An Econometric Analysis of Cocaine use by Methadone Maintenance Therapy Patients.  
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Abstract

This dissertation uses proprietary drug screening data, illicit drug prices from the DEA STRIDE database, and national and local macroeconomic variables to measure the price responsiveness and treatment effectiveness of methadone maintenance therapy (MMT) on patients in a voluntary, methadone-treatment program in a rural Alabama county. This is done using conventional, myopic, and rational models of demand. The demand for illicit drugs is found to be sensitive to national drug prices as estimated from the Drug Enforcement Agency’s System to Retrieve Drug Evidence (STRIDE), length of time in treatment, previous consumption, and the local unemployment rate. An important innovation in this paper is the use of temperature data from coca-plant-growing regions as an instrument for the cocaine prices taken from the DEA STRIDE database. Use of this instrument yields estimation results more in line with the predictions one obtains from economic theory. The estimation results imply that methadone maintenance therapy is a substitute for all illicit drugs under analysis. The implied price elasticity of cocaine use by MMT patients ranges from -0.0003 to -0.01284 and the unemployment elasticity of cocaine use is -0.00385.

**I. Introduction:**

This dissertation studies the demand for illicit drugs using data from a methadone maintenance clinic located in rural Alabama. Because of legal sanctions, lack of enforceable property rights, possible violence, social stigma and other externalities associated with illicit narcotic consumption, it is difficult to obtain an amount of data sufficient to study scientifically the behavior of those addicted to illegal narcotics. As discussed below, the data made available from the clinic allows us to observe whether individual patients at the clinic have used one or more of several drugs (including alcohol) and whether they have taken the methadone distributed to them. This allows us to address questions such as, “How sensitive is the demand for cocaine to the price of cocaine?” One innovation in this dissertation is the use data on positive drug test results as a measure of the demand for Illegal drugs. Another innovation is the use of temperature data from coca-plant-growing regions as an instrument for the cocaine prices taken from the DEA STRIDE database in order to correct for any endogeneity in the STRIDE prices.

The study of the demand for an illicit drug is more complicated than the study of the demand for most licit goods in at least one other way: Because illicit drugs typically are addictive and alter the mood of the user (in a manner the user enjoys), they fall into a category of goods that economists call “experience goods”[[1]](#footnote-1). Experience goods are consumed for the purpose of attaining a targeted level of utility and typically are either habit-forming or addictive. Because they typically are habit-forming, the utility one obtains from using an illicit drug today depends upon past use, and the use of the drug today affects the utility one will receive from using the drug in the future. Hence, as discussed further in section 2 below, the proper specification of the demand for an experience good depends critically upon the extent to which illicit-drug users are forward-looking.

Study of the demand for illicit drugs is further complicated by the difficulty in obtaining data on consumption. Little data exists about demand, market size, structure, history, costs and benefits (Saffer and Chaloupka 1999).

There are many social problems associated with the consumption of those illegal experience goods, such as cocaine and amphetamines, which have the ability to affect adversely the user’s judgment and behavior. For this reason a better understanding of the demand for experience goods can be of help to policymakers, social workers and others who work to alleviate the adverse effects associated with the use of illegal drugs.

The data employed by this study consists of drug-screening test results, treatment variables and demographic variables obtained from a methadone treatment center in a rural county in Alabama. This study also uses DEA STRIDE prices for cocaine, temperature data from coca-plant growing regions in Columbia, and both national and local economic data. Hence one advantage of the study is that it employs objective data on drug use, it does not rely upon the self-reporting by a user. A possible disadvantage is that the sample of possible users is limited to those who have enrolled in a methadone treatment program (either voluntarily or because of a court order). But this disadvantage strengthens at least one of our results: Even though the individual users in our sample are trying to stop using drugs, we find that their behavior is sensitive to the price of cocaine. Higher drug prices reduce the probability that a person in a drug-treatment program will used illicit drugs. Furthermore, if those enrolled in a drug treatment program appear to change their behavior (regarding the use of illicit drugs) in response to changes in economic conditions, then it is also very likely that those not in treatment will do so as well.

Methadone maintenance therapy (MMT) is controversial because some fear that it is simply another source of an addictive drug and is thus a hazard to the community. Those with this view appear to believe that those receiving MMT eventually become more likely to use other drugs, hence they believe that methadone is a complement to other illicit drugs. If this is the case then MMT has the potential to increase the number of addicts. Supporters of MMT argue that it saves lives and provides medicinal support to stabilize patients that otherwise would be involved with illicit drugs. Hence supporters of MMT believe that methadone is a substitute for illicit drug use.

The results presented in this dissertation provide support for the argument that methadone maintenance is both effective and robust at reducing illicit cocaine use. Results that support this position are obtained from a variety of empirical techniques, including estimates of conventional, rational and myopic models of demand (by both OLS and instrumental variables) in which the dependent variable is the percentage of patients who test positive for cocaine use; a probit and logit model of the probability that an individual will test positive for cocaine use; and generalized linear model where the link function is the logit function. All models are estimated using STRIDE (system to retrieve drug evidence) pricing data, demographic variables, and macroeconomic time series gathered from the St. Louis Federal Reserve. When two-stage least squares is used to control for the effect of demand on STRIDE prices, the estimation results obtained are more in accordance with what an economist would predict. The estimation results imply that the demand for illicit drugs declines as price increases and (when the rational model is used) provide some support for the argument that users are rational or forward-looking in their consumption of illicit substances.

The two-stage least squares results rely on the use of mean quarterly temperatures for Colombia. It is found that they are a significant predictor of cocaine price and purity in the United States. The demand modeling employed here with the EPH price series follows the technique of Saffer and Chaloupka (1998) and Grossman and Chaloupka (1999) and shows evidence that EPH prices are endogenous to changes in or shocks to demand.

Modern drug policy in the United States began to take shape with the Comprehensive Drug Abuse Prevention and Control Act of 1970. But the United States has not been able to eliminate the market for illegal drugs; rather the drugs are traded illegally or on the black market. The black market for narcotics is believed to be large. The United Nations estimates the international black market for narcotics in 2003 to have been $400.19 billion in 2012 US dollars.

Economists disagree as to whether the prohibition of dangerous, addictive drugs is a better alternative to legal, but regulated markets. The cost effectiveness of prohibition has been questioned by economists (Levitt 2001) and efforts by law enforcement to eliminate smuggling tactics by organized criminal narcotics suppliers have been described by the DEA as “frustrating”. The failure to prevent the illegal production and importation of narcotics has led to the development of an industry of treatment professionals which help individuals and families cope with the human costs of narcotic consumption. In recent years, courts and legislatures have turned from models of criminal punishment to treatment models as a solution to problems caused by narcotic offenders. Empirical studies of treatment suggest it is a more cost effective policy tool than traditional regulatory tactics of criminal enforcement (Mcvay et. al 2004). However, critics still question the effectiveness of methadone maintenance at reducing illicit drug consumption.

Currently there are no economic studies on the demand for narcotics by individuals in MMT. Most studies of the effects of MMT on narcotic consumption are medical studies. As a result, they do not take into account the possibility that market conditions may affect the behavior of patients in treatment. This dissertation is an attempt to fill this void in the literature. A better understanding of the behavior of drug addicts in MMT may help policy-makers develop more effective drug policies.

***2. Models of the demand for addictive substances***

Economists have used three models to map the demand for addictive drugs. These models are called the conventional, the myopic and the rational models of demand. Conventional models are adapted from models of the demand for non-addictive goods, treating addiction as a preference with the standard conventional assumption that preferences are intertemporally independent. Myopic models, first developed during the 1970’s, relax this assumption by assuming that past consumption affects current preferences for an addictive good. Finally, the rational addiction model, as presented by Becker and Murphy (1988), builds on the myopic model by adding the assumption that addicts are forward looking. The conventional and myopic models are nested in the rational model[[2]](#footnote-2). We now examine these three models in turn.

**2.a. Conventional Demand Modeling**

Conventional demand models are relatively simple, but convenient. One advantage of conventional models is that they can be estimated when past and future consumption quantities are not available as they exclude the effects of future and previous consumption on the current utility obtained from consuming the addictive good. The conventional model assumes the consumer takes price to be given and maximizes a utility function in which utility increases with the consumption of both the addictive and the non-addictive good. Letting ***c*** be consumption of the addictive good, ***y*** that of the non-addictive composite good, and ***w*** income, in the two good case the conventional model assumes the consumer maximizes the following Lagrangian:

(1)

where ***U*** is utility, ***pc*** is the relative price of the addictive good and ***Uc, Uy*** > 0, ***Ucc, Uyy*** < 0. To make it easy to compare the conventional model with the myopic and rational models, it is helpful to assume that utility is quadratic[[3]](#footnote-3), and also depends on a random shock to preferences, *et*. This changes the Lagrangian to:

(2)

where *Ct* is consumption of the addictive good during period *t*, *Yt* is consumption of a numeraire composite good, *et* be the (random) effect of unobservable factors that affect utility, *Wt* is period *t* income, the *ui* >0 (i=*c,y,e*), *uii*<0, and the sign of depends on how consumption of the addictive good affects the marginal utility of the composite good. If consumption of the addictive good has no effect on the utility of the composite good then =0, if consumption of the addictive good raises (lowers) the marginal utility of the composite good, then > 0 (<0). The resulting first-order conditions are:

(3)

(4)

(5)

Solving for *Ct* yields a conventional Marshallian demand function for the addictive good of the form:

, (6)

where , , < 0 , and . Neither past nor future consumption (as well as neither past nor future prices) affects quantity demanded during period *t*.

**2.b. Myopic Model**

Myopic models assume that the current utility from consuming the addictive good depends on past consumption; however, the consumer does not take into account the ensuing effect on future utility. As a result, current consumption depends on previous consumption but not future consumption. The parameters of the model are chosen so they capture hangover, withdrawal, and tolerance effects commonly observed with the consumption of addictive and intoxicating substances, as well as the effects of prior consumption on the current consumption of addictive but non-intoxicating consumer goods[[4]](#footnote-4). Following the derivation presented by Fenn et. al (2001), let *Ct* be consumption of the addictive good during period *t*, *Yt* be consumption of a numeraire composite good, *et* be the (random) effect of unobservable factors that affect utility, *Wt* be period *t* income, and *At* the capital stock of addiction. The one period optimization problem becomes:

(7)

The capital stock of addiction is a way of measuring the effect of past consumption of the addictive good on present utility. In the general case, it is defined as *At=(1-δ)Ct-1*, where *0≤δ≤1*, is the rate at which the capital stock of addiction depreciates, or the rate at which the addiction (or experience effect) depreciates. If δ=1, the addictive stock depreciates 100% in one period, or is reduced to zero and the model becomes the normal two good non-addictive case. If δ=0, At=Ct-1, and the stock of addiction does not depreciate, this is the case examined by Becker, Grossman and Murphy (1990). If the utility function is quadratic in Y and C, the Lagrangian is

, (8)

where the *ui* >0 (i=*c,y,A,e*) and *uii*<0, >0, >0.[[5]](#footnote-5) As in the conventional case the sign of depends on how consumption of the addictive good affects the marginal utility of the composite good. It turns out that in order for past consumption to have a positive effect on current consumption of the addictive good—a property we desire—it must be the case that , >0 and >0 (A.J. Fenn et al., 2001). (This follows also from a discussion in Becker, Grossman and Murphy (1990). These assumptions cause the parameters (defined below after equation 10) and (defined below after equation 12) to both be positive.

The first order conditions are:

. (9)

(10)

Letting , , < 0,  
 and , the above equations can be solved for the following equation for the demand for the addictive good:

(11)

Consumption of the addictive good in equation (11) is entirely backward looking. A good is addictive if previous consumption influences current preferences and therefore current demand (Pollak 1970). Empirically, this is interpreted as finding to be positive and significantly different from zero.

Rational Model:

The rational addiction model builds on the myopic model and was introduced by George Stigler and Gary Becker (1977) and further developed in the seminal paper, “A Theory of Rational Addiction” by Becker and Murphy (1988). Once again *Ct* is the amount of the addictive good consumed in period *t*, *Ct-1* is the quantity of the addictive good consumed in period *t-1*, *Yt* is the consumption of a composite (non-addictive) commodity in period *t*, et is an unobservable shock, and r is the discount rate. Letting the non-addictive good *Yt* be the numeraire, and setting the rate of interest equal to the rate of time preference, the Lagrangian for the discrete time version of the Becker and Murphy (1988) model (as shown by Becker, Murphy and Grossman (1990)) is:

, β=, C0=C0 .

The quadratic version of the model is

where the signs of the *uij* are the same as in the myopic model. The first order conditions are:

(12)

(13)

Solving (12) for *Yt* in terms of *𝛌* and *Ct* yields

(14)

Substituting (14) into (13), and solving determines the consumption of the addictive good as a function of past and future consumption of the addictive good, the current price of the addictive good, Pt, and the unobservables, et, et+1:

+ (15)

Where ,

> 0,

> 0,

< 0,

,

,

Note that the coefficient on Ct-1 from the myopic model is greater than the equivalent coefficient from the rational model when the discounted marginal utility of future consumption is positive, . The relationship between consumption and addiction in the rational model is positive; that is, prior consumption increases consumption in all periods. The relationship between addiction and consumption is given by the effect of previous consumption on current consumption in the quadratic utility function. In the case where previous consumption raises the marginal utility of consumption, the good is said to be addictive. The case assumed by BGM (1994) argues that the signs of the coefficients on all terms that affect marginal utility must make positive by the definition of an addictive good, and the consumer is risk adverse. Thus, , , , and are all positive, while , , , , and are all negative. may be positive or negative, while may be positive, negative or zero. Chaloupka (1991) assumes consumption of the addictive good, in his paper on rational cigarette demand, does not affect the marginal utility of the composite good and increases in income do not affect the marginal utility of the addictive good[[6]](#footnote-6), =0 ((A.J. Fenn et al. (2001)).

Because equation (15) is a second order difference equation, we must solve it before we can find the long-run price elasticity of demand for the addictive good. Following Becker and Murphy (1994) it can be shown that the characteristic roots of (15) are , and. As a result, the solution to the second order difference equation can be written as:

, (16)

where the ***ξi*** are functions of the parameters in equation (15).

In equation (16), changes in price have larger effects over time in the model since changes in price in previous or future periods result in changes in consumption in all periods. The short-run price elasticity of consumption is the effect on current consumption from a permanent reduction in price at the beginning of the current period.

(17)

In equation (17), setting t=1, substituting for 1, rearranging and multiplying by current period average price and current period average consumption yields the short-run price elasticity of consumption:

(18)

The long-run elasticity of consumption is the limit as t goes to infinity of the effect of a permanent reduction in price in all periods multiplied by average price divided by average consumption as shown in equation (19):

(19)

Comparing the short-run elasticity, equation (18), to the long-run elasticity, equation (19), the denominator in equation (18) is larger. In the rational addiction model, the long-run price elasticity always is greater than the short-run elasticity. The elasticity from the myopic model is a special case of equations (18) and (19) where and (Collet, Lapparent, and Hivert (2010)). The short-run and long-run elasticities respectively for the myopic model are:

(20)

(21)

with 4 <1 for stability, comparing equation (20) with equation (18) shows that in the myopic model the short-run elasticity is less than its analogous short-run elasticity from the rational model. Furthermore, and the long-run elasticity from the myopic model is also less in absolute value than the long-run elasticity from its analogous long-run elasticity in the rational model.

**3. Empirical Work**

Most comprehensive studies of the demand for an addictive good estimate both rational and myopic models. A few studies estimate only conventional or myopic models. There are empirical works in addiction that estimate demand for alcohol, cigarettes, coffee, opium, marijuana, cocaine, and heroin. Although conventional demand models ignore the effects of both prior and future consumption of the addictive substance on current consumption, they are simple and allow estimation when previous and future consumption data are unknown or not available. If there are significant effects of previous or future consumption on current consumption, then the conventional demand model is underspecified and the estimated coefficients are biased and inefficient. In all demand models as long as price is determined by an interaction between demand and supply, price is an endogenous variable and a failure to take this into account when estimating the demand curve causes the estimated coefficient on price to be biased.

Saffer and Chaloupka (1999) use a conventional demand framework to estimate the effect of and income on the demands for cocaine, heroin, marijuana, and alcohol. They use the DEA calculated expected purity hypothesis (EPH) prices to correct for the endogeneity of price. The authors reason that EPH prices are exogenous to the system because EPH price is already regressed on supply side factors. Prices retrieved from STRIDE are assumed accurate as they are used by undercover narcotics enforcement officers to make bid offers from distributers. Inaccurate bids could alert distributers and endanger law enforcement personnel.

Using a probit model, Saffer and Chaloupka (1999) regress marijuana, cocaine, and heroin participation from the National Household Surveys on Drug Abuse (NHSDA 1988, 1990, 1991) on own price, alcohol price, marijuana decriminalization, income, gender, marital status, age, race and time indicator variables. The probit model assumes the probability that a dependent variable Y conditional on an independent variable X is equal to the normal distribution’s probability density function of the parameters of the model.

The formulation of the probit model as a latent variable model is discussed below in the section on myopic estimations in the literature.

