance use for which they choose either treatment or no treatment. The figure shows that employed individuals choose treatment at lower levels of natural substance use.

2.4 Policy Implications

If the goal of policymakers is to reduce substance use through decreased demand by way of drug treatment, employment policies are key instruments. Not only do employed individuals have longer lengths of stay, which are associated with greater reductions in substance use, but employed individuals are more likely to enter treatment. One possible policy to take advantage of Prediction 3 would be focusing employment policies on individuals that are at a higher risk of substance abuse.

3. Data

The data comes from the Substance Abuse and Mental Health Data Archive (SAMHDA) sponsored by the U.S. Department of Health and Human Services Substance Abuse and Mental Health Services Administration (SAMHSA). Specifically, the data, which are accessible through the Inter-university Consortium for Political and Social Research (ICPSR), comes from the Treatment and Episode Data Set (TEDS). We use the 2006 to 2008 discharge (TEDS-D) data set. The TEDS-D data set is a collection of treatment data reported by states to monitor state licensed or certified treatment facilities that receive federal funding. Using data for individuals older than 18, whose treatment was not ended by death and who have no missing values leaves a sample of 532 548 individuals. In the sample there are 350 836 males and 181 712 females.

Length of stay data are reported in the number of days if the person's treatment episode lasted 30 days or less. For treatment episodes exceeding 30 days the data are classifiedinto 7 categories; 31 to 45 days, 46 to 60 days, 61 to 90 days, 91 to 120 days, 121 to 180 days, 181 to 365 days and greater than 365 days. Due to the categorization of length of stay, general summary statistics are misleading. Therefore, the percentage of individuals in each length of stay category is presented in Table 1.

Table 1. Length of Stay Percentages

# of Days	Full Sample	Men	Women
1	11.57%	12.86%	9.06%
2	4.89%	5.16%	4.39%
3	4.16%	4.43%	3.64%
4	2.55%	2.48%	2.68%
5	2.02%	2.01%	2.03%
6	2.02%	2.02%	2.03%
7	1.81%	1.67%	2.08%
8	1.44%	1.30%	1.71%
9	0.87%	0.80%	1.00%
10	0.71%	0.65%	0.84%
11	0.59%	0.55%	0.68%
12	0.56%	0.49%	0.69%
13	0.90%	0.95%	0.80%
14	0.96%	0.84%	1.18%
15	1.04%	0.97%	1.17%
16	0.68%	0.64%	0.75%
17	0.60%	0.57%	0.67%
18	0.58%	0.56%	0.63%
19	0.57%	0.54%	0.64%
20	0.93%	0.95%	0.89%

21	1.18%	1.21%	1.13%
22	1.00%	0.92%	1.13%
23	0.63%	0.60%	0.70%
24	0.61%	0.57%	0.67%
25	0.87%	0.89%	0.83%
26	0.71%	0.68%	0.77%
27	1.32%	1.37%	1.23%
28	1.96%	1.93%	2.02%
29	1.54%	1.39%	1.83%
30	1.08%	0.98%	1.27%
< 31	50.44%	50.99%	48.89%
31 to 45	9.35%	9.14%	9.74%
46 to 60	6.48%	6.48%	6.74%
61 to 90	10.65%	10.31%	11.30%
91 to 120	7.62%	7.81%	7.27%
121 to 180	6.8%	6.83%	6.96%
181 to 365	6.86%	6.75%	7.09%
> 365	1.80%	1.69%	2.01%
Observations	532,548	350,836	181,712

Note: The category < 31 is added to the table to show the percentage of the population with a length of stay less than or equal to 30 days. This category is not specified in the data, but is presented for comparison to the other groups.

Employment data are reported in several categories; full time, part time and unemployed. Data is also categorized for individuals not in the labor force; student, homemaker, retired or disabled and other or inmate of an institution. Table 2 presents summary statistics for employment data. As the variables are categorical, the means represent the percentage of the population belonging to each category.

