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Bayesian Inference for the Distribution of Grams of Marijuana in a Joint

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ABSTRACT. As debates about marijuana legalization intensify in the United States and abroad, there is increased focus on creating credible measures of marijuana consumption. This information is not only important for projecting tax revenues and implications for drug trafficking organizations, but knowing how much marijuana users are consuming is useful for understanding health and other behavioral consequences. This paper advances the methodology for estimating marijuana consumption by using a large dataset of over 10,000 marijuana transactions spanning 11 years and 43 communities, adapting the Brown-Silverman drug pricing model to these data, and conducting a non-parametric Bayesian analysis to flexibly synthesize marijuana price and weight data.

1. Introduction

Estimating how much marijuana is in the average joint may initially appear to be an amusing, even recreational, activity. However, knowing the average weight of a joint turns out to be a key factor in major drug policy debates that are active today. A handful of states have legalized marijuana production and possession and several other jurisdictions are actively debating legalization. Some of the arguments cited in favor of legalization include an increase in tax revenue derived from legal marijuana sales and the reduction of revenues to drug trafficking organizations. The average weight of a joint turns out to

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be an important factor in assessing the latter two issues. Official government estimates of drug usage and expenditures hinge on having a good estimate of the average weight of marijuana in a joint (Office of National Drug Control Policy, 2014).

We actually have little information on how much marijuana an average user consumes and, therefore, projecting how much revenue can be diverted from Mexican drug trafficking organizations and how much revenue might flow into state coffers post-legalization turns out to be challenging. While there are multiple ways to consume marijuana, joints continue to be a common method for consuming marijuana. Schauer et al. (2016) found in a nationally representative consumer panel that for half of marijuana users who responded joints were the preferred method of marijuana use and 89% of respondents reported having smoked a joint at some in their lives. Some sources for understanding drug use ask about the number of joints smoked rather than weight of loose marijuana. Therefore, in order to obtain good estimates of the quantity of marijuana consumed we need to know how much marijuana is in those joints on average. Perhaps as important as the point estimate for the average weight, a good understanding of the uncertainty around the estimate can prevent policymakers from placing too much confidence in their projections.

A number of studies reported that the typical weight of a marijuana joint ranges from 0.3 to 0.5 grams (Kilmer and Pacula, 2009). Using self-report purchase data from arrestees who purchased either 1 gram or 1 joint of marijuana between 2000–2003, Kilmer et al. (2010) estimate that the average weight of a joint was 0.46 grams (95% CI: 0.43, 0.50). Mariani et al. (2011) had marijuana users measure out an amount of oregano comparable to what they would ordinarily consume and estimated that joints average 0.66 grams of marijuana (with a standard deviation of 0.45g!), but the relative density of oregano to marijuana is unknown. Many discussions among users in online forums frequently cite figures between 0.5 and 1.0 grams per joint. Gettman (2015) suggests that 0.75 grams is the norm and his informal web survey of *High Times* readers indicated that 80% believed that their joints were between 0.5 and 1.0 grams. For comparison, the typical cigarette has about 1 gram of tobacco.

Kilmer et al. (2010) note a few reasons why their estimate of 0.46 grams may have been an overestimate. First, drug dealers tend to be on the light side when selling "one gram" so a reported purchase of one gram was likely a bit less than one gram. However, we have no data to verify this or understand the distribution of weight of "one gram" of marijuana. Second, the price per gram for a transaction in grams is estimated at a (marginally) higher "market level" than is the price per gram for a single joint. Price as a function of weight is often modeled as a power function so that the price per gram will tend to be lower for larger quantities (Brown and Silverman, 1974; Caulkins and Padman, 1993). The Kilmer et al. (2010) analysis did not use the power function, but we remedy that in this paper with a richer model that allows for volume discounting.