Saffer and Chaloupka (1999) report significant[[7]](#footnote-7) and negative price responsiveness, significant income effects, and significant cross price effects for alcohol, marijuana, cocaine, and heroin. They note that the negative cross price elasticities between illicit substances suggests illicit substances are compliments. Saffer and Chaloupka report negative income effects for participation in the past month for marijuana, cocaine, and heroin[[8]](#footnote-8). Income effects for participation in the past year are positive for marijuana and cocaine and negative for heroin[[9]](#footnote-9). Marijuana prices are excluded from all reported results[[10]](#footnote-10). Average participation elasticity reported[[11]](#footnote-11) for cocaine use in the past month is -.28 and -.44 for the past year. The average elasticity of heroin participation for the past month is -.94 and -0.82 for the past year[[12]](#footnote-12). Income effects are insignificant in all five reported specifications of marijuana participation for the past month and significant in all five reported specifications of cocaine participation for the past year[[13]](#footnote-13). Income effects are significant in one specification of cocaine participation in the past year and none of the specifications of participation in the past month. Income effects are significant for seven out of ten heroin participation specifications, four for participation in the past year and three for participation in the past month. Data means are not reported[[14]](#footnote-14).

Saffer and Chaloupka (1999) find that a married person[[15]](#footnote-15) is less likely to use addictive substances in all model specifications, while men are found to be more likely to report addictive drug use in all model specifications for all substances of abuse. The estimated coefficient in the latter case is statistically significant and is consistent with the commonly held belief that men use intoxicating substances more frequently than women. While the estimated coefficient on indicators for race, black and Hispanic, are negative and significant in all specification for alcohol use[[16]](#footnote-16), the indicator for being Black is insignificant for marijuana participation during the past month, and negative and significant for participation in the past year. Hispanics are found to be less likely to use marijuana in all specifications for marijuana use. Black is positive and significant in cocaine participation in the past month and insignificant in participation in the past year. Hispanic is positive and significant in all substance abuse specifications for participation in the past month and negative and significant for three out of five specifications of participation in the past year. The sign on indicator variables for race is consistent for all model specifications within participation classification except for black for heroin participation in the past year. Black is positive and insignificant in three model specifications for participation in the past year and negative and insignificant in two model specifications. It is positive and insignificant in two model specifications for participation in the past month and positive and significant in three model specifications. Hispanic is positive and insignificant for all model specifications of participation in the past month and significant in one model specification for participation in the past year and negative for all model specifications of participation in the past year. An indicator variable for marijuana decriminalization[[17]](#footnote-17) is positive and significant in all marijuana participation equations, negative in both alcohol specifications, significant in one and insignificant in the other. Marijuana decriminalization is positive and insignificant in both specifications for which it is included for cocaine participation in the past month and positive and significant in one specification for cocaine participation in the past year and positive and insignificant in the other model specification of cocaine participation in the past year.

Measures of substance use are dichotomous for marijuana, cocaine, and heroin and cardinal for alcohol[[18]](#footnote-18). Elasticity is measured as participation elasticity, calculated as the marginal effect[[19]](#footnote-19) of the respective price coefficient of the probit model evaluated at the unweighted mean of the data multiplied by own mean price and own mean participation. Marijuana is excluded from the elasticity calculations. Cocaine participation elasticity for past month ranges from -0.34 to 0.01. The two upper elasticity values -0.01 and 0.01 are not statistically significant at any conventional level, and one of the price coefficients has the wrong sign. Excluding the upper two elasticity calculations, the elasticity for past month ranges from -0.34 to -0.24, with an average of -0.28. Elasticity for participation in the past year ranges from -0.57 to -0.19. The maximum value -0.19 is calculated from an insignificant price coefficient. Excluding the maximum value of -0.19, the range on participation elasticity for past year is -0.57 to -0.30. Ranking all model specifications for cocaine participation in the past year by the statistical significance of the cocaine price coefficient, the signs are ordered lowest to highest, most statistically significant to least statistically significant respectively. The same ranking for all model specifications for cocaine participation in the past month yields the same result, evidence of endogeneity[[20]](#footnote-20). Cross price elasticity with heroin and alcohol are negative and significant for all estimations except for one alcohol price coefficient[[21]](#footnote-21).

Heroin participation elasticity for the past month from all model specifications is between -1.03 to -0.82 and for the past year -1.02 to -0.60. Prices for the demand model estimations of heroin consumption participation do not exhibit the same signs of endogeneity as those from the cocaine model estimations. The t-statistics from the price coefficients are larger in absolute value. P-values for all price coefficients in monthly participation are estimated to be less than 0.02 and less than 0.021 for yearly participation. Cross price elasticity with cocaine is positive but insignificant. Compared to the cocaine model specifications, income effects are more significant in the monthly participation specifications and less significant in the yearly participation specifications[[22]](#footnote-22). R-square for all model estimations, cocaine, alcohol and heroin is within the range 0.058 and 0.203. Sample size range is 44,889 to 49,802.

Roddy, Steinmiller, and Greenwald (2011) estimate price and income elasticity for heroin among a sample of long term, non-treatment seeking heroin users[[23]](#footnote-23) treating price as exogenous and using conventional demand modeling. They regress four measures of heroin use[[24]](#footnote-24) on price, primary heroin route, distance to dealer, unit cost, purchase time, total income, number of suppliers and weekly non-heroin opiate purchases. Consumption elasticity calculated from the Roddy et. al estimates at the mean of the data is -0.88 for heroin. Unit cost is significant only in the consumption model specification. Of explanatory variables in all model specifications, income effects are the most robust, positive, and significant in all model specifications except heroin expenses ÷ income. Their findings report participant responses indicating significant reductions in the consumption of heroin due to changes in income, increases in living expenses, changes in supply, and increase in the likelihood of arrest. Roddy, Steinmiller, and Greenwald (2011) report no significant change in the reported purchasing quantity of heroin with increases in income, evidence consistent with the assumption consumers of addictive substances optimize by holding utility fixed with respect to the addictive good. These same authors report evidence that subjects optimize behavior on economic factors other than price. Purchase time is negative and significant as an explanatory variable for the number of purchases/week. Number of suppliers is negative and significant as an explanatory variable for unit purchase and positive and significant in the number of purchases per week. Their findings show heroin users optimize their consumption quantity based on economic variables.

Myopic estimations

Myopic model estimations are rare in the literature and generally reported with rational estimations in empirical works. Econometrically, the myopic model is a nested form of the rational model, although theoretically the coefficients on lagged consumption, and are not equivalent for the two models[[25]](#footnote-25). Myopic modeling assumes current consumption is tied to previous consumption and is more appropriate if the consumer does not know that the substance is addictive. The rational model is more appropriate if the consumer is aware of the harmful consequences of a substance (Fenn et al (2001)).[[26]](#footnote-26)

Myopic estimations include lagged consumption to capture pharmacological and psychological effects of addictive goods on the body[[27]](#footnote-27). Theoretical work in myopic addiction assumes effects of prior consumption are observed in current consumer choice, but required consumption does not affect current consumer utility[[28]](#footnote-28). However, a myopic model with endogenous prior consumption is appropriate “because of the high likelihood that the unobserved variables that affect current utility (et) are serially correlated…In the rational-addiction model, Ct-1 depends on et through the optimizing behavior implied by the first-order conditions“(Becker and Murphy (1994)).

Dorsett (1999) estimates the probability of smoking prevalence among single mothers in Britian using a myopic dynamic probit model with a correction for initial conditions. He includes the interaction variable “laggedsmoking\*age” [[29]](#footnote-29) and income effects in his myopic model. The relationship between the dichotomous dependent variable (observed smoking) and the exogenous explanatory variables is given by the following relationship:

(22)

Where is the unobserved variable where ~N(0,1) and determines the value of the binary variable according to the following formula:

in the case of a panel of data the model becomes:

, *i*=1…N, *t*=1,…,T (23)

with the regression of the form:

*i*=1…N, *t*=1,…,T (24)

is the probability of smoking and is smoking in the previous period, is the generalized residual and is a vector of explanatory variables. The results show cigarette consumption is dependent on prior consumption. The interaction between lagged smoking and age is positive, and effects of prior smoking are smaller after correcting for the initial conditions problem. Income and education effects for the corrected initial conditions random effects probit model estimation are negative. Estimated income elasticity is -0.04[[30]](#footnote-30).

Rational estimations

Becker, Grossman, and Murphy (1988) present the theory of rational addiction mathematically derived above. The theory of rational addiction builds on previous work in addiction by nesting the conventional and myopic demand models of addictive consumption into a model that assumes consumers are forward looking in consumption. Although the model has been criticized,[[31]](#footnote-31) underlying assumptions of the rational model are more intuitively appealing than myopic model assumptions. Quadratic utility delineates linear first order conditions and a linear Marshallian demand equation in . The first order difference equation for in the rational model is dependent on the values of previous and future consumption and , current price and random shocks to utility. Unlike the first order difference equation for the myopic model, equation (7), equation (13) suggests the consumer is forward looking in consumption. The main predictions of the theoretical model of Becker and Murphy (1988) are: adjacent complementarity of consumption, both coefficients on Ct-1 and Ct+1 should be positive by the definition of addiction and rationality respectively, the estimated coefficients on Ct-1 and Ct+1 should differ only by the discount rate, β[[32]](#footnote-32) and >β, that is, the estimated coefficient of Ct-1 should be greater than the coefficient of Ct+1, consumption should respond more negatively to permanent price changes than to temporary price changes, and greater previous or future consumption of the addictive good raises the current marginal utility of consumption.[[33]](#footnote-33)

It is not possible to distinguish between harmful and beneficial addictions from the Marshallian demand function alone in the Becker and Murphy model. Whether an addiction is harmful or beneficial depends on the addictions effect on earnings. If the full effect of [[34]](#footnote-34), the change in utility with respect to addiction on earnings is positive, the addiction is beneficial. If ’s effect is negative, the addiction is harmful. Both harmful and beneficial addictions exhibit complementarity in consumption[[35]](#footnote-35) between time periods. If consumption in a prior or future period raises the marginal utility of consumption in the present, the good exhibits adjacent complementarity.

Whether a good is defined as addictive is a function of the difference of the capital stock of addiction and the difference between the time path of the capital stock of addiction, the Euler equation(s).

, (25)

, (26)

with characteristic roots:

. (27)

Whether a good is addictive in the model depends on the signs of the parameters of equation (27), the second-order linear difference equation in A(t). A good is defined as addictive if the left-hand side of the following inequality is greater than the right-hand side.

(28)

Where δ is defined as the rate of depreciation on previous consumption, σ is time preference for the future, is the marginal utility of consumption of the addictive good with respect to addiction, and is the concavity of the utility function in addiction. When = there is no depreciation of the capital stock of addiction and the sign ofdetermines whether a good exhibits adjacent complementarity of consumption. In the conventional demand model, addiction is treated as a preference. In the equation above, if =and 0<δ<1 a good is myopically addictive if the left hand side of equation (28) is greater than the right hand side of equation (28) and = ∞, there is no time preference for the future. When the left-hand side of equation (28) is greater than the right side of equation (28) and < ∞ the good is said to be rationally addictive.

In the rational addiction model, where the dynamics of consumption give rise to three steady state equilibria, two stable and one unstable. The three steady states capture the bimodal extrema of consumption patterns of addictive substances observed in the natural world. Each equilibrium is dependent on the time path of consumption and the relationship between the capital stock of addiction (A) and the marginal utility of consumption of the addictive good, c[[36]](#footnote-36). The relationship between σ,δ,and determine the time path of the capital stock of addiction (A) and the marginal utility of the addictive good with respect to addiction, . The concavity of the utility function in addiction, determines the full price of consumption of the addictive good to the consumer. Any positive consumption of an addictive substance places consumption on the time path of addiction. If the full price of consumption of the addictive good is greater than the capital stock of addiction, consumption of the addictive good falls to zero over time. The unstable steady state balances the relationship between the concavity of the utility function in addiction and the increase in the marginal utility of consumption of the addictive good. Consumption of the addictive good at the unstable steady state must be positive for all periods but less than the quantity necessary to raise the marginal utility of consumption above the full price of the addictive good. Consumption of the addictive good at the unstable steady state is positive and reflects the inability of most consumers to hold their consumption path on the saddle point of positive but small quantities of addictive substances. A perturbation below the unstable path lowers the marginal utility of consumption below the full price of the addictive good and consumption falls to zero, a corner solution. A perturbation above the unstable path raises the marginal utility of consumption above the full price of the addictive good and consumption increases along the consumption path until a permanently higher level of consumption is reached at the second stable steady state equilibrium. At the new higher consumption path, steady state equilibrium, the full price of consumption of the addictive good is equal to the marginal utility of the addictive good at a permanently higher level of addiction. Consumption of the addictive good is positive and equals the rate of depreciation of the capital stock of addiction. A negative perturbation lowers the marginal utility of consumption below the full price of increased consumption of the addictive good, and consumption falls below the steady state equilibrium. A utility maximizing consumer would increase consumption until the marginal utility of consumption is equal to the full price of the addictive good and the depreciating capital stock of addiction. A positive perturbation at the steady state places consumption on the consumption time path above the full price of consumption of the addictive good and the depreciating level of the capital stock of addiction. Because the full price of consumption of the addictive good is greater than the depreciating capital stock of addiction, consumption declines until the full price of consumption of the addictive good is equal to the depreciating capital stock of addiction and the marginal utility of consumption of the addictive good. Here the unstable steady state is interesting analytically, explaining the balancing act narcotics consumers’ exhibit before reaching full blown addiction or permanent abstention.

In the analysis above, it is impossible to tell whether an addiction is beneficial or harmful simply from the dynamics alone. In the Becker and Murphy model, addiction is defined by the relationship between the full cost of consumption of the addictive good and its relative relationship with the marginal utility of consumption. Whether the addiction is beneficial or harmful is defined by the effect of consumption of the addictive good on earnings. If an addiction is beneficial then a future benefit of current consumption is subtracted from the current full price of consumption of the addictive good; whereas, a harmful addiction exhibits a future cost of current consumption to be added to the full price of consumption of the addictive good.

Empirical estimations of the rational addiction model of Becker and Murphy (1988) have been estimated for alcohol, coffee, cigarettes, opium, and cocaine. Becker, Grossman, and Murphy (1994), first presented in a working paper by Becker, Grossman and Murphy (1990), estimate the theoretical model of Becker and Murphy (1988) using cigarette data. BGM (1994) estimate a modified version of equation (13) where previous and future consumption are endogenous and estimated in a reduced form model. Empirically, a good is said to exhibit addictive properties if prior consumption is positive and significant. A good is rationally addictive if prior and future consumption are both positive, significant, and differ only by a reasonable discount rate. The rational addiction equation Becker, Grossman, and Murphy estimate is:

(29)[[37]](#footnote-37)

where the reduced form equations of the structural form equation (29) are:

(30)

(31)

p is price, y is income, and z is a vector of explanatory variables. Becker, Grossman and Murphy (1994) argue

“Fortunately, the specification in equation [29] suggests a way to solve this endogeneity problem, since it implies that current consumption is independent of past and future prices when Ct-1 and Ct+1are held fixed. That is, any effect of past or future price must come through their effects on Ct-1 or Ct+1. Provided that the unobservables are uncorrelated with prices in these periods, past and future prices are logical instruments for Ct-1 and Ct+1, since past prices directly affect past consumption, and future prices directly affect future consumption. Therefore, our empirical strategy is to estimate [] and [], the main parameters of equation [13], by using past and future price variables as instruments for past and future consumption.”

The empirical evidence they report in support of the rational addiction model is mixed. Treating prior and future consumption as endogenous, they estimate myopic and rational demand models for cigarettes. They find past and future consumption positive and significant commenting “testing for the effects of future prices on current consumption distinguishes rational models of addiction from myopic models. The results strongly reject myopic behavior, while they tend to support the model of rational addiction.” BGM interpret findings of the significance of future consumption instrumented with future prices as evidence of forward-looking behavior by cigarette consumers. The significance of previous consumption instrumented with previous prices is interpreted as evidence that cigarettes are addictive. Finding the coefficient of instrumented future consumption is less than the coefficient of instrumented previous consumption where the ratio of the two presents a plausible discount rate is interpreted as strong evidence. Positive and significant previous and future consumption when instrumented with previous and future prices is interpreted as evidence of rational addiction even when the ratio yields implausible discount rates. The discount rate, the ratio of , is “implausible” in all BGM (1994) cigarette demand estimations to support the rational addiction model, either too high or too low, the authors argue. Endogenous myopic model estimations for the elasticity of cigarette demand in the short-run range from -0.20 to -0.75 with a mean of -0.67. Long-run price elasticity of demand estimates for the endogenous myopic model specifications range from -0.72 to -0.83 with mean -0.76. Rational addiction model estimations of the price elasticity using the full set of instruments are -0.36 to -0.44 in the short-run with mean -0.40 and long-run price elasticity estimates range -0.73 to -0.79 with mean -0.75. R-square myopic model estimations range 0.969 to 0.979, with mean 0.974. R-square rational model estimations for the full set of instruments range 0.975 to 0.987, with mean 0.98. Excluding future prices and taxes from the instruments, the R-square ranges 0.926 to 0.979 with mean 0.96. The Wu test rejects the null hypothesis of consistent estimates for all myopic and rational model specifications reported in the paper.