Table 2. Employment Descriptive Statistics

VARIABLES	Full Sample	Men	Women
Full Time	0.272	0.324	0.173
	(0.445)	(0.468)	(0.379)
Part Time	0.0844	0.0793	0.0942
	(0.278)	(0.270)	(0.292)
Unemployed	0.405	0.380	0.454
	(0.491)	(0.485)	(0.498)
Homemaker	0.0149	0.00145	0.0409
	(0.121)	(0.0381)	(0.198)
Student	0.0131	0.0123	0.0145
	(0.114)	(0.110)	(0.120)
Retired	0.0911	0.0927	0.0881
	(0.288)	(0.290)	(0.283)
Other or Inmate	0.119	0.111	0.135
	(0.324)	(0.314)	(0.341)
Observations	532,548	350,836	181,712

Note: Standard deviations in parentheses. Since variables are dummies, means represent the portion of the population in each category.

4. Econometric Model

We are interested in three gender specific results. First, we test whether employment, of any type, significantly increases length of stay for both men and women. Second, we examine how different types of employment affect length of stay for men. Third, we analyze the effect on length of stay of different types of employment for women. We are particularly interested in the difference, or similarity, the different types of employment have across genders.

To obtain the three results of interest we conduct an econometric analysis of the TEDS-D data from 2006 to 2008. Many times for length of stay data duration analysis is used. However, due to the nature of our length of stay data we employ the interval regression technique using the employment and non-labor force data as dummy variables.

$$y_i^* = x_i^{/}\beta + z_i^{/}\alpha + \varepsilon_i \tag{5}$$

Where index i refers to the i^{th} participant and the latent variable y^* is the exact length of stay in days. For individuals with lengths of stay less than or equal to 30 days y^* is observed. However, since the data are presented in categories for lengths of stay greater than 30 days y^* is unobserved for these individuals. The vector x is the vector of employment dummy variables, z is the vector of other factors contributing to an individual's length of stay in treatment and β and α are the associated coefficient vectors, respectively. Finally, ε is the stochastic error term and $\varepsilon \sim N(0,\sigma^2)$.

Since the observed length of stay data, y, is given in categories we specify the dependent variable as having a lower bound, y^L and an upper bound, y^U.

$$\begin{aligned}
&y_i^L = y_i^U = y_i^* \quad \text{if } y_i \le 30 \\
&y_i^L = 31; y_i^U = 45 \quad \text{if } 31 \le y_i \le 45 \\
&y_i^L = 46; y_i^U = 60 \quad \text{if } 46 \le y_i \le 60 \\
&\dots \\
&y_i^L = 366; y_i^U = \infty \quad \text{if } y_i > 365
\end{aligned} \tag{6}$$

Therefore, the estimated dependent variable is the exact length of stay in days, but with interval censoring. The coefficients, β and α, are estimated using maximum likelihood, with Stata (StataCorp, 2007), and represent the marginal effects of the respective variables.

The vector of other factors contains data on gender, the reason for the treatment episode ending, year of discharge, age, race, ethnicity, pregnancy, veteran status, living arrangements, income, marital status, the type of service received, medication assisted opioid therapy, days waited for treatment, referral source (including detailed criminal justice referrals), number of prior treatment episodes, other psychiatric problems, health insurance, primary form of payment, education level, region of treatment, number of substances reported at admission, combination of alcohol and other drugs and the exact substances reported. Many of these variables are controlled for using binary variables due to the data being reported in categories. The resulting estimation has 108 independent variables (for the full sample).