In this paper we take advantage of a high quality dataset on information collected from arrestees as part of a US Department of Justice initiative that tracked trends in illegal drug markets. Conveniently, arrestees are asked how much they paid for their drugs and what they purchased. Some arrestees report the weight of loose marijuana purchased and the purchase price, while other arrestees report the number of joints purchased and the purchase price. We use a Bayesian model to infer the average weight of a joint by modeling marijuana prices, accounting for variation in price by location and time, and using those prices effectively to impute the unobserved joint weights.

2. Data, Methods, and Results

This section provides an introduction to the data, a description of our model, and our estimates of the average weight of marijuana in a joint.

2.1. **ADAM - Arrestee Drug Abuse Monitoring.** The Arrestee Drug Abuse Monitoring (ADAM) Program is a jail-based interview that asks arrestees about their substance use, drug market transactions, and additional information such as their treatment experiences, employment status, and housing stability. The information is only used for research purposes and results are not shared with law enforcement officials. At the end of the interview arrestees are asked to take a urinalysis test. The program was formerly known as Drug Use Forecasting and was converted to the probability-based ADAM in 2000 when attempts were made to obtain representative samples of male arrestees (not just those arrested for drug offenses). In the early 2000s ADAM was operational in over 35 counties with more than 20,000 arrestees agreeing to participate each year (U.S. Dept. of Justice, National Institute of Justice, 2002). Funding for the program was eliminated beginning in 2004 and a smaller version of the program (ADAM II) was resuscitated in 2007 with only 10 counties exclusively focused on adult males. By 2011 ADAM II had shrunk to five counties and after 2013 was eliminated, again (Kilmer and Caulkins, 2014).

Our analysis is based on a subset of ADAM data consisting of reported marijuana price and quantity from 24,910 arrestees between 2000-2003 and 2007-2010 in a total of 43 counties (but only 10 counties participated in all 8 years). Arrestees reported marijuana in terms of grams or ounces, but also in terms of the number of bags, blunts, or joints. For this study we used data only on marijuana measured in grams ($n = 5,845$), ounces ($n = 8,027$), or joints ($n = 2,230$). We converted all ounce measurements to grams.

Of those cases, 4 were missing measurements of weight or quantity, 21 were missing price, and 1 had price given as \$0. We eliminated these cases from the dataset.

We further narrowed the dataset to focus only on those drug quantities most relevant for learning about the amount of marijuana in a joint. Quantities of a half kilogram of marijuana or 50 joints and their associated prices are more likely to have been procured from a distributor rather than a retail sale. If we include them, then our analysis would lean more heavily on parametric assumptions and risk greater bias. Therefore, we focused the dataset on quantities of less than 10 grams of marijuana (64% of loose marijuana quantities) and less than 10 joints (98% of quantities of joints). The final dataset included price data and weight data on 8,561 reports of loose marijuana and 2,136 reports of joints.

For loose marijuana, the recorded price per gram varied between \$0.14 and \$1,200 with a median price of \$7.05. A price of \$1,200 for a gram of marijuana is simply not credible. In fact, prices in excess of \$40 for a gram are highly suspicious, likely the result of errors in the data collection or data entry. As a result we dropped cases less than \$1.25 per gram (the smallest 1%) or greater than \$40 per gram (the largest 3%), eliminating 315 cases from the dataset. The resulting median price per gram remained \$7.05 with 80% of the values falling between \$2.82 and \$20 per gram.

The recorded prices per joint ranged from \$0.25 to \$525 with a median price of \$3.33. Again errors in data collection or data entry are likely responsible for values like \$525. We dropped 32 cases with prices per joint less than \$1 (1% of cases) or greater than \$20 per joint (0.5% of cases). The resulting median price per joint remained \$3.33 with 80% of the values falling between \$1.67 and \$10.

We can use these figures to obtain an estimate of the average weight of a joint. Since the average price per gram in our dataset is \$6.81 and the average price of a joint is \$3.50, then we should expect the average weight of a joint to be $3.50/6.81 = 0.51$ grams. This simple estimate does not account for several key issues including variation in the price by location, variation in price across years, and volume discounting. In fact, the Bayesian analysis described next has 0.51 falling well outside the 95% posterior interval, indicating that properly accounting for time, place, and quantity discounting impacts the estimate. Again it is plausible that dealers are selling "grams" that are actually less than one gram. If this is the case then the estimated price per gram is too small and, therefore, the grams per joint estimate is too large.