BGM (1994) conclude by commenting the empirical evidence for tobacco favors the rational addiction model over the myopic model despite the empirical nuisances. They make several empirical recommendations to follow when estimating rational addiction models. First, the structural endogeneity problem present in equation (27) can be solved using leads and lags of price as instruments for forward and past consumption. BGM (1994) argue forward and past price will be correlated with forward and past consumption but not current consumption[[38]](#footnote-38). They note the use of lead price as an instrument is limited to the degree which consumers can correctly anticipate changes in the forward price[[39]](#footnote-39). Rational addiction estimates of tobacco excluding future prices and taxes[[40]](#footnote-40) have less favorable results than those that include future prices and taxes as instruments Chaloupka (1991). Hausman’s procedure, a Wald test between the rational addiction model coefficients that include future price and taxes as instruments, and those that exclude future prices and taxes under the null hypothesis that consumers predict future prices perfectly, is rejected. BGM (1994) recommend using future prices as instruments for future consumption anyway reasoning “models that use future price and future taxes as instruments are much less sensitive to changes in the specification of the structural demand function than those that exclude these instruments.” Finally, they recommend imposing a constraint on the coefficient of future consumption to equal a reasonable discount factor.

Other empirical evidence of rational addiction for tobacco is mixed. Most studies report positive and significant coefficients for previous and future consumption or evidence that there is adjacent complementarity in consumption. Some authors report implausible or negative discount rates. Chloupka (1991)[[41]](#footnote-41) estimates the Becker-Murphy model using data from the second National Health and Nutrition Examination Survey. All empirical estimations of the rational addiction model use two stage modeling and assume quadratic utility. Chloupka (1991) regresses current cigarette consumption on lead, lagged, and current price, instrumented previous and future consumption, calculated addictive stock, age, age-squared, number of years of formal education completed, real family income, and indicators of sex, race ethnicity, marital status, and labor force status. Current and future consumption are instrumented with leads and lags of price, excluding the current and one period lead and lag of price in the structural form equation. Addictive stock is calculated as 0 for non-smokers. For current smokers it is estimated by the maximum consumption multiplied by the number of years smoking and the depreciation rate. For former smokers, the number of years smoking in the equation for smokers replaced by (1-δ)q where 0<δ<1 and q is the number of years the consumer has abstained from smoking. The coefficient on addictive stock is positive in all model specifications. The estimated coefficients on both lagged and future consumption are positive and significant and the coefficient of lagged consumption is greater than the coefficient of future consumption except for estimations for ages 65-73. All coefficients on lagged and future consumption model specifications meet the stability condition 4 <1. The coefficient on the measure of the addictive stock is greater in individuals with less education and individuals that are younger, evidence that younger and less educated people face a higher risk of addiction. The estimates of the price elasticities show the full price effects for a change in price are greater in the long-run than in the short-run for most smokers. Implied discount rates in the models are low except for model estimations among educated smokers and older smokers. R-square for the model specifications in the paper is not reported. The implied discount rate for smokers over the age of 65 has an average of 1.05. The average implied discount rate for smokers with less than a high school education is .09585. Smokers with at least a high school education have an estimated implied discount rate average of .974. The average discount rate among smokers ages 17-24 is 0.1745 and for smokers ages 25-64 the average discount rate is 0.4465. The discount rate between age groups is consistent with varying time discounting preferences between ages with the largest discounts by those who are younger and less educated. The coefficient estimates on forward and lagged consumption for all models support the theory that smoking is addictive, that smokers are rational, and smokers are price responsive.

T.E. Keeler, Hu, Barnett, and Manning (1993), using aggregate monthly time series data, estimate Poisson myopic, rational, and constrained rational addiction models for cigarettes for individual years 1980 to 1990 and using full information maximum likelihood techniques (FIML). They reject the BGM (1990) assumption of exogeneity of price arguing such an assumption excludes the possibility the marginal supply curve is upward sloping and “that such an upward-sloping short-run cost curve is an important determinant of the price.” Instead, they favor a time series estimation with an auto regressive process at the first and fourth lag to solve endogeneity of prior and future consumption. For years 1980 thru 1990 assuming no addictive behavior, they estimate the price elasticity for tobacco to be between -0.15 and -0.30, having a mean of -0.20, for the Poisson model with time trend and between -0.35 and -0.65, with a mean of -0.46, for the Poisson model without time trend. Elasticity estimates for the myopic model range from -0.21 to -0.65, with mean -0.34, in the short-run and -0.30 to-0.91, with mean -0.47, in the long-run. Elasticity estimates for the rational addiction model estimations range from -0.23 and -0.70, mean -0.36, for the short-run price elasticity, and long-run estimations from -0.38 to -1.13,[[42]](#footnote-42) mean -0.58. Model estimates using full information matrix maximum likelihood techniques with instrumental variables, corrected for first-order and fourth–order autoregressive error structure, yield a coefficient on lagged consumption for the rational addiction model that is not significant, evidence inconsistent with cigarettes being addictive. Reported r square for FIML estimations for the nonaddictive Poisson model specification with time trend is 0.9843 and 0.9728 without time trend. Reported adjusted r-square for the myopic model is 0.86, 0.87 for the rational addiction model, and 0.87 for the constrained rational addiction model. Income elasticities are negative in the Poisson weighted GLS with instrumental variables model, positive and close to 0 in the addictive models. Reported income elasticities are: -0.0013, -0.023, 0.0093, 0.072, 0.1067 for the Poisson time trend, Poisson without time trend, myopic addiction, rational addiction, and constrained rational addiction model. None of the income coefficients from any full information matrix maximum likelihood estimation model specification are statistically significant, results inconsistent with other empirical estimations of the income effects on tobacco[[43]](#footnote-43).

Olekalns and Bardsley (1996) estimate the rational demand for coffee following the method of Chaloupka (1991). Chaloupka’s (1991) method is similar to BGM (1990) except it includes one lead and lag of price in the structural form equation and instruments past and future consumption with past and future prices and an exponential trend. Coefficients on past and future consumption are statistically significant and positive, evidence that coffee is rationally addictive. The discount rate in the model is 0.908. The current price coefficient is negative and statistically significant. The denominator in the long-run price elasticity calculation is close to 0, evidence it is not an accurate estimate of the true long-run price elasticity of coffee.

Using nonlinear panel data methods, Labeaga (1999) estimates Spanish demand for tobacco using a double hurdle model with unbalanced panel data correcting for unobserved heterogeneity. A double hurdle model first specifies a participation equation then, given a consumer participates, estimates consumption. Labeaga (1999) corrects for unobserved heterogeneity and censoring of the dependent variable using the within-groups GMM method suggested by Bover and Arellano (1988). Discount rates calculated from the rational addiction estimates are greater than unity. Estimates range from 1.05 to 1.12 with an average of 1.07. Income elasticity estimates are positive and statistically significant in all reported myopic and rational model specifications. Myopic model estimations for the income elasticity of demand are 2.07 and 2.52. Labeaga reports two rational addiction model specifications, one with exogenous expenditure and the other with endogenous expenditure. Rational addiction model specifications estimate income elasticity between 2.06 and 4.09 with an average elasticity of 2.75. Coefficients on the first lead and lag of prior consumption are positive for all models. Labeaga includes myopic and rational model specifications with additional leads and lags of consumption. All additional lags of consumption are positive and significant in the myopic model specification. The two rational models that include additional leads and lags of price have mixed signs. The third lag and third lead of consumption is negative in both rational addiction model specifications. Both are significant in one model while only the negative coefficient on lead consumption is negative and significant in the other. Price is significant in only one rational addiction model specification and one myopic model specification. Price is positive and insignificant in one of the six model specifications. Where total expenditure is endogenous, both models reject the null of over identification of the restrictions. The author comments the model estimations do not use good instruments for total expenditure on cigarettes. Reported price elasticities for the two rational addiction models are for exogenous expenditure. The reported short-run price elasticity of tobacco ranges from -0.172 to -0.498. It has an average price elasticity of -0.275. The reported long-run price elasticity of tobacco ranges from

-0.230 to -0.665, with an average long-run price elasticity of -0.3681. Rational addiction model estimates where total expenditure is endogenous range from -0.078 to -0.228. They have an average of

-.1261 for the short-run price elasticity, and long-run estimates range -0.112 to -0.328 with an average of -.1811.

Escario and Molina (2001) estimate the demand for tobacco using a rational addition model and aggregate data from the Spanish National tobacco company. Following estimation procedures outlined in Becker et al., 1994, they estimate equation (27) using an instrumental variables regressions with four leads and lags of price. They assume consumer foresight is perfect. Time indicator variables are included in their estimations marking years which sales, marketing and consumption restrictions were implemented on tobacco similar to A.J. Fenn et al (2001). They also included time indicator variables that record production process improvements. They report only results from model specifications with imposed rates of time preference. Imposed time preference rates are 5%, 10%, and 20%. A Wald test on reported models fails to reject the null of model over-specification. All coefficients on previous and future consumption are positive and statistically significant. For the 5%, 10%, and 20% imposed discount rates, r square is 0.9430, 0.9428, 0.9425 respectively. Prices are negative in all model specifications with a statistically signification negative coefficient of -0.00076. Data means and elasticities are not reported in the paper. A Breusch-Godfrey test of first-order autocorrelation fails to reject the null of no autocorrelation.

Baltagi and Griffin (2001) estimate a rational addiction model for cigarettes using a forward-filter first-difference two-stage least squares generalized method of moments estimator to get consistent estimates. The authors note the problematic results of BGM (1994)’s Wald test of overidentifing restrictions and suggest a FE2SLS GMM estimator using panel data. They estimate the panel data version of equation (29), equation (32).

(32)

Where the addition variable, , is the minimum real price of cigarettes in any border state. Equation (30) is estimated in first differences:

(33)

The authors estimate two rational addiction model specifications estimated by BGM (1994), including and excluding future price as a model instrument, and add an additional model specification with more instruments with variables orthogonal to price. Hausman’s test between a fixed-effects and a first differenced model rejects the FE2SLS in favor of FD2SLS. All reported models reject the null test of the overidentifing restrictions. Given the results from all models, Baltagi and Griffin (2001) recommend using model results from the fixed effects two stage least squares model, reasoning the implied discount rate appears most appropriate. The implied discount rate from the FE2SLS estimator is 0.71. Short-run price elasticity of demand for cigarettes of the FE2SLS model is estimated to be -0.69 and long-run elasticity is -1.38. Their estimates are lower but higher in absolute terms, than other price elasticity of demand rational addiction model estimates for cigarettes in the literature. The coefficient on income is negative and insignificant for the FE2SLS model. Short-run price elasticity for all reported models ranges -0.28 and -0.82 with an average of -0.59. Long-run price elasticity ranges -0.56 and -2.55 with an average of -1.34. Baltagi and Griffin’s remark that microdata, like data used by Chaloupka (1991), but with large T, be used to more accurately estimate rational addiction models.

Fenn, Antonovitz, and Schroeter (2001), using American cigarette data following estimation procedures outlined by Becker and Murphy et al. (1994), add time indicator variables for regulation changes in the cigarette industry similar to Escario and Molina’s (2001) estimation of cigarette demand for Spanish tobacco consumption. However, they use a FE2SLS estimator. They split the data at the year 1979 and estimate four FE2SLS model specifications. An F test of structural stability between the pre-1979 and post-1979 regimes is rejected for all model specifications at the level of 1%. The data is split pre and post 1979 to test the hypothesis that the Surgeon General’s report on the addictiveness of cigarettes created a structural shift in the demand equation for cigarettes. In the case of cigarettes, it is plausible that cigarette consumers behaved myopically prior to the Surgeon General’s 1979 report on cigarette smoking and behaved rationally thereafter. The authors report empirical results supporting the rational model both pre and post 1979. Coefficients on prior and future consumption are positive and significant in all model specifications. All coefficients on prior consumption are positive and significant. All coefficients on future consumption are positive and significant excluding one post 1979 model specification. For each respective model specification, the estimated pre 1979 discount rates are smaller than the post 1979 discount rates, evidence that consumers placed more weight on the future consequences of smoking after the Surgeon General’s warning. Price is negative in all model specifications and income is positive. Data means and elasticities are not reported in the paper. However, based on the rational model results using equations (18) and (19) and assuming the mean price real price of cigarettes and consumption quantity was the same pre and post 1979, the average short-run and long-run price elasticity of demand for cigarettes fell.

Grossman, Chaloupka and Sirtalan (1998) estimate the demand for alcohol using data from monitoring the future panels and conventional and rational addiction models. In the conventional model, they regress alcohol consumption on price, drinking age, and the drinking age of border states. They add instrumented second lead and lag of past and future consumption for the rational models. They slightly modify the model of BGM et al. (1994) by instrumenting the second lead and lag of consumption in the structural form demand equation. From the rational addiction model, they report long-run price elasticities that range -0.260 to -1.265 with mean -0.648 and short-run price elasticity ranged -0.181 to -0.857 with mean -0.412. Elasticity from the conventional model estimation is -0.198 and -0.375 with average -0.287. Their results suggest the true price elasticity of consumption for alcohol is greater than reports from conventional model estimations. The authors note policies and taxes used to curtail drinking that appear too expensive under conventional model estimations are cost effective using rational model elasticity calculations. Discount rates in the rational addiction models are greater than unity for all model specifications.

Bentzen, Eriksson and Smith (1999) estimate the demand for alcohol in Denmark, Finland, Norway and Sweden over the 1960 to 1992 period with myopic and rational addiction models following the method of Becker et. al (1994), instrumenting forward and lagged consumption with forward and lagged prices. Reported models results for Denmark, Finland, Norway and Sweden indicate that alcohol consumption is addictive and consumers are forward looking. They regress beer, wine and spirits consumption on prices, income, instrumented past consumption, instrumented future consumption, and regulation variables. They report myopic and rational model results. Instrumented future and lagged consumption are significant in all reported models. R-square for beer consumption for all countries ranges 0.815 to 0.984 with mean 0.957. R-square for wine consumption for all countries ranges 0.976 to 0.995 with mean 0.988. R-square for spirits for all countries ranges 0.917 to 0.99 with mean 0.93. Data means are not reported. Where significant, income elasticity is positive except for spirits in Denmark. Data means are not reported. Reported price elasticities range -0.3 to -0.7 for wine. Elasticity for spirits varies significantly between Denmark and the other countries in the analysis. Reported elasticity for spirits in Denmark is between -0.4 and -1.1. The authors remark that estimated elasticities are twice as high in Finland, Norway, and Sweden. Calculated discount rates for beer range from 0.898 to 0.90, more reasonable than those estimated for tobacco using the methodology of Becker et al. (1994). Discount rates from wine estimates range 0.898 to 0.902 and for spirits range 0.899 to 0.902.

Baltagi and Griffin (2002) estimate the demand for liquor for 42 states over the period 1959-1994 with panel data using the panel data version of the rational addiction demand equation, equation (30). They choose the average retail price of 750ml of Seagram 7 adjusted by the CPI as a price instrument in all reported estimations. They estimate the model with a FE2SLS equation similar to Baltagi and Griffin (2001) but add additional OLS and 2SLS model specifications estimations allowing coefficients to vary by time and state. Calculated discount rates from reported consumption coefficients on the heterogenous estimates are greater than unity in all model specifications excluding the averaged 2SLS by year model specification, which has a calculated discount rate of 0.98. The discount rate from the homogenous coefficient estimate is 0.40. Income elasticity is not significant in any reported model specification. Price is negative and significant in all model specifications. Coefficients on previous and future consumption are positive and significant in all model specifications. Short-run and long-run price elasticity by heterogenous estimates, averaged, at means of the data are -0.52 and -1.39. Short-run and long-run price elasticities for the homogenous estimate are -0.10 for the short-run and -1.24 for the long-run. Time and state indicator variables were jointly significant and included in all model specifications but are not reported. All FESLS model specifications fail to reject the null of Hausman’s over-identification test.

Grossman and Chaloupka (1998) estimate rational and myopic addiction models for cocaine using panel data from the Monitoring the Future Panels and DEA STRIDE pricing data. Using Cragg’s (1971) two-part model for an outcome, they use a linear probability estimate of a variant of equation (13). Following the convention of Becker et. al instrumenting one lead and lag of consumption on the second lead and lag of price, second lead and lag of marijuana decriminalization indicator, and second annual lags of two measures of the legal drinking age[[44]](#footnote-44).The authors note the presence of measurement error in the dependent variable, cocaine participation, and frequency given participation is likely to bias results and their assumption of perfect foresight by cocaine users in the reduced form equations. Model estimations for the discount rate for participation range 1.03 to 3.21 with mean 1.63. Discount rate for frequency given participation ranges 0.965 to 1.03. One discount rate is invalid due to a negative future consumption coefficient. Frequency elasticity has a mean 0.993. Future and past consumption are both positive and significant in all model specifications. Frequent and infrequent religious participation is negative and significant in the participation equation. Infrequent religious participation is not significant in the frequency estimation. Frequent religious participation is negative and significant in the frequency model specification. R square for all models ranges 0.015-0.181 with mean 0.075. The authors note the implausible discount rates are not unexpected. The conventional belief in the literature is demand model specifications for addictive substances are not “rich enough”[[45]](#footnote-45) to accurately measure the discount rate, citing Becker et al. (1994) and Grossman et al. (1998). Means of the data are not reported[[46]](#footnote-46). Long-run participation elasticity ranges -1.26 to -2.01 with mean -1.60. Short-run participation elasticity ranges -0.68 to -1.55 with mean -0.95. Long-run frequency given participation elasticity is -0.44, and short-run frequency give participation elasticity is -0.35. The authors report the unconditional price elasticity in the long-run is -2.04 and -1.30 in the short-run. The coefficient on income is positive in all rational addiction model specifications and significant in three out of four model specifications.