5. Econometric Results

To test the economic model presented and to confirm with previous research, we estimate the above model for the full sample of men and women. The interval regression results for the full sample are presented in Column 2 of Table 3. The results agree with previous literature and the economic model presented. Both full time and part time employment significantly increase length of stay. As the estimates represent marginal effects, full time employment increases length of stay by 5.964 days and part time by 4.078 days, over being unemployed. To examine the model's fit we calculate the R^2 for both lower and upper bounds of the independent variable. To do so we simply square the correlation between the predicted length of stay and the lower and upper bounds of the dependent variable. However, these statistics should be interpreted with care. We have very large ranges of length of stay for categories in the higher end of the distribution. Also, we have an infinite upper bound for observations staying in treatment longer than one year.

The difference between full and part time employment is tested using a Wald test.

$$W = \left[\frac{\beta_{Full\,Time} - \beta_{Part\,Time}}{\sqrt{s^2_{\beta_{Full\,Time}} + s^2_{\beta_{Part\,Time}} - 2s_{\beta_{Full\,Time},\beta_{Part\,Time}}}} \right]^2$$

Where W is the Wald statistic, $W \sim \chi^2$ with one degree of freedom. The 1.886 difference is shown to be significant. From this it is concluded that full time work is more impactful than part time at increasing length of stay. However, this ignores possible gender specific employment effects.

Table 3. Length of Stay Interval Regression Results

Dependent Variable = Length of Stay			
VARIABLES	Full Sample	Men	Women
Full Time	5.964***	8.117***	2.283***
	(0.351)	(0.414)	(0.655)
Part Time	4.078***	4.158***	3.671***
	(0.409)	(0.486)	(0.731)
Homemaker	3.024***	3.904	2.576***
	(0.804)	(2.859)	(0.860)
Student	-2.299***	-0.389	-4.380***
	(0.813)	(1.049)	(1.285)
Retired	-0.907**	-0.628	-1.458**
	(0.424)	(0.538)	(0.711)
Other or Inmate	12.49***	13.68***	9.244***
	(0.305)	(0.378)	(0.515)
Constant	60.98***	48.89***	79.16***
	(6.720)	(8.087)	(11.88)
LN(sigma)	4.125***	4.096***	4.169***
	(0.00238)	(0.00300)	(0.00394)
Full Time – Part Time	1.886***	3.959***	-1.388**
Wald Test: Full Time = Part Time	24.97	79.64	3.86
Wald Test p-value	0.000	0.000	0.0495
R2 Lower Bound	0.342	0.367	0.308
R2 Upper Bound	0.271	0.288	0.251
Observations	532,548	350,836	181,712

Note: Robust standard errors in parentheses. Unemployed is the omitted employment status binary variable. The Wald test is for the null hypothesis that the coefficient of full time equals the coefficient of part time. Full estimation results are available from the author. * $p \leq 0.10$. ** $p \leq 0.05$. *** $p \leq 0.01$%.

5.1 Men

The econometric model is estimated on the stratified sample only including the 350 836 men. The results are presented in Column 3 of Table 3. For men it is clear that both full time and part time work significantly increase length of stay. Full time employment increases length of stay by 8.117 days and part time employment by 4.158 days.

To determine if the effects are significantly different from each other we conduct a Wald test. The Wald test shows that the 3.959 difference is significant. To provide reference to the importance of these effects we compare them to the effects of age. Age has been shown to be an important determinant of drug treatment outcomes, including retention (Butzin et al., 2002; Saum, Scarpitti, &Robbins, 2001). Men aged 25-29 significantly spend 1.383 days less in treatment than those 35-39.

For men it is beneficial to be employed. Furthermore, it is more beneficial to be employed full time rather than part time. Therefore, if the goal is to increase length of stay, policies for men should attempt to not only gain employment for individuals, but gain them full time employment.

5.2 Women

The interval regression results for the stratified sample of 181 712 women are reported in Column 4 of Table 3. Again, for women employment is beneficial to increasing length of stay. Both full time and part time employment significantly increase time in treatment. However, unlike men, for women the coefficient of part time employment is greater than that of full time employment. Full time employment increases length of stay by 2.283 days and part time employment by 3.671 days, over being unemployed. Also, women receive much lower benefits from both full time and part time employment.