Table 1 shows a summary of the number of arrestees in our ADAM dataset with complete weight and price data from quantities of less than 10 grams and less than 10 joints and without suspiciously large or small prices.

2.2. **A Bayesian model for marijuana weight.** We first consider the data on arrestees reporting loose marijuana transactions. Let p_{ijk} be the price paid

Table 1. Number of marijuana arrestees in the ADAM data by year by location

	2000	2001	2002	2003	2007	2008	2009	2010	Total
Sacramento	83	134	132	110	59	63	64	95	740
Indianapolis	76	117	102	81	58	51	71	77	633
Portland	85	116	92	70	55	50	58	58	584
Denver	75	86	86	60	48	57	77	86	575
Seattle	164	130	150	108	0	0	0	0	552
Minneapolis	62	96	109	72	45	42	43	79	548
Phoenix	135	158	125	91	0	0	0	0	509
San Jose	94	133	108	90	0	0	0	0	425
Cleveland	135	85	127	72	0	0	0	0	419
Las Vegas	89	110	90	94	0	0	0	0	383
Atlanta	32	0	50	102	34	41	66	51	376
Anchorage	105	98	88	72	0	0	0	0	363
Spokane	84	81	108	56	0	0	0	0	329
Charlotte	6	37	45	44	56	31	34	66	319
Chicago	10	12	80	44	46	38	34	51	315
Omaha	58	66	84	86	0	0	0	0	294
Oklahoma City	76	72	72	59	0	0	0	0	279
San Diego	52	67	64	82	0	0	0	0	265
Albany	32	62	75	62	0	0	0	0	231
Salt Lake City	61	49	65	52	0	0	0	0	227
Dallas	31	10	73	94	0	0	0	0	208
Honolulu	52	57	58	34	0	0	0	0	201
Des Moines	45	51	48	52	0	0	0	0	196
New York City[1]	13	12	27	21	16	23	32	49	193
Tucson	57	58	47	25	0	0	0	0	187
Tulsa	0	15	62	88	0	0	0	0	165
San Antonio	31	36	50	47	0	0	0	0	164
Birmingham	24	20	30	52	0	0	0	0	126
Detroit	79	43	0	0	0	0	0	0	122
Albuquerque	19	44	24	28	0	0	0	0	115
New Orleans	25	35	23	14	0	0	0	0	97
Tampa	0	0	0	91	0	0	0	0	91
Philadelphia	11	23	17	31	0	0	0	0	82
Washington DC	0	0	10	23	7	1	2	6	49
Miami	27	0	0	22	0	0	0	0	49
Houston	42	0	0	6	0	0	0	0	48
Los Angeles	0	0	10	25	0	0	0	0	35
Fort Lauderdale	28	0	0	0	0	0	0	0	28
Jackson County MO	0	28	0	0	0	0	0	0	28
Laredo	10	9	6	0	0	0	0	0	25
Boston	0	0	0	21	0	0	0	0	21
Woodbury County IA	0	0	11	7	0	0	0	0	18
Rio Arriba NM	0	0	4	10	0	0	0	0	14
Total	2008	2150	2352	2198	424	397	481	618	10628

Note: Two ADAM sites (St. Louis and Elkhart County, IN) had no marijuana arrests reported in the ADAM data

[1] New York City data come only from the borough of Manhattan

for marijuana weighing w_{ijk} grams as reported by arrestee i in city j in year k. Price as a function of weight is commonly modeled with the Brown-Silverman drug pricing model, by a power relationship of the form

$$p_{jk} = e^{\beta_j} e^{\alpha_k} w_{ijk}^{\gamma} \tag{1}$$

where β_j and α_k are location and year factors respectively that scale the price for regional variation and inflation (Brown and Silverman, 1974; Caulkins and Padman, 1993; Kilmer et al., 2010). Caulkins and Padman (1993) found that this model provided a reasonable fit to a variety of drug market transactions. The exponent γ accommodates volume discounting; a doubling of the weight would mean the price would not necessarily double, but would go up 2^γ times. Caulkins and Padman (1993) estimated γ to be around 0.7 for marijuana and that a constant γ across a range of quantities fit reasonably well.