Auld and Grootendorst (2004) criticize the empirical estimation strategy of BGM (1994) et al. to estimate rational addiction models. They report evidence that the BGM (1994) rational addiction model estimation methodology tends to yield spurious results. Their Monte Carlo simulation of demand on data where rational addiction is not present, shows the rational addiction model is likely to find evidence of itself. Following the method suggested by BGM (1994) et al., the authors estimate the demand for milk, eggs, oranges, apples, and cigarettes and simulated demand. The empirical results for the model parameters for milk show it to be more addictive than cigarettes. The authors list four conditions that lead the rational addiction model to yield spurious results, when: “(1) the consumption series is highly autocorrelated, (2) even a small amount of the variation in prices is endogenous, (3) a common linear restriction—that the ratio of the coefficient on the lead of consumption to that on the lag is the discount rate is imposed on the model, or (4) overidentified instrumental variable estimators are used.” They make the empirical suggestions for estimating the model with aggregate time series data based on their results.

“First, estimating the model in differences is likely to yield better small-sample properties than estimation in levels for commodities exhibiting moderate to high serial correlation in consumption. Second, exactly identified instrumental variable models are likely to be preferable to overidentified models. Third, if the goal is to test for rational addiction, the discount rate should not be imposed as a constraint on the model. Fourth, methods which do not succumb to the biases we have identified such as the analysis of anticipated versus unanticipated cigarette tax shifts (Escario and Molina, 2000; Gruber and Koszegi, 2001) are better tests of the rational addiction hypothesis than the canonical empirical model.”

They emphasize that their results do not necessarily apply to studies that utilize microdata. The authors’ most important recommendation is the removal of imposed discount rates constraining the coefficients on future and lagged consumption.

Liu, Liu, Hammitt, and Chou (1999) estimate the price elasticity with myopic, rational, and conventional demand models of opium consumption in Taiwan using data from 1914-1942. The Japanese government licensed and treated opium addicts and strictly enforced laws prohibiting black market opium operations between the years 1895-1945 to eliminate opium smoking in Taiwan. The authors report the number of licensed users declined from a peak of 180,000 around 1903 to less than 500 by 1942. Reported quantities of opium sold by licensed dealers declined from 197,465 kilograms in 1900 to 7940 kilograms in 1942. The decline in opium smokers exhibits a logarithmic decay pattern. The authors estimate the models using a logit. The dependent variable for the conventional model specifications is the log-odds ratio of the fraction of opiate users, the fraction of total opium users for the year, and the log of consumption. The log-odds ratio and log of consumption models are estimated with OLS. The fraction of opium users is estimated with maximum likelihood estimation. Price is negative in three out of four conventional model specifications for which it is included[[47]](#footnote-47). Price is negative and significant in both myopic model specifications, and two out of three rational model specifications. It is insignificant in one rational model specification. The myopic and rational models fail to reject the null of overidentifying restrictions. Conditional and overall estimated price elasticity of consumption for the short-run and long-run in the myopic model is greater than the estimated price elasticity of consumption for the short-run and long-run in the rational model. Two stage models are estimated with forward and lagged prices as instruments for forward and lagged consumption. Short-run conditional elasticity from the myopic model is estimated to be -0.271 and the long-run elasticity for the two stage myopic model is reported to be -1.167. The average short-run conditional elasticity reported from the two stage rational model is -0.25, and the average long-run price elasticity from the rational model is -0.43. Overall short-run and long-run elasticity from the two-stage myopic model is estimated to be -0.481 and -1.377 respectively. Overall average short-run and long-run elasticity for the rational models are -0.468 and -0.647.

**4. Data**

The data for this dissertation consists of proprietary data from an outpatient database of treatment- seeking MMT patients, drug price series from DEA STRIDE, local and United States macroeconomic data series as well as weather data from coca plant growing regions of Columbia. The consumption portion of the data is assembled from the proprietary medical data base tracking patient treatment records and drug screens from years 1999 to present. The data base contains demographic information, prescriptions, and drug screening results. Individual observations were assembled from database tables of drug screens from 2,707 patients from the years 1999-2009. The data set for the two stage economic analysis is limited to years 1999-2007, the dates for which DEA STRIDE prices are available. The data is able to be used with a diverse set of economic tools. Depending on the way it is shaped, it affords itself to probit analysis, time series, longitudinal panel data analysis, OLS, and related regressions.

The data is assembled from record tables in the master data base to create longitudinal time series data. It is summed by month and quarter to form time series data. First, each patient is de-identified and assigned a unique patient identification number running in numerical sequence of admission by patient. Each patient number is used one time per patient. Patients who have been discharged and later reenter treatment are reassigned the same unique patient identifier. Patients that reenter treatment multiple times retain the same patient identifier. Drug screening information is listed by patient identification number. Indicator values of 0 or 1 are assigned for negative and positive drug screening results respectively. Prescriptions for narcotics are controlled to exclude false positives that may occur because of doctor’s prescriptions. The indicator values are set back to 0 if a patient has a doctor’s prescription for the substance. A standard drug-screening tests for the use of methadone, amphetamines, barbiturates, opiates, benzodiazepines, alcohol, cocaine, marijuana, and subxone. The seven most popular illicit drugs in the list are: amphetamines, barbiturates, opiates, benzodiazepines, alcohol, cocaine, and marijuana. These are used for the illicit drug analysis and used to calculate a generic substance abuse indicator set to 1 if any drug in the list is positive and zero otherwise. The data are then grouped by month and quarter and collapsed to create total sum of drug usage and count for each month and quarter. The monthly and quarterly time series data may be seen in appendix A. The data for suboxone and methadone are excluded as they are treatment drugs and the vast majority of the positive test results for these drugs are the result of prescriptions from a physician.

Some trends are apparent in the raw time series data. First, the data are not reliable in the first five months and first two quarters of the data series. Second, it appears that there is a structural break in the amphetamine data during the mid-2000’s, possibly related to an increase in the intensity of pseudoephedrine regulation. The data exhibits autocorrelation and seasonal persistence. In the monthly series for amphetamines, barbiturates, opiates, benzodiazepines, alcohol, cocaine, and marijuana the Q statistics are significant at the 5% level for all substances up to 24 lags. For the quarterly series the Q statistics are significant at the 5% level up to eight lags. For the monthly series, all substances reject the null of a Dickey Fuller unit root test with trend and no trend at the 5% critical value. For the quarterly series amphetamines, opiates, benzodiazepines, cocaine and marijuana fail to reject the null of no unit root at the 5% level with no trend. Amphetamines, benzodiazepines, alcohol, cocaine, and marijuana fail to reject the null of no unit root at the 5% level with trend.

For the panel data analysis, the two stage analysis and the hazard analysis patients are grouped by patient cohort. A cohort is calculated as a single continuous period in treatment. Patients who are discharged and then reenter treatment are grouped in the next treatment cohort. Each treatment cohort is smaller than the preceding cohort. Treatment cohorts range from one to over ten. It is generally assumed that patients that are more compliant appear in fewer treatment cohorts. Patients may be discharged from treatment for financial, behavioral and medical reasons. Financial discharges occur when patients have failed to pay for treatment. Behavioral discharges occur when patients fail to comply with treatment regulations such as abstention from illegal drugs or alcohol. Medical discharges occur when patients complete treatment or for other medical reasons. The database flags patients that are discharged or AWOL (away without leave) from treatment. Suspended patients are ignored in the dataset. AWOL and suspended patients are counted in the same treatment cohort upon their return to treatment.

For the panel data, patient identifiers, cohort numbers, and date are concatenated by date and patient identification number with test number calculated by cohort, drug screening result, drug price as calculated by the quarterly predicted EPH drug price from the DEA STRIDE database and demographic data are assembled to the panel this way. The number of observations between the third quarter of 1999 and the first quarter of 2009 totaled 73,491. Demographic variables and treatment variables change in the dataset as they are updated in the system. Patient information tables include age, gender, race, background and treatment variables. Day-in-treatment like test number is calculated by cohort. The variable is reset to one when patients are discharged and reenter treatment in a higher treatment cohort. Treatment variables are treatment level information as determined by a doctor and organized by screen. Treatment level is based on time in treatment and stability of the patient’s recovery. The treatment level determines how often a patient must visit the clinic to receive his methadone, and the length of time the periodic random testing interval is for each patient.

Each observation in the dataset is selected by the following process. The first observation for the first cohort is always a patient’s first day in treatment when demographic information is collected and a preliminary drug screen is given to the patient. Subsequent observations occur for one of two reasons: either a random interval drug screen or a non-random drug screen. Non-random drug screens are drug screens performed by nursing staff because a patient is thought to be under the influence of narcotics. Random drug screens are drug screens that occur because the random selection mechanism in the system has triggered a screen. Once a screen is triggered, a patient must take the screen or face suspension from treatment. Nonrandom screens replace random screens in the system. A failed screen may result in a change in treatment classification, suspension, or discharge from treatment. Any patient may be readmitted to treatment after a discharge for any reason with the doctor’s permission. The time distance between interval screens occurs based on the treatment level of a patient, and the actual screen date is calculated by the random selection mechanism of the database system. Most are bimonthly screens. The time between random screens gets longer as patients stabilize and advance through treatment. Treatment table and demographic table updates occur on the date treatment is received or demographic information on the patient is updated. However the data are not updated in the master dataset until the next observation which will be when a random or nonrandom screen occurs.

Public data on narcotics prices and production is limited. The United States Drug Enforcement Administration tracks narcotics prices using the system to retrieve drug evidence (STRIDE). Limited pricing data from STRIDE are available publicly on the internet. Quarterly time series from the period 1981-2007 for different quantity categories of heroin, cocaine, marijuana, methamphetamine and crack (1986-2007) are available in the Institute for Defense Analysis report “Price and Purity of Illegal drugs”. Median and expected purity hypothesis prices (EPH) for the series are contained within the report. EPH prices are calculated from all STRIDE data prices. The EPH price is the estimated price of one pure gram of substance, if it were available, calculated from purchase prices, quantities and purities of seized narcotics. Because illicit drugs are considered experience goods, EPH prices are used to control dealer cuts in the retail market for illegal drugs. Prices for the three categories of reported narcotics are then calculated by predicting the log(price) of each category with the addition of the constant and the beta coefficient multiplied by its respective amount value. Prices are adjusted when the predicted price does not “fit the data well” (Fries et al. *Technical report 2008*). Because the equation used to estimate EPH price includes both the quantity sold and a measure of purity, some writers believe that it can be treated as an exogenous variable. It is the position of this dissertation that this is not the case.

Table 1 contains summary statistics for a subset of the data for drug use. The remainder of the paper discusses the modeling of the data. The two-stage modeling of the aggregate time series of the data as well as the duration, linear probability, Probit and fractional Logit modeling are discussed. The panel nature of the data and the treatment of narcotics addiction as a disease make duration modeling appropriate for analysis.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 1 | | | | | |
|  | Number | Mean | Std. Dev. | Min | Max |
| Age | 72597 | 32.214 | 8.545 | 17.334 | 70.323 |
| Sex | 73491 | 0.595 | 0.491 | 0 | 1 |
| Methadone | 73491 | 0.929 | 0.499 | 0 | 1 |
| Subxone | 73491 | 0.001 | 0.031 | 0 | 1 |
| Amphetamines | 73491 | 0.007 | 0.082 | 0 | 1 |
| Barbiturates | 73491 | 0.087 | 0.282 | 0 | 1 |
| Opiates | 73491 | 0.087 | 0.282 | 0 | 1 |
| Benzodiazepines | 73491 | 0.125 | 0.331 | 0 | 1 |
| Alcohol | 73491 | 0.012 | 0.109 | 0 | 1 |
| Cocaine | 73491 | 0.051 | 0.220 | 0 | 1 |
| Marijuana | 73491 | 0.175 | 0.380 | 0 | 1 |

Section 5 presents an analysis of the effect of cocaine price on the share of MMT patients in the sample that test positive for cocaine during a given quarter. The dependent variable is the logistic transformation of the share of patients who test positive for cocaine. Section 6 presents results obtained from applying a binary-choice model (estimated by Probit) to the panel data set in which the dependent variable is either 0 if the patient did not test positive for cocaine use during the quarter and 1 if he did. The results in both sections section imply that patients in methadone maintenance therapy are more likely to test positive for cocaine use as the price of cocaine declines. The results in section 6 also imply that the longer a patient is in MMT the less likely he is to use drugs use declines during treatment and that drug use declines as the local unemployment rate increases but increases as GDP grows more rapidly. In both sections it is found that the use of “predicted” cocaine price yields results more consistent with theory than the use of the standard EPH price typically used in the literature on cocaine demand. The nonparametric hazard functions show negative duration dependence for all substance of abuse during treatment. Finally, there is evidence of a drug screening effect. The more drug screens a patient has been given the less likely the patient is to fail the next drug screen.

***5. Quarterly Time Series Analysis of the Use of Cocaine***

This section presents estimates of an equation for the share of MMT patients that test positive for cocaine use. Since the dependent variable in this case only varies from zero to 1 (and is usually quite small), we transform that variable using the logistic function. Hence the dependent variable, y, is represented by:

.

We assume that y is positively correlated with the overall quantity of cocaine demanded in the local market. Let be the quantity of cocaine consumed (which is equal to the quantity of cocaine demanded) and be a vector of variables that affect the demand for cocaine, so that we can write the following equation for cocaine demand:

(35)

where is the price of cocaine. Now assume that the supply of cocaine depends on price as well as , which is a vector of variables that affect the supply of cocaine. Then we can write the supply of cocaine equation as:

(36)

Since quantity demanded must equal quantity supplied in equilibrium we can solve the above two equations for price, obtaining

, (38)

which shows that *pt* in equation (36) is correlated to the shock to demand, . If, however, we estimate (38) to obtain the fitted values for price, *t,* and replace price with the fitted values, then the estimated coefficient on price in equation (36) will not be correlated with the shock to demand. In practice, however, all we need to do is find at least one variable in the vector *Wt*.

Since cocaine is obtained from growing a crop, it is very probable that temperature in coca growing regions is an element in the vector *Wt*. Hence, it can be used as a variable exogenous to demand, but which affects supply, in the first stage regression of a two-stage least squares estimate of the demand for cocaine. (For a full explanation of instrumental variables regression, see Greene 2003.) The following paragraph summarizes our considerations is coming up with a temperature instrument for the price of cocaine.

Cocaine is processed from the Coca plant. The coca plant is cultivated almost exclusively in Colombia, Boliva and Peru. U.S. Government documents report that twice as much cocaine is supplied from Colombia than from Boliva and Peru combined. Be that as it may, the coca plant is grown over a wide area, so it seemed appropriate to use temperature data from a location close to the geographical center of the cocaine-growing area. Since it takes 6 to 12 months for the coca plant to reach maturity, it was expected that lagged temperature data would do a better job of explain current cocaine prices than more recent temperature data. The second lag of the quarterly temperature from Leticia, Colombia was found to be the best temperature instrument. Although cocaine is not grown near Leticia, it is closer to the center of the coca growing region than other locations for which temperature data is available. To obtain a fitted or predicted value for price we regressed the STRIDE EPA price of cocaine on a constant, three quarterly dummies and the lagged temperature in Leticia. The coefficient on temperature in Leticia was data has a positive constant and a negative beta coefficient on temperature, the sign we would expect if warmer temperatures result in a larger crop of cocaine.