To examine the significance of the different effects of full time versus part time employment we conduct a Wald test. The Wald test shows that the 1.388 difference is significant. This may seem like a small number of days. Therefore, we compare the 1.388 day difference to the effect of age. Women who are 25 to 29 year of age spend a significant 1.718 fewer days in treatment than those 35 to 39. The difference between part time and full time employment is not negligible when considering the magnitude of the effect of age.

For women employment, full or part time, is beneficial. However, part time employment is more beneficial than full time employment. Therefore, policies aimed at increasing length of stay should attempt to gain employment for women, but place emphasis on part time employment. Furthermore, women who are employed part time will actually reduce their length of stay in treatment by becoming fully employed. This result is in accord with previous literature pertaining to women, employment and drug treatment. Mathis, Navaline, Metzger and Platt (1994) report that women were less likely to be seeking employment and more frequently reported that they did not want work (Platt, 1995).

5.3 Effect on Post-Treatment Outcomes

The results suggest gender specific effects of employment on length of stay. This sub-section explores the impact gender specific employment effects have on post-treatment outcomes by way of length of stay. French et al. (1993) estimate the effects of length of stay in the Treatment Outcome Prospective Study (TOPS) on several post-treatment indicators for residential clients. They find a 10% increase in length of stay leads to reductions of 2.9% in the Drug Problem Index (DPI), 2.2% in the Drug Use Severity Index (DUSI), 3.3% in the Predatory Illegal Act Index (PIAI) and 2.4% in the Criminal Behavior Index (CBI).

We calculate the expected number of days in treatment from the model for unemployed individuals with all other independent variables set to their means. By using the estimated employment effects we calculate the percentage change in predicted length of stay from becoming employed. Then, using the French et al. (1993) estimates, we calculate the estimated change to post-treatment outcome measures.

For men the unemployed predicted length of stay is 53.87 days. Full time employment increases length of stay for men by 8.117 days, or a 15.07% increase in predicted length of stay. Part time employment improves length of stay by 4.158 days, or a 7.19% increase in predicted length of stay. The predicted length of stay for unemployed women is 59.69 days. The predicted value for women increases 3.82% for full time employment and 6.15% for part time employment. The subsequent estimated changes in post-treatment outcome measures are reported in Table 4, Columns 2-3 for men and Columns 4-5 for women.

Table 4. Subsequent Changes in Post-Treatment Outcomes

	Men		Women	
	Full Time	Part Time	Full Time	Part Time
Predicted Length of Stay	53.87		59.69	
Δ Predicted Length of Stay	+15.07%	+7.19%	+3.82%	+6.15%
Δ DPI	-4.37%	-2.09%	-1.11%	-1.78%
Δ DUSI	-3.32%	-1.58%	-0.84%	-1.35%
Δ PIAI	-4.97%	-2.37%	-1.26%	-2.03%
Δ CBI	-3.62%	-1.73%	-0.92%	-1.48%

Note: Predicted length of stay is for unemployed individuals with all other independent variables set to their means.

It should be noted that the post-treatment effects are derived from estimates for residential clients in TOPS treatment. Therefore, they should be seen as a first approximation to the subsequent gender specific post treatment benefits derived from the different employment types.

6. Conclusion

We present a simple economic model that predicts increased length of stay for employed versus unemployed individuals. Along with the noted psychological impact of employment on drug treatment there is also an economic component. Employed individuals choose longer lengths of stay as a result of the higher opportunity costs to substance use.

From the econometric analysis it is clear that employment, full or part time, significantly increases length of stay in treatment for men and women. However, men receive greater benefits from both full time and part time employment. There is another major difference between genders when analyzing different types of employment. If the results do not consider the gender specific effects of employment it would be concluded that full time work is more beneficial. This is true for men who realize the greatest gain from full time employment. Women, on the other hand, realize the greatest increase in length of stay from part time employment. The decisions and experiences of men and women differ in labor markets, so too do the length of stay benefits from employment. The results further echo the need for gender specific treatment policies (Ashley, Marsden and Brady, 2003).Policies should target full time employment for men, but part time employment for women.