Since price distributions tend to be skewed we modeled p_{ijk} using a log-normal distribution with a mean depending on the location and year.

$$\log(p_{ijk}) \sim N(\beta_j + \alpha_k + \gamma \log(w_{ijk}), \sigma^2) \tag{2}$$

Estimating these parameters is straightforward as this is a standard log-normal regression model. However, some of the locations have few observations resulting in highly uncertain estimates of β_j. To stabilize these values but still allow for flexibility in their distribution, we took a non-parametric Bayesian approach and put a Dirichlet process prior (Müller and Mitra, 2013) on the β_js, $\beta_j \sim DP(\mathbf{1}, N(1.5, 4))$, to shrink the β_js toward each other. We centered this prior on a normal with mean 1.5 to suggest that 1 gram in the year

2000 would cost about \$4.50. However, with a prior variance of 4.0 and a flat Dirichlet process, this prior is fairly uninformative.

Once we establish the relationship between price and weight as in (1), this imposes a relationship on the price of joints. The distribution of the price paid by arrestee i in location j in year k for n_{ijk} joints is

$$\log(p_{ijk}) \sim N(\beta_j + \alpha_k + \gamma \log(w_{ijk} n_{ijk}), \sigma^2) \tag{3}$$

The difference between (3) and (1) is that in (3) the w_{ijk} are the unobserved weight per joint and we include the number of joints purchased, n_{ijk}. Since the price per gram data are informative for estimating α, β, γ, and σ^2, the extra variation around the observed joint prices provides information for inferring the ws, from which we can infer their distribution.

Besides expecting the vast majority of joints to weigh well less than 2 grams, we have no preconceived idea about the distribution of the weight per joint, w_{ijk}. Therefore, we considered three forms for the distribution of weight per joint, a normal, a mixture of two normals, and a non-parametric distribution implemented with a Dirichlet process allowing for substantial flexibility. The Dirichlet process prior was

$$w_{ijk} \sim DP(\mathbf{1}, \text{LogNormal}(\log(0.4), 0.25)). \tag{4}$$

This distributional prior is centered on a log-normal distribution that puts 95% of its mass between 0.15 and 1.07 with a mean of 0.45.

We used uninformative priors for the remaining model parameters: $N(0, 1000)$ for the α_k (with the exception of α_1 which was fixed at 0), a $U(0, 1000)$ prior for σ, and a $U(0.4, 1.0)$ on γ, the discounting parameter. All computations were conducted using JAGS (Plummer, 2003).

2.3. **Results.** Of primary interest is the posterior distribution of the unobserved joint weights, $f(\mathbf{w}|\text{data})$, shown in Figure 1. The normal and normal mixture both produce essentially the same posterior density. The normal mixture has 97% of its mass in the prominent component centered near 0.3 grams/joint. The remaining 3% of the mass is in a second component with large variance that is essentially spread flat over the range shown in the figure.

The non-parametric estimate of the distribution also contains a single prominent mass, though shifted left from the normal and normal mixture models. However, there is a second large flat mode centered near 0.6 grams/joint. Under this model, the posterior probability of a joint exceeding 0.4 grams is 0.18. This second mode suggests that there is a second class of joints filled with a much larger amount of marijuana, more consistent with anecdotal reports from web surveys.

The posterior mean, the average weight of a marijuana joint, depends on the model used for the distribution of the grams of marijuana in a joint as shown in Table 2. However, regardless of the choice of model, the posterior mean is between 0.31 and 0.32 grams/joint.