Although our data on drug-screening tests begins in late 1999, is this section we do not use our first 8 quarters of the data. The clinic opened in 1999 and the business was growing through early 2001. During this early period there was an unusually low percentages of positive test results for cocaine use, that do not appear to be drawn from the same sample as the remainder of the data. Table 2 presents results of various estimates of a conventional demand for cocaine equation using the logistic transformation of the percentage of MMT patients that test positive for cocaine use during the quarter. Tables 3 through 8 present estimates of the myopic and rational demand models of demand using the same dependent variable as the results in Table 2 and using the same methodology as Chaloupka (1991) and Becker and Murphy (1988).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 2 | | | | |
| **Conventional Demand Model** | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
|  | (1) | (2) | (3) | (4) |
| EPH Price | 0.00147 |  | -0.00432 |  |
|  | (0.444) |  | (-1.077) |  |
| 2SLS Predicted Price |  | -0.04161 |  | -0.01361\*\* |
|  |  | (-1.16) |  | (-2.54) |
| Trend |  |  | -0.0359\*\* | -0.0453\*\*\* |
|  |  |  | (-2.777) | (-3.28) |
| q1 |  |  | 0.126 | 0.0841 |
|  |  |  | (0.563) | (0.33) |
| q2 |  |  | 0.0478 | 0.0181 |
|  |  |  | (0.216) | (0.01) |
| q3 |  |  | 0.0586 | .2911507 |
|  |  |  | (0.274) | (1.09) |
| Constant | -3.056\*\*\* | -2.2561 | -1.818\*\* | -.3959264 |
|  | (-6.501) | (-4.32) | (-2.577) | (-0.45) |
| N | 26 | 26 | 26 | 26 |
| Adjusted R-squared | -0.033 | 0.0174 | 0.145 | 0.464 |
| Durbin-Watson | .3809 | .3163 | .4273 | .8409 |
| t-statistics in parentheses | |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |  |  |

The first and third columns of Table 2 present results obtained from regressing the rate at which MMT patients test positive for cocaine use based on the conventional model of demand using the EPH price. In column 1 the coefficient on price is positive, though not significantly different from zero, while in column 3 (which adds seasonal dummies and a time trend) the coefficient is negative, but not significantly different from zero. Columns 2 and 4 use predicted price instead of the EPH price. In these two estimates the coefficient on price is negative, but statistically significant only in the estimate presented in column 4. The estimate in column 4 has a much higher adjusted R2 than the comparable estimate in column 3 that uses the EPH price. Although the Durbin-Watson statistic in column 4 is much higher, it is still quite low.

There are problems with the estimates that use the EPH price. For example, for the estimate in column 2, a Breusch-Pagan test of heteroskadasticity rejects the null of constant variance with a marginal significance level of 0.033, while the same test for the model in column 4 fails to reject the null of constant variance at the 0.10 level. For the model in column 2 a Ramsey reset test rejects the null hypothesis of no omitted variables at the .01 level of significance, while the same test applied to the column 4 model fails to reject the null of no omitted variables at the 0.10 level. Finally, a Wu-Hausman F-test of the exogeneity of the EPH price is rejected at the 3% level of significance for the model in column 2.

Hence the estimates of the conventional demand model presented in Table 2 imply that treating the EPH price as if it is endogenous results in a model that not only implies that price has a small and statistically insignificant effect on the use of cocaine, but the model fails 3 specification tests. But using the predicted price yields an effect of price on cocaine use that is much larger and in one specification statistically significant. Furthermore, the model using the predicted price does not fail two specification tests. Nevertheless, the Durbin-Watson statistic is relatively low, suggesting the existence of serial correlation, something that is predicted by both the myopic and rational models.

As discussed in sections 2 and 3, myopic models capture the effects of previous consumption on current consumption and yield a demand function in which lagged consumption is an explanatory variable. Table 3 presents estimates based on the myopic model. In these estimates previous consumption is treated as an endogenous variable because consumers choose both prior and current consumption through optimizing behavior. In the estimates presented in Table 3 previous consumption is instrumented with one lag of the respective price used as the instrument. (Previous writers who estimate the myopic model assume that the previous price is correlated with previous consumption but not current consumption, although previous consumption affects current consumption and current consumption may affect previous consumption because they are jointly determined by the optimizing behavior of consumers.) Since previous price does not affect current consumption except through its effect on previous consumption, previous price an ideal instrument for prior consumption.

The first and third columns of Table 3 present results obtained from regressing the rate at which MMT patients test positive for cocaine use based on the myopic model of demand and using the EPH price. In both of these columns the coefficient on EPH price is small and not statistically significant, while that on lagged consumption is large but clearly estimated with a very large variance (causing the sign in column 1 to be positive while that in column 3 is negative) resulting in the two t-statistics being close to zero. In columns 2 and 4 which use predicted price instead of the EPH price, the coefficients on price are about 20 times larger in absolute value than the corresponding values in columns (1) and (3), while the coefficients on lagged consumption are positive and of more reasonable magnitude than those in columns 1 and 3. Although the column 4 estimate has the highest R2 in Table 3, and the highest Durbin-Watson statistic, the relatively small number of observations along with some multi-collinearity being creating by using lagged price as an instrument, is probably the reason why the coefficient on lagged consumption is greater than 1. A Breusch-Pagan test of constant variance for the estimate in column 4 rejects the null hypothesis of no heteroskadasticity at the 0.01 level, while the same test applied to the estimate in column 2 fails to reject the null of no heteroskadasticity at the 0.10 level. Furthermore a Ramsey rest test applied to the estimate in column 4 rejects the null of no omitted variables, while a link test of the null that the model is correctly specified is also rejected. The estimates of the myopic model in Table 3 are not particularly encouraging.

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| --- | --- | --- | --- | --- |
| Table 3 | | | | |
| **Myopic Demand Model One Lag of Price as Instrument** | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
|  | (1) | (2) | (3) | (4) |
| EPH Price | -0.00025 |  | -.0044818 |  |
|  | (-0.00) |  | (-0.04) |  |
| 2SLS Predicted Price |  | -.005431 |  | -0.07993 |
|  |  | (-1.25) |  | (-0.63) |
| C(t-1) | 44.846 | .3321 | -23.4581 | 2.3755 |
|  | (0.02) | (0.35) | (-0.02) | (0.75) |
| Trend |  |  | -.03892 | -0.0527\* |
|  |  |  | (-0.10) | (-1.91) |
| q1 |  |  | .10722 | -.10883 |
|  |  |  | (0.02) | (-0.21) |
| q2 |  |  | .009269 | -0.2262 |
|  |  |  | (0.00) | (-0.41) |
| q3 |  |  | .019632 | -0.0771 |
|  |  |  | (0.00) | (-0.11) |
| Constant | 123.0205 | -1.16 | -67.597 | 5.7168 |
|  | (0.02) | (-0.48) | (-0.02) | (0.69) |
| Observations | 25 | 25 | 25 | 25 |
| Adjusted R-squared | -0.050 | 0.0095 | 0.092 | 0.58144 |
| Durbin-Watson | .2939 | .5814 | .40952 | .9273 |
| t-statistics in parentheses |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 |  |  |  |  |
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In an attempt to get better estimates of the myopic model in Table 3, Table 4 uses the same regression specifications except 4 lags of previous price are used as instruments for previous consumption instead of one. The estimates in columns (1) and (3) which use EPH price are slightly improve because the coefficients on lagged consumption are smaller is absolute value, but it remains negative in column 3. Although the coefficient on lagged consumption in column 1 is statistically significant, the fact that is greater than 1 is not plausible. A positive coefficient on previous consumption is consistent with the theory that cocaine is an addictive substance, but if the coefficient

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| --- | --- | --- | --- | --- | --- |
| Table 4 | | | | | |
| **Myopic Demand Model Four Lags of Price as Instruments** | | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | | |
|  | (1) | | (2) | (3) | (4) |
| EPH Price | .0008198 | |  | -.0040701 |  |
|  | (0.21) | |  | (-0.39) |  |
| 2SLS Predicted Price |  | | -0.00558 |  | -.005533 |
|  |  | | (-1.33) |  | (-0.41) |
| C(t-1) | 1.087724 | | 0.4432 | -.5045348 | 2.09 |
|  | (2.29) | | (0.37) | (-0.33) | (1.01) |
| Trend |  | |  | -0.05054 | -0.06479\* |
|  |  | |  | (-1.47) | (-1.85) |
| q1 |  | |  | .125762 | -.204382 |
|  |  | |  | (0.32) | (-0.35) |
| q2 |  | |  | .0638544 | -.26510 |
|  |  | |  | (0.16) | (-0.45) |
| q3 |  | |  | .0119749 | -.1034216 |
|  |  | |  | (0.03) | (-0.16) |
| Constant | .0785273 | | -0.8538 | -3.064406 | 4.922749 |
|  | (0.05) | | (-0.52) | (-0.72) | (0.90) |
| Observations | 22 | | 22 | 22 | 22 |
| Adjusted R-squared | 0.024 | | 0.0348 | 0.068 | 0.6644 |
| Durbin-Watson | 2.89 | | .345 | .1720153 | 1.5231 |
| t-statistics in parentheses | |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |  |  |  |

is greater than one, it implies that use will grow over time, which is not consistent with the fact that our sample consists of MMT patients. The coefficient on price in column 1 is small, positive and not significantly different from zero, while that in column 3 is negative and not statistically significant. The coefficients on price are about the same in columns 2 and 4 which use the predicted price, small and negative, with a much higher t-statistic in column 2, the estimate with more precise coefficient estimates. The estimates with predicted price in Table 4 do better on specification tests than the estimates using EPH price. A Breush-Pagan test for heteroskedasticity rejects the null of constant variance at the 0.05 level when applied to the estimate in column 3, but does not reject the null of constant variance when applied to the estimates in columns 2 and 4 (with respective marginal significance levels of 0.68 and 0.56). Finally, when applied to the estimate presented in column 4, the Ramsey RESET test fails to reject the null hypothesis that the model is correctly specified.

Although theory suggests that we should use an instrument for lagged consumption when estimating the myopic model, since our instrument for lagged consumption is lagged price, there is clearly some multi-collinearity in the estimates presented in Tables 3 and 4. Hence Table 5 presents estimates of the myopic model under the assumption that previous consumption is exogenous to current consumption (or is pre-determined). In each of the columns in Table 5 the coefficient on lagged consumption is positive and significantly different from zero at the level of 1%. Although each of these point estimates is less than one, only the coefficient on lagged consumption in column 4 is significantly different from one statistically. The coefficient on price is negative in all four columns model specifications but not statistically significant. However, the coefficient on price in column 4 is significant at the 0.10 level using a one-tailed test. Because of the serial correlation in the rate at which MMT patients test positive for cocaine use (and hence the positive coefficients on lagged consumption), the adjusted R-squares are all above 0.65 in Table 5. A Brush-Pagan test for heteroskadasticity fails to reject the null hypothesis of constant variance in all four specifications included in Table 5. A Ramsey RESET test when applied to the model in column 4 fails to reject the null hypothesis of a correctly specified model at the 0.17 level, while a link test fails to reject the null of no omitted variables at the 0.22 level.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 5 | | | | |
| **Myopic Demand Model Exogenous Lagged Consumption** | | | | |
| Dependant Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
|  | (1) | (2) | (3) | (4) |
| EPH Price | -0.000624 |  | -0.00339 |  |
|  | (-0.250) |  | (-1.140) |  |
| 2SLS Predicted Price |  | -0.0011 |  | -.00622ª |
|  |  | (-0.42) |  | (-1.56) |
| C(T-1) | 0.976\*\*\* | .953\*\*\* | 0.865\*\*\* | .701\*\*\* |
|  | (6.814) | (6.37) | (5.534) | (3.46) |
| Trend |  |  | -0.0169\* | -0.0220428 |
|  |  |  | (-1.883) | (-2.08) |
| q1 |  |  | 0.0417 | .0571317 |
|  |  |  | (0.287) | (0.38) |
| q2 |  |  | -0.0847 | -.06673 |
|  |  |  | (-0.587) | (-0.44) |
| q3 |  |  | -0.00570 | .1020 |
|  |  |  | (-0.0404) | (0.61) |
| Constant | -0.0335 | -0.0252 | 0.266 | 0.270 |
|  | (-0.0602) | (-0.05) | (0.429) | (-0.48) |
| Observations | 25 | 25 | 25 | 25 |
| Adjusted R-squared | 0.65 | .6523 | 0.661 | .6892 |
| Durbin-Watson | 2.611 | 2.624 | 2.6976 | 2.844282 |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | |
| ªSignificant at 0.1 level in one-tailed test | | | | |

It appears the when we assume that lagged consumption is predetermined (or exogenous) to current consumption, then the estimation results based on a model that uses the predicted price is slightly better than those that use the EPH price. We now turn to estimates of the rational model.

As pointed out in sections 2 and 3 above, the rational model implies that current consumption of an addictive drug depends upon both past and expected future consumption of the good. The theory of a rational consumer of an addictive good predicts that the coefficient on future consumption is positive but less than the coefficient on past consumption. Letting be the coefficient on future consumption and be the coefficient on past consumption, we can write (from equation (38), above):

,

Which can be rearranged to yield . Recall that the discussion of the rational model that *β* is the rate at which consumer discounts future utility. If addicts do not put much weight on the future, then *β* will be relatively low, while the more forward-looking the addict is, the closer *β* will be to one.

Table 6 presents estimates of the rational model. Since both lagged and future consumption are presumed to be endogenous in this system, one lag of price and one lead of price are used as instruments for lagged and future consumption respectively. The estimates in columns 1 and 3 in Table 6 use the EPH price, while those in columns 2 and 4 assume current price is endogenous, so they use the predicted price. In column 1 the coefficients on lagged and future consumption are both positive but greater than one. The coefficient on lagged consumption is clearly implausibly high. In column 3 the coefficients on lagged and future consumption are both negative which also contradicts the rational model. Clearly, the estimates in Table 6 that use EPH price do not support the rational model.

Although the estimates in columns 2 and 4 are closer to results that one would expect if the rational model holds, they do not provide much, if any support for the rational model. The coefficient on lagged consumption in column 2 is negative (thereby contradicting the rational model), while the coefficient on lagged consumption is column 4 is positive and greater than 1. But since it is not significantly different from zero, clearly it is estimated with a very high standard error. Since all of the results in Table 6 are not supportive of the rational model, the estimates in Table 7 were made, which use 4 lags of prices as instruments for lagged consumption and 4 leads as instruments for future consumption.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 6 | | | | |
| **Rational Demand Model One Lag and Lead of Price as Instruments** | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
| EPH Price | -0.00212  (-0.52) |  | -0.0061468  (-0.05) |  |
| 2SLS Predicted Price |  | -.004132 |  | -0.0031 |
|  |  | (-1.62) |  | (-0.14) |
|  |  |  |  |  |
| C(t-1) | 46.67 | -.08766 | -22.19129 | 2.2203 |
|  | (1.042) | (-0.17) | (-0.01) | (0.49) |
| C(t+1) | 1.397 | .68065 | -3.89 | 0.9751 |
|  | (0.325) | (1.79) | (0.03) | (0.33) |
| Trend |  |  | -.0366043 | -0.0457 |
|  |  |  | (-0.08) | (-1.06) |
| q1 |  |  | -0.0267375 | -.148884 |
|  |  |  | (-0.00) | (-0.19) |
| q2 |  |  | -0.0789294 | -.1335936 |
|  |  |  | (-0.01) | (-0.14) |
| q3 |  |  | -.1074766 | -0.2243 |
|  |  |  | (-0.02) | (-0.22) |
| Constant | 132.4 | -.536404 | -74.81956 | 7.367 |
|  | (1.053) | (-0.34) | (-0.02) | (0.55) |
| N | 24 | 24 | 24 | 24 |
| Adjusted R-squared | -0.081 | 0.00208 | -0.039 | 0.481 |
| Durbin-Watson | .4101 | 1.523 | .4349 | 1.0855 |
| t-statistics in parentheses |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 |  |  |  |  |

As in the previous tables, the results presented in columns 1 and 3 use EPH price, while those in columns 2 and 4 used the predicted price. The estimates in columns 2 and 3 produce negative coefficients on both future and lagged consumption thereby contradicting the rational model. But in the estimates in columns 1 and 4 coefficient on both lagged and future consumption are positive with the coefficient on lagged consumption larger. These coefficient estimates are consistent with the rational model. The implied discount rate in column 1 is 0.03, while that in column 4 is 0.44. Although these discount rates are too small to be plausible for the typical economic actor who is not an addict, if one is willing to assume that an addict puts only one-half the weight on the future that a non-addict does, then they are quite plausible. Although the point estimates of coefficients on consumption are plausible in column 4, and the estimated coefficient on price is negative, none of these point estimates is statistically significant because they are estimated with a relatively large standard error.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 7 | | | | |
| **Rational Demand Model Four Lags and Leads of Price as Instruments** | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
| EPH Price | -.0033391 |  | -0.0034234 |  |
|  | (-0.35) |  | (-0.26) |  |
| 2SLS Predicted Price |  | -0.0035 |  | -0.00176 |
|  |  | (-0.89) |  | (-0.10) |
| C(t-1) | -.1344436 | 0.551 | -.2348894 | 1.4889 |
|  | (-0.11) | (1.06) | (-0.12) | (0.61) |
| C(t+1) | -.1350549 | 0.3018 | -.1408197 | 0.601512 |
|  | (-0.04) | (0.40) | (-0.03) | (0.22) |
| Trend |  |  | -.003661 | -0.0331 |
|  |  |  | (-0.07) | (-0.57) |
| q1 |  |  | .0674548 | -0.171601 |
|  |  |  | (0.13) | (-0.25) |
| q2 |  |  | .0652094 | -0.09976 |
|  |  |  | (0.13) | (-0.15) |
| q3 |  |  | -.0071469 | -0.163297 |
|  |  |  | (-0.01) | (-0.21) |
| Constant | -2.987071 | 0.1527 | -3.24 | 3.91319 |
|  | (-0.27) | (0.07) | (-0.22) | (0.40) |
| Observations | 18 | 18 | 18 | 18 |
| Adjusted R-squared | -0.1349 | 0.3267 | -0.5464 | 0.4748 |
| Durbin-Watson | .7501207 | 1.2734 | .7677654 | 1.992263 |
| t-statistics in parentheses | | | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | |

For this reason, in an attempt to reduce the standard errors of the estimates, we estimated the rational model an additional time using four lags of EPH prices as instruments for lagged consumption and 4 leads of the predicted price as instruments for future consumption. These results are in Table 8.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 8 | | | | |
| **Rational Demand Model Four Lags EPH and Four Leads of Predicted Price as Instruments** | | | | |
| Dependant Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens for the quarter | | | | |
| EPH Price | -.002281 |  | -0.003 |  |
|  | (-0.57) |  | (-0.34) |  |
| 2SLS Predicted Price |  | -.00533 |  | -0.00693 |
|  |  | (-1.30) |  | (-0.93) |
| C(t-1) | -.17405 | -.08046 | -0.65343 | -0.66760 |
|  | (-0.35) | (-0.13) | (-0.47) | (-0.56) |
| C(t+1) | .8727059 | .3844129 | 1.327977 | .614157 |
|  | (1.44) | (0.45) | (0.95) | (0.42) |
| Trend | -.002281 |  | -.019181 | -0.0219 |
|  | (-0.57) |  | (-0.53) | (-0.70) |
| q1 |  |  | 0.0968026 | .0736102 |
|  |  |  | (0.27) | (0.24) |
| q2 |  |  | .1345542 | .06534 |
|  |  |  | (0.38) | (0.21) |
| q3 |  |  | -0.014353 | 0.110875 |
|  |  |  | (-0.04) | (0.33) |
| Constant |  |  | -0.342702 | -1.73503 |
|  |  |  | (-0.08) | (-0.44) |
| Observations | 18 | 18 | 18 | 18 |
| Adjusted R-squared | 0.0299 | 0.22 | -0.1392 | 0.1011 |
| t-statistics in parentheses |  |  |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 |  |  |  |  |
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As can be seen by briefly examining Table 8, this does not help much. In each column although the coefficient on future consumption that is positive, the coefficient on previous consumption is negative, a result that contradicts the rational model. Furthermore, although the coefficient on price is negative in each column, it is statistically insignificant.