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Appendix

A1. Proof of Prediction 1

The FOC for an employed individual is

$$\frac{\partial U}{\partial S_E} = \frac{\partial q}{\partial p}\frac{\partial p}{\partial S_E}\left[U^E - U^U\right]$$

By definition $\partial q/\partial p \leq 0$ and $\partial p/\partial S_E \leq 0$.Since utility is increasing in consumption, we have$U^E - U^U \geq 0$. Therefore,$\partial U/\partial S_E \geq 0$.

The FOC for an unemployed individual is

$$\frac{\partial U}{\partial S_U} = 0$$

Therefore, $\partial U/\partial S_E \geq \partial U/\partial S_U$. Since $\partial^2 U/\partial S^2 < 0$ we know that $S_U \geq S_E$.

For a constant level of natural substance consumption, S_0, it follows that $T_E \geq T_U$.

$$\begin{aligned} S_E &= S_0 - \alpha T_E \\ S_U &= S_0 - \alpha T_U \\ S_0 - \alpha T_E &\leq S_0 - \alpha T_U \\ T_E &\geq T_U \end{aligned}$$

A2. Proof of Predictions 2 and 3

The optimal level of treatment for unemployed individuals solves the FOC.

$$\frac{\partial U}{\partial S_U} = 0$$

By definition, the interior optimum is achieved at the level of substance use $\bar{S}$. Treatment only reduces substance consumption, $S = S_0 - \alpha T$. Therefore, when $S_0 \geq \bar{S}$ the optimal level of treatment for unemployed individuals is

$$T_U^* = \frac{S_0 - \bar{S}}{\alpha}$$

If $S_0 < \bar{S}$ then $\partial U/\partial S_U > 0$. Since $\partial^2 U/\partial S^2 < 0$ the optimal treatment is $T_U^* = 0$.

$$if \begin{cases} S_0 > \bar{S}; T_U^* = \dfrac{S_0 - \bar{S}}{\alpha} \\ S_0 \leq \bar{S}; T_U^* = 0 \end{cases}$$

The optimal level of treatment for employed individuals solves the FOC.

$$\frac{\partial U}{\partial S_E} = \frac{\partial q}{\partial p} \frac{\partial p}{\partial S_E} \left[U^E - U^U \right]$$

The optimal level of substance consumption is defined by $S_E^* = S_0 - \alpha T_E^*$. From the FOC we know $\partial U/\partial S_E \geq 0$; therefore, $S_E^* \leq \bar{S}$. If $S_0 \geq S_E^*$ then the optimal treatment can be written as

$$T_E^* = \frac{S_0 - S_E^*}{\alpha}$$

If the solution to the FOC yields $S_0 \leq S_E^*$ then $T_E^* = 0$.

$$if \begin{cases} S_0 > S_E^*; T_E^* = \dfrac{S_0 - S_E^*}{\alpha} \\ S_0 \leq S_E^*; T_E^* = 0 \end{cases}$$

Combining the results for employed and unemployed individuals we can compare the optimal levels of treatment.

$$if \begin{cases} S_0 > \bar{S}; T_E^* = \dfrac{S_0 - S_E^*}{\alpha} \text{ and } T_U^* = \dfrac{S_0 - \bar{S}}{\alpha} \\ \bar{S} \geq S_0 > S_E^*; T_E^* = \dfrac{S_0 - S_E^*}{\alpha} \text{ and } T_U^* = 0 \\ S_0 \leq S_E^*; T_E^* = 0 \text{ and } T_U^* = 0 \end{cases}$$

In all cases $T_E \geq T_U$. Also, the when $\bar{S} \geq S_0 > S_E^*$ employed individuals will choose treatment, but unemployed individuals will not.