TABLE 2. Posterior mean and 95% high posterior density interval for the mean grams of marijuana per joint

Model	mean	95% HPD interval
Normal	0.31	(0.286, 0.323)
Normal mixture	0.31	(0.299, 0.344)
Dirichlet process	0.32	(0.301, 0.354)

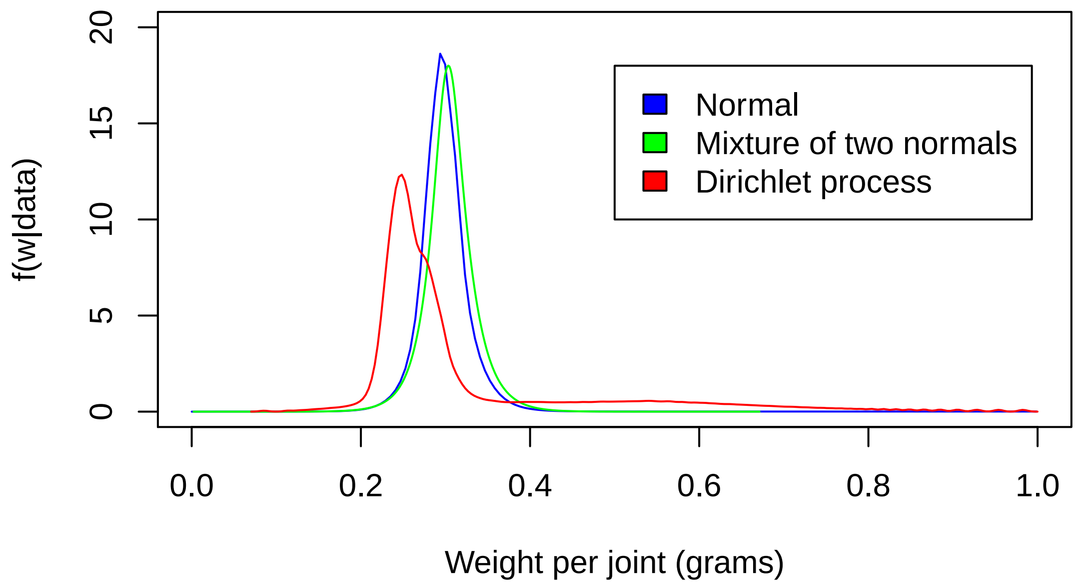

FIGURE 1. Posterior mean density of grams of marijuana in a joint considering three different distribution choices

Importantly, the posterior distribution and mean shows a much smaller amount of marijuana per joint than has been previously reported and used in developing projections for drug policy. One of the reasons that this estimate is smaller than Kilmer et al. (2010) is the introduction in this paper of the volume discounting parameter γ. The posterior mean of γ, regardless of the three modeling choices, is 0.57 (95% posterior interval: 0.55–0.58). This is a very steep discount since this implies that two grams of marijuana cost 1.5 times the cost of one gram of marijuana. It is also substantially lower than the 0.7 estimate reported in Caulkins and Padman (1993).

Even with the correction for volume discounting, our estimate may still be a little large. If dealers tend to be light on a "gram" of marijuana, then this estimate is too high. If, for example, dealers on average sold 0.9 grams as 1 grams, then multiplying the estimated grams per joint by 0.9 would recover the actual grams per joint. Sifaneck et al. (2007) studied 99 retail marijuana transactions in Manhattan in 2005 and found that actual weights ranged from 11% higher to 24% lower than the advertised weight and that 75% of the transactions were less than 90% of the advertised weight. We do not have any more comprehensive data than this on the likely weight of "a gram" of marijuana.

We explored whether there was evidence of changes in the weight of marijuana in a joint over time, but found that the average weight appears to remain roughly constant over the study period.

2.4. **Pricing variation by location and year.** Besides revealing the distribution of the weight of marijuana in a joint, the model captures price variation by city allowing us to inspect that variability. Figure 2 shows the relative difference in prices by location relative to their median.