Tables 2 through 8 present results from estimating different specifications of conventional, myopic and rational demand models. The results presented in these tables are not strongly supportive of economic theories of the demand for an addictive good. The only estimate that produces a statistically significant effect of price on demand is that for the conventional demand function presented in column 4 of Table 2. This estimate uses predicted price, supporting our contention that EPH prices are endogenous. The only estimates that provide some support for the myopic theory of the demand for an addictive good are in column 2 of Table 3, column 2 of Table 4 and columns 2 and 4 of Table 5. Again these estimates use predicted price rather than EPH price, but the estimated coefficients on price are not statistically significant with the exception of the barely significant (in a one-tailed test) coefficient in column 4 of Table 5. This is the estimate that provides the strongest support for the myopic model. It is safe to say that the results in Tables 6-8 provide little support for the rational model.

**6. Estimates Based on Panel Data**

The data from the clinic employed here forms a somewhat messy, unbalanced panel. This section uses various panel data techniques to estimate the demand for cocaine. This has the advantage of removing missing variables and increases the degrees of freedom of the estimates. For each test result we know the sex and age of the patient as well as how long the patient has been in MMT. We also know whether the patient has previously left therapy and how many previous times he or she has tested positive for cocaine use. The probability that an individual tests positive for cocaine use might be correlated with these observable variables. We first use the generalized linear model and will then use a Probit model.

The generalized linear model is robust and allows the estimation of dependent variables that are non-linear in nature. Although the stochastic errors are heteroskedastic under the GLM, coefficient estimates are not biased. For each observation on a patient who is tested for cocaine use, the dependent variable is 0 if the test is negative for cocaine and 1 if the test is positive. In GLM estimation the mean of the dependent variable is given by the following relationship:

with variance:

=Var(𝜇)=V(

where is the link function.

Table 9 presents the estimation results for the conventional model. In the table the variable “sex” is zero for a female and one for a male. Columns 1 and 2 employ the EPH price, while columns 3 and 4 use the predicted price. Columns 1 and 3 only include sex and age as additional explanatory variables, while columns 2 and 4 include quarterly dummies, cohort number, total tests and total tests within the current cohort. The estimated coefficient on price is small and negative in column 1 and small and positive in column 2, the estimates that use EPH price. Neither one is statistically significant but this could be the result of the EPH price being endogenous. In both column 3 and column 4, however, the coefficient on predicted price is negative and statistically significant at the 0.01 level, implying that cocaine users respond to price and suggesting that EPH price is positively correlated with cocaine demand.

In all four columns of Table 9 the coefficient on sex is positive and statistically significant at the 0.01 level, implying that men are more likely than women to use cocaine. In all four columns the coefficient on age is negative and statistically significant at the 0.01 level, implying that cocaine use declines with age. These results are consistent with previous literature on drug use and common knowledge about substance abuse patterns.

Columns 2 and 4 in Table 9 include the following variables of interest, the cohort number of the individual, the test number within the cohort, and the total number of tests the patient has received. In both columns 2 and 4 the coefficient on cohort is positive, implying that clients in higher treatment cohorts are more likely to be less compliant with treatment. This may be because of poly substance abuse or other unobserved factors that make their treatment compliance less stable. However, the coefficient on test number within a cohort is negative and statistically significant which is

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| --- | --- | --- | --- | --- |
| Table 9 | | | | |
| **GLM conventional demand model where the link function is Logit.** | | | | |
| Dependent Variable is log(pcf/(1-pcf) | | | | |
| pcf is the percentage of failed cocaine screens | | | | |
| EPH Price | -0.000247 | 0.00129\* |  |  |
|  | (-0.346) | (1.653) |  |  |
| 2SLS Predicted Price |  |  | -0.0351\*\*\* | -0.0488\*\*\* |
|  |  |  | (-4.581) | (-5.125) |
| Sex | 0.391\*\*\* | 0.381\*\*\* | 0.398\*\*\* | 0.395\*\*\* |
|  | (9.725) | (9.327) | (9.876) | (9.655) |
| Age | -0.0394\*\*\* | -0.0306\*\*\* | -0.0395\*\*\* | -0.0307\*\*\* |
|  | (-15.10) | (-11.67) | (-15.08) | (-11.63) |
| q1 |  | 0.206\*\*\* |  | 0.158\*\*\* |
|  |  | (3.721) |  | (2.884) |
| q2 |  | 0.122\*\* |  | -0.0584 |
|  |  | (2.165) |  | (-0.897) |
| q3 |  | 0.0350 |  | -0.0272 |
|  |  | (0.645) |  | (-0.478) |
| Test Number by Cohort |  | -0.0370\*\*\* | | -0.0369\*\*\* |
|  |  | (-19.65) |  | (-19.58) |
| Total Test number |  | 0.000530 |  | 8.01e-06 |
|  |  | (0.749) |  | (0.0115) |
| Cohort |  | 0.104\*\*\* |  | 0.101\*\*\* |
|  |  | (16.09) |  | (15.60) |
| Constant | -1.769\*\*\* | -1.946\*\*\* | 6.816\*\*\* | 10.30\*\*\* |
|  | (-13.33) | (-12.72) | (3.616) | (4.369) |
| Observations | 51,363 | 51,363 | 51,363 | 51,363 |
| Robust Z-statistics in parentheses \*\*\* p<0.01, \*\*p<0.05, \*p<0.1. | | | | |
| Sex is 1 if client is a male. |  |  |  |  |

also consistent with the casual observation that the longer a MMT patient is in treatment, the less likely he is to use illicit drugs. (The coefficient on total tests is close to zero and not statistically significant. The total tests variable is somewhat, but not exactly like an interaction variable between cohort number and test number within the cohort.) This implies that it is the length of continuous time in treatment, not total time in treatment that results in a decline in positive test results.

We now turn to estimates based on the linear probability model (lpm), the simplest form of binary choice models where the probability of an event occurring, *p*, is assumed to be a linear function of a set of explanatory variables. *p* is unobservable. One of the critical underlying assumptions about the binary choice model is that the distribution is linear.

This can be expanded to the panel data case where the outcome for individual *i* at time *t* with binary outcomes. In the case where may be thought of as an index of desire the model is referred to as the latent variables model with:

>0

The linear probability model applied to panel data is:

The results for the linear probability model are presented in Table 10. Like the results for the general linear model, this approach pools the data and does not make use of any panel data techniques. The estimates presented in columns 1 and 2 use EPH price, while columns 3 and 4 use the predicted price. Columns 1 and 3 include the growth rate of real GDP, while columns 2 and 4 include the local unemployment rate as addition economic variables of interest. In columns 1 and 2 though negative, the coefficient on price is not statistically significant, while it is statistically significant at the 0.10 and 0.05

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| --- | --- | --- | --- | --- |
| Table 10 | | | | |
| Linear Probability Model with Pooled Data | | | | |
| Dependent Variable is 1 if Cocaine screen is positive | | | | |
| EPH | -4.05e-05 | -1.60e-05 |  |  |
|  | (-0.814) | (-0.328) |  |  |
| Predicted Price |  |  | -9.50e-05\* | -0.000114\*\* |
|  |  |  | (-1.834) | (-2.252) |
| Sex | 0.0183\*\*\* | 0.0183\*\*\* | 0.0182\*\*\* | 0.0183\*\*\* |
|  | (8.773) | (8.778) | (8.767) | (8.771) |
| % Change in GDP | -0.00171\*\* |  | -0.00125\* |  |
|  | (-2.452) |  | (-1.766) |  |
| Day in Treatment | -2.60e-05\*\*\* | -2.59e-05\*\*\* | -2.59e-05\*\*\* | -2.59e-05\*\*\* |
|  | (-13.08) | (-12.99) | (-13.04) | (-12.99) |
| Age | -0.000764\*\*\* | -0.000763\*\*\* | -0.000763\*\*\* | -0.000761\*\*\* |
|  | (-5.998) | (-5.996) | (-5.990) | (-5.980) |
| Avg. % male | -0.108\*\*\* | -0.136\*\* | -0.130\*\*\* | -0.145\*\*\* |
|  | (-2.772) | (-2.451) | (-3.656) | (-2.733) |
| Avg. Age | -0.0221\*\*\* | -0.0193\*\*\* | -0.0213\*\*\* | -0.0194\*\*\* |
|  | (-10.79) | (-9.680) | (-10.42) | (-9.722) |
| Q1 | 0.00412 | 0.00362 | 0.00138 | 0.000130 |
|  | (1.346) | (1.184) | (0.395) | (0.0381) |
| Q2 | 0.00337 | 0.00349 | 0.00169 | 0.00112 |
|  | (1.132) | (1.165) | (0.538) | (0.355) |
| Q3 | -1.40e-05 | -0.000929 | -0.00319 | -0.00418 |
|  | (-0.00485) | (-0.320) | (-0.999) | (-1.321) |
| Cohort | 0.00880\*\*\* | 0.00882\*\*\* | 0.00881\*\*\* | 0.00882\*\*\* |
|  | (15.12) | (15.15) | (15.15) | (15.15) |
| Test Number by Cohort | -0.000753\*\*\* | -0.000754\*\*\* | -0.000754\*\*\* | -0.000755\*\*\* |
|  | (-16.00) | (-16.03) | (-16.02) | (-16.04) |
| Local Unemploy-ment Rate |  | 0.00199 |  | 0.00133 |
|  |  | (1.061) |  | (0.703) |
| Constant | 0.869\*\*\* | 0.779\*\*\* | 0.876\*\*\* | 0.816\*\*\* |
|  | (11.22) | (11.09) | (11.31) | (11.31) |
| Observations | 51,363 | 51,363 | 51,363 | 51,363 |
| Adjusted R2 | 0.030 | 0.030 | 0.030 | 0.030 |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | |

levels respectively in columns 3 and 4. Again, we get results more consistent with economic theory using predicted price rather than EPH price. In both column 1 and column 3 the coefficient on the growth rate of real GDP is negative, implying that patients are less likely to test positive for use of cocaine when the economy is growing more rapidly. Likewise, in columns 2 and 4 the estimated coefficient on the local unemployment rate is positive (though not statistically significant), a result also consistent with the idea that improved economic opportunities reduce drug use. These results for GDP growth and local unemployment are not consistent with the idea that illicit drug use is a normal good and are contradicted by the results obtained using a logistic panel data model. In all columns in Table 10, the longer a patient has been in treatment, the older he or she is, and the less likely he is to test positive for cocaine use. Hence these results support the notion that cocaine use declines during treatment. The positive and statistically significant coefficient on cohort number is evidence that patients in higher treatment cohorts are less compliant with treatment than patients in lower treatment cohorts.

Table 10 also includes the effect of two additional variables: the average age and the average sex (1=male and 0=female) of those given a drug screen during the month of the observation. To understand the reason for including these two variables consider the following argument. Suppose patients in MMT pay attention to the probability that they will be tested. The greater the perceived probability of being tested, the less likely the patient will be to use and therefore the less likely a positive test for cocaine use. Since males are more likely to use and test positive, the greater the probability that a male will be tested, the greater the incentive that males have to avoid use of cocaine. Hence we would then expect a negative coefficient on the percentage of males tested. Indeed in all four columns of Table 10 the estimated coefficient on average percentage male is negative and statistically significant at the 0.01 level. Likewise, since younger patients are more likely to test positive, we would expect younger patients to be less likely to use cocaine if they believe their probability of being tested is higher. Hence we would expect a positive coefficient on the average age of those tested during the month (since this implies that a younger MMT patient is less likely to be tested). However, in all four columns of Table 10 the coefficient on average age is negative and statistically significant at the 0.01 level. Hence the sign of this estimated coefficient is not consistent with our reasoning.

One problem with using both the general linear model and the basic linear probability model is that these estimation techniques (when applied to our data) use pooled data and do not address any unobserved heterogeneity across the individuals in the data set. To see if this can, perhaps, explain some of the troublesome signs on the coefficients in Table 10 we re-estimate the equation for the probability that an MMT patient will test positive for cocaine use using a logistic panel data model. The results are presented in Table 11.

There are three sets of results in Table 11: for random effects, for fixed effects, and population averaging. The first row has the estimated coefficient for being male. In this effect cannot be measured using fixed effects. But in the case of random effects and population averaging the coefficient on “male” is positive and statistically significant at the 0.01 level. In all three cases the coefficient on predicted price is negative and significant at the 0.01 level, indicating that MMT patients are responsive to cocaine prices (and less likely to use test positive as prices increase). The coefficient on the local county unemployment rate is negative and significant at the .01 when using fixed or random effects and at the 0.05 level when using population averaging. Hence in this case we find that the higher the unemployment rate, the less likely an MMT patient is to test positive for cocaine use. This is consistent with the contention that illicit drugs are normal goods. Hence, the results in Table 11 imply that MMT patients are responsive to economic conditions, including price.

Also in Table 11 the coefficient on age is negative and significant at at least the 0.05 level in each of the three estimates (while as mentioned above) the effect of being male is positive. But the coefficient on the “Average Percentage of Males Tested” (which is the quarterly average of the monthly percentage of males screened) is negative, but only significant when fixed effects are used. Although males are at a higher risk to abuse substances than women and cocaine is no different, this implies that the typical patient is less likely to test positive if a larger share of those tested are male. There are two reasons this could be the case, first it may be that when the higher risk group is screened more often cocaine users leave treatment because of the adverse consequences of failing a drug screen. The second reason is cocaine users stop using cocaine because of the higher risk and cost to failing a drug screen[[48]](#footnote-48).

Table 11 also includes the results of tests for the other drugs in the typical drug screening. The signs on the result for use of other drugs (0=negative and 1=positive) are all positive and statistically significant at at least the 0.05 level. This implies that if a patient tests positive for amphetamines, barbiturates, opiates, benzodiazepines, alcohol or marijuana, the patient is more likely to also test positive for cocaine use. Hence the use of these other substances in general is complimentary to the use of cocaine. That is, cocaine users tend to prefer to use different substances together, or these goods are complements. One is tempted to interpret the positive sign on marijuana as evidence against the gateway theory of drug use as it would be more likely that cocaine would be a substitute for marijuana if this were the case.

The treatment variables included in the estimations in Table 5 but not reported in Table 5 are reported in Table 6. The coefficient on cohort number indicates that patients in higher treatment cohorts are less compliant with treatment than patients in lower treatment cohorts. The signs on the day in treatment variable and test number by cohort and total test number are negative. One possibility is that patients who have been in treatment longer and taken more drug screens are better at avoiding testing positive for cocaine. The other possibility is that cocaine use declines with treatment. The latter finding is more consistent with reports from treatment specialists at the clinic.