The model also allows us to extract information on the year effects to examine trends in pricing. Figure 3 shows a general price increase over the study period with prices increasing by about 5% over the 10 years. Over this same period the average THC in a joint likely increased from 5% in 2000 to about 8% in 2010, indicating a modest increase in price for a large increase in potency (Office of National Drug Control Policy, 2014).

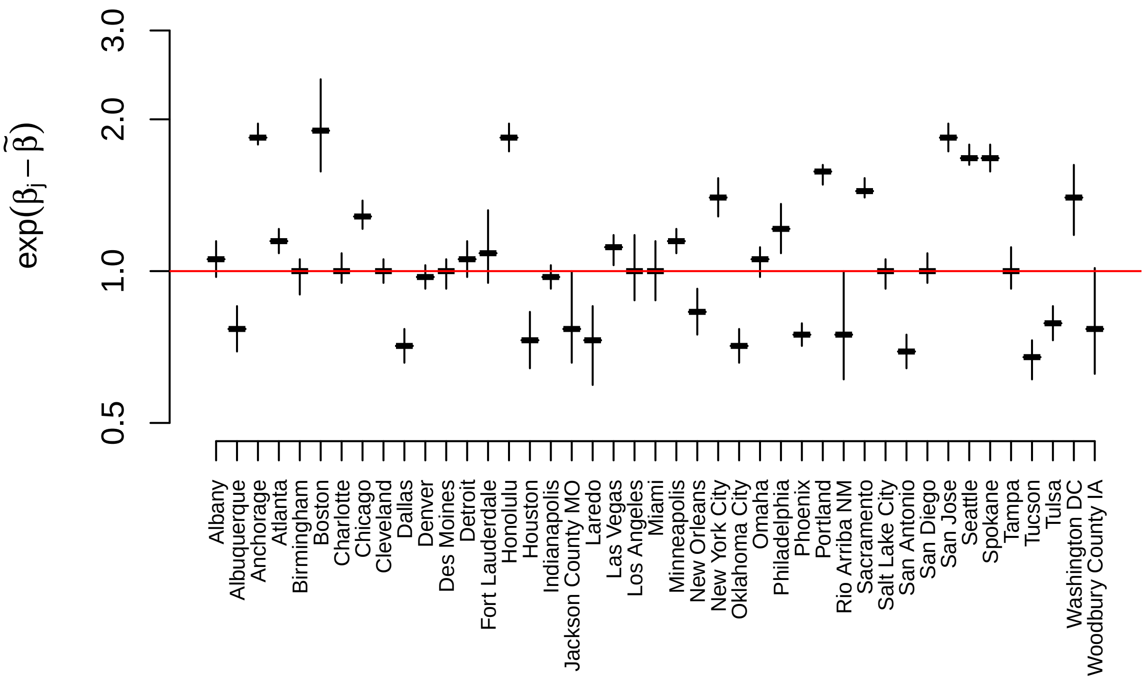

FIGURE 2. Posterior medians and 95% posterior intervals for location marijuana price inflation factors relative to their median, $\exp(\beta_j - \tilde{\beta})$

3. DISCUSSION

As debates about marijuana legalization intensify in the U.S. and abroad, there is increased focus on creating credible measures of marijuana consumption at the individual and aggregate levels. This information is not only important for projecting tax revenues and implications for drug trafficking organizations, but knowing how much marijuana users are consuming is useful for understanding health and other behavioral consequences (Kilmer et al., 2010). Unfortunately, most jurisdictions are not collecting information about the quantity of marijuana consumed. In the U.S., for example, the annual

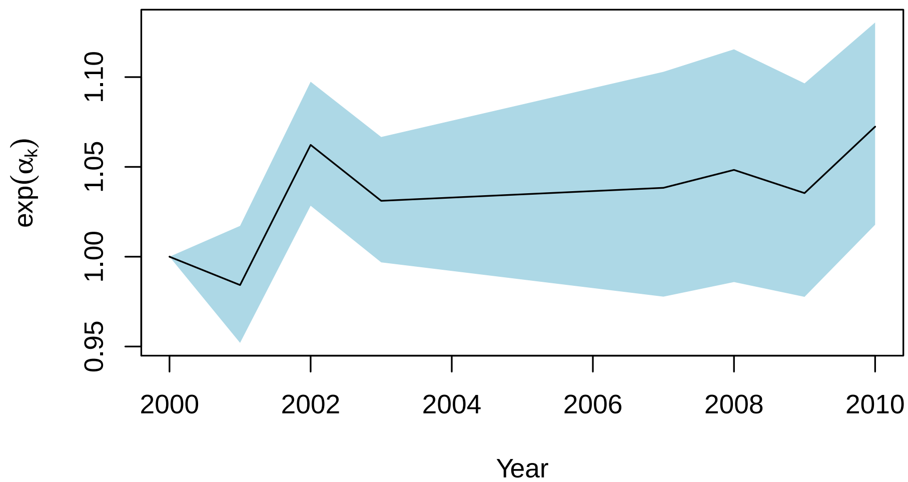

FIGURE 3. Posterior medians and 95% posterior intervals for $\exp(\alpha_k)$

household survey on drug use stopped asking questions about joints consumed per marijuana use day in 1995.

Indeed, it is difficult to collect accurate information on quantity consumed. Many users do not precisely know (or remember) how many grams they consumed during the previous use day. This is compounded by the fact that marijuana is often shared by multiple users (Kilmer et al., 2013). Some recent efforts have used web surveys with pictures of unrolled joints of various sizes next to common items (e.g., coins, credit cards, rulers) to obtain more accurate information about quantity consumed (Korf et al., 2007; Kilmer et al., 2013; van der Pol et al., 2013; van Laar et al., 2013). However, this picture card approach is in its infancy and one study that used it found that "Self-report measures relating to cannabis use appear at best to be associated weakly with objective measures. Of the self-report measures, number of joints per gram, cannabis price and subjective potency have at least some validity" (van der Pol et al., 2013).

This paper uses a unique approach for improving our understanding of the amount of marijuana that is in a joint. By drawing insights from expenditure data, we avoid any measurement issues associated with sharing. While our estimates depend on self-report information about the amount purchased and paid, we have no reason to believe there is more bias than would be associated with asking about how much was consumed during the most recent use day. Indeed, since a purchase is a distinct event versus amount consumed per use day, which can include multiple use sessions of different durations, we speculate that information from a purchase may be more accurate.

Our estimate of the average marijuana joint weighing 0.31–0.32 grams is lower than common perception, but still within the 0.3-0.5 gram range derived from one summary of the literature (Kilmer and Pacula, 2009). While it is not uncommon for connoisseurs in on-line forums to cite figures between 0.5 and 1.0 grams per joint, this could be a very different population than the arrestees who were booked into jail and participated in the ADAM interviews. Indeed, the vast majority of marijuana use days in the U.S. are by those with less than a college degree, fluctuating between 83% and 89% from 2002-2013 (Burns et al., 2013; Humphreys, 2015).

While the non-parametric Bayesian method presented here was applied to information from arrestees, it could also be applied to data from other populations that are surveyed about substance use (e.g., high school students). Of course, that would require those surveys to not only inquire about marijuana transactions, but also allow respondents to respond in weight units or joints (or pipe bowls, etc). Between 2004 and 2013 the National Survey on Drug Use and Health (NSDUH) technically has the potential to refine the estimates for a nationally representative sample consisting of roughly 200 purchases of joints and 5,000 loose marijuana transactions per year. However, the public use dataset has no information on the location of the transaction and the data contain broad ranges for transaction values, such as 1–5 grams and \$11–\$21.

With a better estimate of the amount of marijuana in a joint, and the uncertainty in that estimate, analysts can make more refined projections of marijuana use. These estimates can be incorporated into drug policy discussions to produce better understanding about illicit marijuana markets, the size of potential legalized marijuana markets, and health and behavior outcomes.

References

Brown, G. and L. Silverman (1974). The retail price of heroin: Estimation and applications. *Journal of the American Statistical Association 69*, 595–606.