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| Table 11 | | | |
| Logistic Panel Data Models | | |  |
| Dependent variable is binary, 1 if cocaine screen is positive. | | | |
| VARIABLES | Random Effects | Fixed Effects | Population Averaged |
| Male | 0.500\*\*\* | -- | 0.324\*\*\* |
|  | (2.868) | -- | (3.228) |
| Two Stage Price | -0.00876\*\*\* | -0.00833\*\*\* | -0.00620\*\*\* |
|  | (-4.513) | (-4.153) | (-4.399) |
| County Unemployment Rate | -0.158\*\*\* | -0.331\*\*\* | -0.107\*\* |
|  | (-2.600) | (-4.339) | (-2.547) |
| Day in Treatment | -0.000624\*\*\* | -0.000467\*\* | -0.000489\*\*\* |
|  | (-4.456) | (-2.141) | (-5.018) |
| Age | -0.0506\*\*\* | -0.193\*\* | -0.0197\*\*\* |
|  | (-4.435) | (-2.289) | (-2.985) |
| Avg. % Male Screened | -0.979 | -4.679\*\* | -0.744 |
|  | (-0.488) | (-2.124) | (-0.517) |
| Average Age of Client Screened | -0.418\*\*\* | -0.380\*\*\* | -0.300\*\*\* |
|  | (-6.086) | (-5.312) | (-6.110) |
| Amphetamines | 0.464\*\*\* | 0.370\*\*\* | 0.358\*\*\* |
|  | (4.147) | (3.297) | (4.167) |
| Barbiturates | 0.369 | 0.315 | 0.292 |
|  | (1.277) | (1.112) | (1.264) |
| Opiates | 0.381\*\*\* | 0.365\*\*\* | 0.265\*\*\* |
|  | (3.847) | (3.595) | (3.728) |
| Benzodiazepines | 1.416\*\*\* | 1.370\*\*\* | 0.972\*\*\* |
|  | (17.18) | (16.25) | (16.25) |
| Alcohol | 0.559\*\* | 0.516\*\* | 0.412\*\* |
|  | (2.235) | (2.032) | (2.303) |
| Marijuana | 0.789\*\*\* | 0.687\*\*\* | 0.582\*\*\* |
|  | (8.889) | (7.369) | (8.833) |
| Constant | 13.94\*\*\* | -- | 10.13\*\*\* |
|  | (5.653) | -- | (5.732) |
| Observations | 42,547 | 16,731 | 42,547 |
| Number of Patients | 1,393 | 466 | 1,393 |
| z-statistics in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | |
| All regressions include quarterly indicators and treatment variables. | | | |

The treatment variables included in the estimations in Table 11 but not reported in Table 11 are reported in Table 12. The positive and significant coefficient on cohort number indicates that patients in higher treatment cohorts are less compliant with treatment than patients in lower treatment cohorts. Since these patients have left treatment more times, this is the sign we would expect. The signs on total test number and test number within the cohort are negative and statistically significant. As a MMT patient remains in treatment, his or her probability of testing positive for cocaine declines. Finally, the coefficient on the number of days since the last test is positive, evidence that more frequent testing leads to less “cheating” and reduced cocaine use by patients at the clinic.

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| --- | --- | --- | --- |
| Table 12 | | | |
| Treatment Variable Results not reported in Table 11 | | | |
|  | Random Effects | Fixed Effects | Population Averaged |
| Number of Days Since the Last Test | 0.0128\*\*\* | 0.00889\*\*\* | 0.0131\*\*\* |
|  | (5.441) | (3.372) | (7.138) |
| Cohort Number | 0.133\*\*\* | 0.0981\*\*\* | 0.0930\*\*\* |
|  | (5.394) | (3.389) | (6.221) |
| Test Number by Cohort | -0.00760\*\* | -0.00340 | -0.00966\*\*\* |
|  | (-2.339) | (-0.779) | (-4.020) |
| Total Test Number | -0.0106\*\*\* | -0.00960\*\* | -0.00863\*\*\* |
|  | (-4.650) | (-2.351) | (-5.244) |

Table 13 reports that indicator values on cohort groups from a random effects panel logit estimation on cocaine use where the comparison group is the cohort group one through three. The signs are all positive and rank lowest to highest with the numbers of the cohort groups, further supporting the theory that the higher cohort groups are less compliant with treatment protocol and at a higher risk for cocaine usage. The marginal effects for the cohort groups are 0.42% for cohort groups 4-6, 0.567% for cohorts groups 7-9 and 1.983% for cohort groups 10+. The risk of being in a 10 plus cohort group is the highest risk factor identified in this study, the second is the use of benzodiazepines which increases the risk of failing a cocaine screen by 1.5%, use of marijuana increases the probability of failing a cocaine screen by 0.58%.

|  |  |
| --- | --- |
| Table 13 | |
| Panel Data Logit, Random Effects | |
| Variable |  |
| Cohort Groups 4-6 | 0.578\*\*\* |
|  | (4.235) |
| Cohort Groups 7-9 | 0.704\*\* |
|  | (2.112) |
| Cohort Groups 10+ | 1.537\*\*\* |
|  | (4.667) |

Table 14 presents results from panel probit estimation of the probability of testing positive for cocaine use using random effects and population average effects using specification a with the same variables as in Table 11. One would expect the estimated coefficients in Table 14 to have the same signs and similar magnitudes as those in Table 11 since the only difference in the specification is in the distribution. This is the case. The results presented in Table 14 also imply that MMT patients are responsive to economic variables: cocaine is a normal good (its use increases as the unemployment rate declines) and it is less likely to be used as the price increases. The empirical results support the theory that illicit drugs are complimentary in consumption with benzodiazepines being positive and strongly significant in the explanatory regression.

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| Table 14 | | |
| Probit panel data models | | |
| Dependent variable is binary, 1 if cocaine screen is positive. | | |
| VARIABLES | Random Effects | Population Average |
| Male | 0.250\*\*\* | 0.174\*\*\* |
|  | (2.915) | (3.201) |
| Two Stage Price | -0.00440\*\*\* | -0.00271\*\*\* |
|  | (-4.439) | (-4.046) |
| Local County Unemployment Rate | -0.0717\*\* | -0.0600\*\*\* |
|  | (-2.317) | (-2.941) |
| Day in Treatment | -0.000317\*\*\* | -0.000264\*\*\* |
|  | (-4.757) | (-5.871) |
| Age | -0.0248\*\*\* | -0.0103\*\*\* |
|  | (-4.472) | (-2.981) |
| Avg. % Male Screened | -0.332 | -0.363 |
|  | (-0.324) | (-0.530) |
| Average Age of Client Screened | -0.192\*\*\* | -0.139\*\*\* |
|  | (-5.556) | (-5.992) |
| Amphetamines | 0.263\*\*\* | 0.194\*\*\* |
|  | (4.511) | (4.501) |
| Barbiturates | 0.187 | 0.138 |
|  | (1.183) | (1.142) |
| Opiates | 0.213\*\*\* | 0.140\*\*\* |
|  | (4.080) | (3.865) |
| Benzodiazepines | 0.742\*\*\* | 0.516\*\*\* |
|  | (17.14) | (16.78) |
| Alcohol | 0.291\*\* | 0.186\*\* |
|  | (2.261) | (2.073) |
| Marijuana | 0.405\*\*\* | 0.299\*\*\* |
|  | (8.798) | (8.909) |
| Constant | 6.156\*\*\* | 4.413\*\*\* |
|  | (4.974) | (5.290) |
| Observations | 42,547 | 42,547 |
| Number of patients | 1,393 | 1,393 |
| z-statistics in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1   All regressions include quarterly indicators and treatment variables. | | |

*Treatment and Policy Implications*

Conventional, myopic and rational estimations provide evidence that cocaine users in MMT are price responsive and there is also evidence that cocaine users are forward looking in consumption as future consumption coefficient estimates in the rational model are positive in some model specifications. The implied discount rates from the two rational estimations vary by a wide margin evidence that coefficients may not be well estimated. All two-stage price models suggest that policies that raise the price of cocaine will reduce consumption. Econometrically the standard EPH price used in the literature by other papers on illicit drug consumption is endogenous and may be instrumented with an appropriate temperature instrument to achieve better results.

The results from the panel logit and probit estimations provide evidence about the consumption behavior of cocaine consumers in MMT as well as provide identifying characteristics of high risk patients that can guide clinic screening and cocaine treatment policy. First men, younger patients, and returning patients are at a higher risk of cocaine consumption than other patients, the risk for a patient that has been in and out of treatment over ten times is an additional 1%. The coefficients on the other substances of abuse indicate that illicit narcotic consumption and cocaine consumption are compliments, reducing consumption of any other narcotics will reduce cocaine consumption. The economic evidence indicates cocaine is a normal good and lower cocaine prices or higher incomes will put patients at greater risk. Day in treatment and test number coefficients are negative while cohort and the number of days since the last test are positive. Testing resources may be better allocated to take this into account, testing patients who are newer, patients who are in higher treatment cohorts, patients who have not been tested recently, and patients in higher risk groups more often. Finally effective treatment resources such as counseling, group education and physician resources may reduce overall cocaine consumption if they are reallocated from low risk to high risk patients.

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**Appendix A**

*Monthly data*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| mdate | amp | bar | opi | benz | alcohol | coc | mari | count |
| 1999m3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1999m4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1999m5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1999m6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1999m7 | 0 | 0 | 0 | 4 | 0 | 1 | 7 | 13 |
| 1999m8 | 5 | 9 | 39 | 77 | 6 | 9 | 72 | 335 |
| 1999m9 | 8 | 2 | 52 | 85 | 4 | 11 | 70 | 366 |
| 1999m10 | 4 | 4 | 36 | 77 | 3 | 9 | 72 | 352 |
| 1999m11 | 12 | 3 | 39 | 70 | 5 | 10 | 77 | 370 |
| 1999m12 | 6 | 2 | 40 | 69 | 2 | 5 | 79 | 397 |
| 2000m1 | 6 | 2 | 28 | 47 | 1 | 5 | 51 | 257 |
| 2000m2 | 8 | 1 | 37 | 101 | 2 | 8 | 78 | 400 |
| 2000m3 | 4 | 5 | 36 | 103 | 6 | 11 | 103 | 423 |
| 2000m4 | 11 | 5 | 60 | 112 | 1 | 20 | 117 | 484 |
| 2000m5 | 17 | 13 | 67 | 126 | 2 | 35 | 120 | 532 |
| 2000m6 | 9 | 8 | 66 | 118 | 5 | 31 | 111 | 548 |
| 2000m7 | 11 | 11 | 67 | 136 | 5 | 19 | 99 | 567 |
| 2000m8 | 28 | 6 | 41 | 99 | 5 | 21 | 83 | 440 |
| 2000m9 | 39 | 4 | 65 | 123 | 5 | 19 | 116 | 534 |
| 2000m10 | 54 | 6 | 95 | 184 | 9 | 47 | 159 | 738 |
| 2000m11 | 50 | 5 | 91 | 154 | 7 | 29 | 144 | 722 |
| 2000m12 | 48 | 3 | 87 | 126 | 3 | 31 | 126 | 679 |
| 2001m1 | 74 | 4 | 103 | 191 | 7 | 39 | 162 | 788 |
| 2001m2 | 58 | 2 | 87 | 205 | 5 | 35 | 156 | 709 |
| 2001m3 | 73 | 3 | 82 | 172 | 9 | 40 | 148 | 751 |
| 2001m4 | 66 | 6 | 80 | 160 | 11 | 43 | 163 | 786 |
| 2001m5 | 69 | 7 | 87 | 131 | 6 | 37 | 161 | 828 |
| 2001m6 | 71 | 2 | 59 | 97 | 8 | 39 | 141 | 731 |
| 2001m7 | 69 | 8 | 64 | 103 | 4 | 56 | 155 | 788 |
| 2001m8 | 93 | 2 | 83 | 121 | 17 | 55 | 187 | 876 |
| 2001m9 | 54 | 5 | 61 | 80 | 7 | 33 | 121 | 617 |
| 2001m10 | 92 | 3 | 80 | 114 | 9 | 31 | 161 | 762 |
| 2001m11 | 66 | 8 | 72 | 99 | 7 | 32 | 134 | 748 |
| 2001m12 | 72 | 4 | 63 | 97 | 9 | 45 | 129 | 725 |
| 2002m1 | 83 | 8 | 103 | 135 | 13 | 63 | 173 | 879 |
| 2002m2 | 68 | 2 | 94 | 117 | 10 | 66 | 167 | 754 |
| 2002m3 | 55 | 4 | 66 | 91 | 10 | 46 | 164 | 642 |
| 2002m4 | 55 | 9 | 72 | 114 | 8 | 45 | 174 | 778 |
| 2002m5 | 57 | 9 | 91 | 122 | 10 | 61 | 194 | 826 |
| 2002m6 | 59 | 9 | 99 | 130 | 12 | 59 | 178 | 963 |
| 2002m7 | 42 | 10 | 73 | 98 | 5 | 42 | 121 | 716 |
| 2002m8 | 53 | 5 | 72 | 85 | 6 | 49 | 133 | 726 |
| 2002m9 | 32 | 2 | 59 | 71 | 14 | 32 | 101 | 636 |
| 2002m10 | 45 | 9 | 76 | 88 | 10 | 53 | 91 | 746 |
| 2002m11 | 38 | 6 | 76 | 74 | 11 | 35 | 88 | 598 |
| 2002m12 | 21 | 7 | 51 | 69 | 10 | 23 | 81 | 492 |
| 2003m1 | 50 | 8 | 71 | 91 | 15 | 33 | 111 | 815 |
| 2003m2 | 59 | 7 | 59 | 73 | 8 | 38 | 115 | 692 |
| 2003m3 | 52 | 13 | 62 | 73 | 13 | 36 | 117 | 872 |
| 2003m4 | 55 | 4 | 34 | 73 | 12 | 44 | 109 | 660 |
| 2003m5 | 45 | 7 | 70 | 73 | 11 | 40 | 117 | 709 |
| 2003m6 | 48 | 5 | 65 | 86 | 9 | 39 | 112 | 722 |
| 2003m7 | 47 | 2 | 54 | 77 | 13 | 47 | 101 | 780 |
| 2003m8 | 45 | 3 | 56 | 70 | 16 | 37 | 86 | 716 |
| 2003m9 | 43 | 5 | 60 | 75 | 10 | 32 | 103 | 719 |
| 2003m10 | 45 | 4 | 62 | 78 | 6 | 42 | 113 | 698 |
| 2003m11 | 44 | 3 | 52 | 84 | 10 | 42 | 111 | 676 |
| 2003m12 | 44 | 5 | 59 | 74 | 5 | 38 | 118 | 736 |
| 2004m1 | 50 | 3 | 55 | 66 | 5 | 30 | 109 | 659 |
| 2004m2 | 48 | 2 | 50 | 74 | 8 | 56 | 107 | 647 |
| 2004m3 | 48 | 4 | 31 | 84 | 8 | 47 | 103 | 641 |
| 2004m4 | 24 | 3 | 30 | 66 | 2 | 18 | 63 | 589 |
| 2004m5 | 75 | 4 | 57 | 99 | 11 | 51 | 147 | 782 |
| 2004m6 | 50 | 10 | 72 | 87 | 6 | 58 | 127 | 750 |
| 2004m7 | 31 | 4 | 54 | 74 | 8 | 57 | 105 | 666 |
| 2004m8 | 24 | 3 | 68 | 55 | 9 | 41 | 97 | 623 |
| 2004m9 | 23 | 0 | 57 | 41 | 10 | 36 | 83 | 567 |
| 2004m10 | 39 | 7 | 56 | 59 | 5 | 41 | 94 | 605 |
| 2004m11 | 39 | 4 | 66 | 66 | 3 | 41 | 97 | 628 |
| 2004m12 | 36 | 2 | 62 | 62 | 3 | 43 | 82 | 530 |
| 2005m1 | 39 | 3 | 64 | 73 | 5 | 48 | 122 | 640 |
| 2005m2 | 51 | 9 | 76 | 64 | 5 | 66 | 119 | 657 |
| 2005m3 | 33 | 1 | 73 | 73 | 9 | 59 | 116 | 693 |
| 2005m4 | 33 | 3 | 61 | 68 | 7 | 56 | 105 | 636 |
| 2005m5 | 44 | 3 | 38 | 85 | 8 | 59 | 109 | 598 |
| 2005m6 | 36 | 6 | 64 | 80 | 11 | 51 | 106 | 633 |
| 2005m7 | 46 | 3 | 76 | 80 | 5 | 64 | 114 | 652 |
| 2005m8 | 31 | 2 | 52 | 63 | 7 | 32 | 105 | 588 |
| 2005m9 | 28 | 1 | 47 | 68 | 11 | 32 | 98 | 581 |
| 2005m10 | 22 | 1 | 58 | 78 | 8 | 53 | 96 | 559 |
| 2005m11 | 26 | 3 | 45 | 78 | 4 | 63 | 105 | 561 |
| 2005m12 | 28 | 2 | 45 | 59 | 7 | 40 | 101 | 562 |
| 2006m1 | 22 | 1 | 31 | 50 | 7 | 36 | 96 | 569 |
| 2006m2 | 28 | 6 | 44 | 57 | 4 | 50 | 95 | 565 |
| 2006m3 | 20 | 1 | 51 | 69 | 9 | 32 | 112 | 658 |
| 2006m4 | 19 | 2 | 38 | 57 | 8 | 37 | 101 | 576 |
| 2006m5 | 17 | 0 | 55 | 81 | 14 | 41 | 124 | 644 |
| 2006m6 | 10 | 1 | 44 | 57 | 9 | 29 | 100 | 590 |
| 2006m7 | 14 | 6 | 47 | 59 | 9 | 28 | 104 | 664 |
| 2006m8 | 13 | 1 | 32 | 56 | 10 | 26 | 97 | 621 |
| 2006m9 | 18 | 1 | 35 | 49 | 9 | 35 | 113 | 604 |
| 2006m10 | 15 | 6 | 36 | 57 | 3 | 30 | 99 | 587 |
| 2006m11 | 14 | 2 | 49 | 57 | 10 | 21 | 95 | 565 |
| 2006m12 | 10 | 4 | 35 | 52 | 3 | 18 | 91 | 561 |
| 2007m1 | 12 | 3 | 41 | 68 | 3 | 26 | 106 | 595 |
| 2007m2 | 11 | 4 | 48 | 47 | 4 | 16 | 91 | 549 |
| 2007m3 | 15 | 4 | 43 | 63 | 4 | 28 | 114 | 622 |
| 2007m4 | 8 | 2 | 30 | 40 | 8 | 12 | 89 | 557 |
| 2007m5 | 12 | 6 | 42 | 62 | 14 | 19 | 132 | 735 |
| 2007m6 | 11 | 4 | 38 | 48 | 11 | 12 | 87 | 605 |
| 2007m7 | 8 | 2 | 28 | 70 | 13 | 18 | 88 | 646 |
| 2007m8 | 11 | 1 | 38 | 49 | 7 | 13 | 82 | 560 |
| 2007m9 | 16 | 5 | 45 | 52 | 11 | 13 | 94 | 627 |
| 2007m10 | 20 | 8 | 46 | 59 | 5 | 18 | 111 | 621 |
| 2007m11 | 11 | 5 | 35 | 39 | 9 | 7 | 85 | 577 |
| 2007m12 | 16 | 1 | 37 | 50 | 10 | 8 | 98 | 574 |
| 2008m1 | 14 | 4 | 36 | 57 | 9 | 10 | 99 | 619 |
| 2008m2 | 15 | 2 | 36 | 49 | 11 | 18 | 111 | 604 |
| 2008m3 | 20 | 3 | 37 | 40 | 8 | 12 | 110 | 585 |
| 2008m4 | 14 | 4 | 51 | 51 | 11 | 24 | 122 | 664 |
| 2008m5 | 13 | 6 | 41 | 50 | 10 | 25 | 120 | 674 |
| 2008m6 | 17 | 2 | 46 | 41 | 10 | 16 | 107 | 624 |
| 2008m7 | 17 | 6 | 40 | 48 | 8 | 18 | 121 | 642 |
| 2008m8 | 12 | 6 | 36 | 41 | 5 | 9 | 105 | 648 |
| 2008m9 | 6 | 1 | 31 | 35 | 5 | 7 | 89 | 581 |
| 2008m10 | 19 | 1 | 42 | 46 | 12 | 16 | 111 | 637 |
| 2008m11 | 15 | 4 | 32 | 35 | 3 | 7 | 102 | 567 |
| 2008m12 | 17 | 3 | 29 | 33 | 5 | 8 | 89 | 527 |
| 2009m1 | 13 | 1 | 22 | 26 | 8 | 4 | 88 | 525 |