Burns, R. M., J. P. Caulkins, S. S. Everingham, and B. Kilmer (2013). Statistics on cannabis users skew perceptions of cannabis use. *Frontiers in Psychiatry 4*, 138.

Caulkins, J. P. and R. Padman (1993). Quantity discounts and quality premia for illicit drugs. *Journal of the American Statistical Association 88*(423), 748–757.

Gettman, J. (2015, July 15). Estimating the size of a marijuana joint. *High Times*. `http://www.hightimes.com/vote/estimating-size-marijuana-joint`.

Humphreys, K. (March 12, 2015). The stereotype of the college-educated pot smoker is wrong. *Washington Post*.

Kilmer, B. and J. Caulkins (2014, March 8). Hard drugs demand solid understanding. *USA Today*.

Kilmer, B., J. P. Caulkins, B. M. Bond, and P. H. Reuter (2010). *Reducing drug trafficking revenues and violence in Mexico: Would legalizing marijuana in California help? (OP-325-RC)*. Santa Monica, CA: RAND Corporation. http://www.rand.org/pubs/occasional_papers/OP325.html.

Kilmer, B., J. P. Caulkins, G. Midgette, L. Dahlkemper, R. J. MacCoun, and R. L. Pacula (2013). *Before the grand opening: Measuring Washington State's marijuana market in the last year before legalized commercial sales (RR-466)*. Santa Monica, CA: RAND Corporation. http://www.rand.org/pubs/research_reports/RR466.html.

Kilmer, B. and R. Pacula (2009). *Estimating the size of the global drug market: A demand-side approach (TR-711-EC)*. Santa Monica, CA: RAND Corporation. http://www.rand.org/pubs/technical_reports/TR711.html.

Korf, D. J., A. Benschop, and M. Wouters (2007). Differential responses to cannabis potency: A typology of users based on self-reported consumption behavior. *International Journal of Drug Policy 18*, 168–176.

Mariani, J. J., D. Brooks, M. Haney, and F. R. Levin (2011). Quantification and comparison of marijuana smoking practices: Blunts, joints, and pipes. *Drug and Alcohol Dependence 113*(2–3), 249–251.

Müller, P. and R. Mitra (2013). Bayesian nonparametric inference – why and how. *Bayesian Analysis 8*(2), 269–302.

Office of National Drug Control Policy (February 2014). What America's Users Spend on Illegal Drugs: 2000-2010. Technical report, Washington, DC. https://www.whitehouse.gov/sites/default/files/ondcp/

policy-and-research/wausid_technical_report.pdf.

Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. In *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003)*, Vienna, Austria.

Schauer, G. L., B. A. King, R. E. Bunnell, G. Promoff, and T. A. McAfee (2016). Toking, vaping, and eating for health or fun: Marijuana use patterns in adults, u.s., 2014. *American Journal of Preventive Medicine 50*(1), 1–8.

Sifaneck, S. J., G. L. Ream, B. D. Johnson, and E. Dunlap (2007). Retail marijuana purchases in designer and commercial markets in New York City: Sales units, weights, and prices per gram. *Drug and Alcohol Dependence 90*(Supplement 1), S40–S51.

U.S. Dept. of Justice, National Institute of Justice (2002). Arrestee Drug Abuse Monitoring (ADAM) Program in the United States. http://doi.org/10.3886/ICPSR03815.v1.

van der Pol, P., N. Liebregts, R. de Graaf, D. J. Korf, W. van den Brink, and M. van Laar (2013). Validation of self-reported cannabis dose and potency: An ecological study. *Addiction 108*(10), 1801–1808.

van Laar, M., T. Frijns, F. Trautmann, and L. Lombi (2013). Cannabis market: User types, availability and consumption estimates. In F. Trautmann, B. Kilmer, and P. Turnbull (Eds.), *Further insights into aspects of the illicit EU drugs market*, pp. 73–182. Luxembourg: Publications Office of the European Union.

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