*Quarterly data*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| qdate | amp | bar | opi | benz | alcohol | coc | mari | count |
| 1999q1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1999q2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| 1999q3 | 13 | 11 | 91 | 166 | 10 | 21 | 149 | 714 |
| 1999q4 | 22 | 9 | 115 | 216 | 10 | 24 | 228 | 1119 |
| 2000q1 | 18 | 8 | 101 | 251 | 9 | 24 | 232 | 1080 |
| 2000q2 | 37 | 26 | 193 | 356 | 8 | 86 | 348 | 1564 |
| 2000q3 | 78 | 21 | 173 | 358 | 15 | 59 | 298 | 1541 |
| 2000q4 | 152 | 14 | 273 | 464 | 19 | 107 | 429 | 2139 |
| 2001q1 | 205 | 9 | 272 | 568 | 21 | 114 | 466 | 2248 |
| 2001q2 | 206 | 15 | 226 | 388 | 25 | 119 | 465 | 2345 |
| 2001q3 | 216 | 15 | 208 | 304 | 28 | 144 | 463 | 2281 |
| 2001q4 | 230 | 15 | 215 | 310 | 25 | 108 | 424 | 2235 |
| 2002q1 | 206 | 14 | 263 | 343 | 33 | 175 | 504 | 2275 |
| 2002q2 | 171 | 27 | 262 | 366 | 30 | 165 | 546 | 2567 |
| 2002q3 | 127 | 17 | 204 | 254 | 25 | 123 | 355 | 2078 |
| 2002q4 | 104 | 22 | 203 | 231 | 31 | 111 | 260 | 1836 |
| 2003q1 | 161 | 28 | 192 | 237 | 36 | 107 | 343 | 2379 |
| 2003q2 | 148 | 16 | 169 | 232 | 32 | 123 | 338 | 2091 |
| 2003q3 | 135 | 10 | 170 | 222 | 39 | 116 | 290 | 2215 |
| 2003q4 | 133 | 12 | 173 | 236 | 21 | 122 | 342 | 2110 |
| 2004q1 | 146 | 9 | 136 | 224 | 21 | 133 | 319 | 1947 |
| 2004q2 | 149 | 17 | 159 | 252 | 19 | 127 | 337 | 2121 |
| 2004q3 | 78 | 7 | 179 | 170 | 27 | 134 | 285 | 1856 |
| 2004q4 | 114 | 13 | 184 | 187 | 11 | 125 | 273 | 1763 |
| 2005q1 | 123 | 13 | 213 | 210 | 19 | 173 | 357 | 1990 |
| 2005q2 | 113 | 12 | 163 | 233 | 26 | 166 | 320 | 1867 |
| 2005q3 | 105 | 6 | 175 | 211 | 23 | 128 | 317 | 1821 |
| 2005q4 | 76 | 6 | 148 | 215 | 19 | 156 | 302 | 1682 |
| 2006q1 | 70 | 8 | 126 | 176 | 20 | 118 | 303 | 1792 |
| 2006q2 | 46 | 3 | 137 | 195 | 31 | 107 | 325 | 1810 |
| 2006q3 | 45 | 8 | 114 | 164 | 28 | 89 | 314 | 1889 |
| 2006q4 | 39 | 12 | 120 | 166 | 16 | 69 | 285 | 1713 |
| 2007q1 | 38 | 11 | 132 | 178 | 11 | 70 | 311 | 1766 |
| 2007q2 | 31 | 12 | 110 | 150 | 33 | 43 | 308 | 1897 |
| 2007q3 | 35 | 8 | 111 | 171 | 31 | 44 | 264 | 1833 |
| 2007q4 | 47 | 14 | 118 | 148 | 24 | 33 | 294 | 1772 |
| 2008q1 | 49 | 9 | 109 | 146 | 28 | 40 | 320 | 1808 |
| 2008q2 | 44 | 12 | 138 | 142 | 31 | 65 | 349 | 1962 |
| 2008q3 | 35 | 13 | 107 | 124 | 18 | 34 | 315 | 1871 |
| 2008q4 | 51 | 8 | 103 | 114 | 20 | 31 | 302 | 1731 |
| 2009q1 | 13 | 1 | 22 | 26 | 8 | 4 | 88 | 525 |

1. Price and purity of illegal drugs technical report. [↑](#footnote-ref-1)
2. Empirically, estimating the conventional or myopic model when the rational model is the true model results in biased/inconsistent estimates because the empirical demand equation is underspecified. Estimating the rational model when the true model is the conventional or myopic model leads to unbiased but inefficient estimates because the structural demand equation is overspecified. [↑](#footnote-ref-2)
3. Quadratic utility produces monotonic demand functions. [↑](#footnote-ref-3)
4. Non-intoxicating consumer goods that are traditionally believed to be addictive are television, video games, junk food, and certain kinds of music. Becker and Murphy (1988) make the remark harmful and beneficial goods may exhibit addictive properties. Beneficial goods such as running and religion may exhibit addictive properties according to Becker and Murphy. Classification of whether addictive consumption is bad or good is likely a question of prudence as too much of some beneficial goods, for example running, swimming, working, or exercise, may lead to harmful consequences. [↑](#footnote-ref-4)
5. It is assumed that marginal utility is diminishing in income and in consumption of the composite good. [↑](#footnote-ref-5)
6. Most empirical evidence shows cigarettes to be normal goods with the exception of Dorsett (1999). [↑](#footnote-ref-6)
7. A statistic is considered to be statistically significant at a critical level of 5%. [↑](#footnote-ref-7)
8. None of the income effects for marijuana are significant in any of the model specifications for participation in the past month and income effects are significant for only one model specification for participation in the past year. Income effects for cocaine are marginally significant at p≤0.15 for cocaine. Heroin shows the most statistically significant negative income effects for participation in the past month with a low *z*-score of -1.54. Marijuana prices were excluded from the final reported results. [↑](#footnote-ref-8)
9. Income effects for participation in the past year are more significant than effects for the past month in all model specifications. [↑](#footnote-ref-9)
10. Saffer and Chaloupka (1999) utilize DEA STRIDE EPH prices for cocaine and heroin and marijuana prices from the DEA’s *Domestic Cities Report.* They report unstable coefficients in model specifications that include marijuana prices. [↑](#footnote-ref-10)
11. Model coefficients are estimated with unweighted data. It is not possible to verify elasticity calculations as only weighted means are reported in the paper. All models use probit estimation, where calculation of the elasticity requires the unweighted mean to calculate the marginal effects. [↑](#footnote-ref-11)
12. Rational addiction predicts long-run price elasticities that are larger than short run elasticities. The results for cocaine are consistent with rational addiction; the results for heroin are inconsistent. [↑](#footnote-ref-12)
13. The level of significance used by the authors is the five 5% level. [↑](#footnote-ref-13)
14. An email to the authors was kindly returned explaining the original data are no longer available. [↑](#footnote-ref-14)
15. Marital status is 1 if married, 0 otherwise. A separate indicator variable for missing marital status is included, 1 if marital status is missing, 0 otherwise. The estimated coefficient on the marital status variable is negative and statistically significant. [↑](#footnote-ref-15)
16. Unlike marijuana, cocaine, and heroin alcohol use is measured by number of days used in the past month. [↑](#footnote-ref-16)
17. Marijuana decriminalization is defined as the elimination of incarceration for possession of consumer quantities of marijuana. [↑](#footnote-ref-17)
18. Alcohol consumption is measured by the number of days used in the past month. [↑](#footnote-ref-18)
19. The marginal effect of the probit model is **β** where (.) is the probability density function of the standard normal distribution, and the values of the vector of explanatory variables *x* are the mean values. Participation elasticity is calculated as where is mean price and is mean participation where 0≤≤1. [↑](#footnote-ref-19)
20. In the case of increasing relative drug supply or declining relative drug demand the coefficients on cocaine price will exhibit an upward bias. Times series prices from STRIDE data show the real average price of cocaine in 2007 dollars increased from a real price of $310.88 in 1988 to $342.545 in 1990 and then declined to$297.37 in 1991. Monthly cocaine participation from the national household survey of drug abuse for 1988, 1990 and 1991 was 1.9%, 1.4% and 1.5% respectively. Yearly cocaine participation for years 1988, 1990 and 1991 was 5.1%, 4.8%, and 3.9%. The fall in price and participation is evidence of declining demand over the 1988 to 1991 period. [↑](#footnote-ref-20)
21. The alcohol t-statistics for the model specifications for which they are included are (2.70) and (1.91) for monthly participation and (2.69) and (1.56) for yearly participation. [↑](#footnote-ref-21)
22. From the monthly participation specifications none of the income coefficients are statistically significant at the 5% level. One coefficient from the yearly participation coefficients is statistically significant at the 5% level. [↑](#footnote-ref-22)
23. Roddy et. al reports the participant characteristics as active heroin consumption for an average of 23 years. [↑](#footnote-ref-23)
24. The measures they use are unit purchase, heroin expenses ÷ income, purchases/week, and consumption. [↑](#footnote-ref-24)
25. From the theoretical derivation the myopic model coefficient on Ct-1,α1 is greater than the analogous coefficient θ from the rational model. Where, , [↑](#footnote-ref-25)
26. Estimating the myopic model when consumers are aware that a good is addictive assumes the consumer is entirely backward looking despite knowledge that the substance is addictive. This is not consistent with reports from most studies of behavior on addiction. Assuming the myopic model when a consumer is aware that a good is addictive implies the consumer in the model is aware of addition but does not take action to mitigate the capital stock of addiction. [↑](#footnote-ref-26)
27. These are sometimes referred to as “hang over effects” in the literature. [↑](#footnote-ref-27)
28. The theoretical implications are explored by Pollak, who describes utility models dependent on previous consumption but nonincreasing in previous consumption. Such utility models can be described by a log transformation of a linear utility model with a regularity condition. For example Such utility functions are from the “modified Bergson family” of utility functions. (Pollak 1977) [↑](#footnote-ref-28)
29. Dorsett argues that the coefficient of lagged interaction between smoking and age (smoking\*age) is a measure of the independent effect of the capital stock of addictive consumption and works counter to the effect of age alone as the body is more prone to addiction as it ages, captured by the coefficient of the age measure in his equation. [↑](#footnote-ref-29)
30. Dorsett’s report of an estimated income elasticity of -0.04 is low compared to other estimates of income elasticity and tobacco. Becker et al., and Feijun Luo et. al report positive myopic model estimations of income elasticity for tobacco. The sample cohort demographics considered by Dorsett are different from the cohort demographics of Becker et. al and Feijun Luo et. al. Dorsett considers single mothers while Becker et. al and Feijun Luo et. al. consider the population. [↑](#footnote-ref-30)
31. See Auld and Grootendorst (2004). [↑](#footnote-ref-31)
32. , 0r<1. [↑](#footnote-ref-32)
33. The theory of rational addiction predicts the short-run elasticity<long-run elasticity for the addictive good. The short-run elasticity from equation (19) is , and the long-run elasticity, . [↑](#footnote-ref-33)
34. It is important to note that whether an addiction is beneficial or detrimental is determined by the full effect of consumption on lifetime earrings. It is possible that consumption of a beneficial good in the short-run may lower current earnings but raise them in the long-run or consumption of a harmful good may raise short-run earnings but lower lifetime earnings, for example, cigarette consumption may temporarily make teens more popular but long-term consumption of tobacco lowers productivity. [↑](#footnote-ref-34)
35. Ryder and Heal (1973) first explore the concept of adjacent complementarity. Adjacent complementarity of consumption in financial markets has been proposed as a possible explanation for the equity premium puzzle. See Ryder and Heal (1973), Mehra-Presscott(1985), and Constantinides (1990). [↑](#footnote-ref-35)
36. Becker and Murphy note alcohol to be an exception as the distribution of alcohol consumption is more normal among consumers, ranging from zero to heavy use. Goods such as tobacco, crack cocaine and heroin have more bimodal distribution with clustering either at zero or heavy use. Whether consumption itself is rationally addictive and exhibits adjacent complementarity may explain business cycle fluctuations. [↑](#footnote-ref-36)
37. The included exogenous regressors (Z) for different specifications of equation (24) are religious affliation, taxation, divorce, unemployment, and smuggling distance. ldtax, sdtimp, sdtexp, hs, divorce, Mormon, Catholic, sobapt, unemp. [↑](#footnote-ref-37)
38. This approach is criticized by Auld , M. Christopher & Grootendorst, Paul, 2004. [↑](#footnote-ref-38)
39. Becker and Murphy assume consumers have perfect foresight in their 1994 paper. [↑](#footnote-ref-39)
40. The full list of instruments for Becker, Murphy and Grossman are: Forward and past price, state and year indicator variables, long-distance smuggling incentives, short-distance smuggling incentives across state lines, short-distance smuggling incentives within state lines, state and local excise taxes, leads and lags of taxes. [↑](#footnote-ref-40)
41. Although Chaloupka (1991) is an earlier estimate of the rational addiction model than Becker, Grossman, and Murphy (1994), BGM(1994) is the published version of BGM (1990) working paper. [↑](#footnote-ref-41)
42. Price elasticities for years 1980-1990 for the Poisson and rational addiction models are statistically significant at the 1% level. None of the myopic model elasticities for years 1980-1990 are statistically significant. [↑](#footnote-ref-42)
43. The author’s remark most empirical estimations up to the time of publication on income effects indicate that tobacco is a normal good with some evidence of negative income elasticity after the surgeon general’s warning of the health consequence of tobacco consumption. [↑](#footnote-ref-43)
44. The measures of legal drinking age are the same as those in Grossman, Chaloupka and Sirtalan (1998). The measures are (legal drinking \*age ≤ 21 and lower border drinking age indicator\* age ≤ 21. [↑](#footnote-ref-44)
45. Use of the phrase “rich enough” by the authors likely refers to the weights placed on the consumption of the addictive good by the consumer. [↑](#footnote-ref-45)
46. An email to the authors was kindly returned explaining a computer search for the original data turned up no results. [↑](#footnote-ref-46)
47. Price is not included in one of the log consumption estimations. [↑](#footnote-ref-47)
48. Consequences for failing a drug screen include loss of take home medication privileges, increased monetary costs for treatment, increased monetary costs for drug screens, suspension from treatment, discharge from treatment and increased costs due to counselor intervention meetings. [↑](#footnote-ref-48)