The Market for Mules: Risk and Compensation of Cross-Border Drug Couriers

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Abstract:
This paper uses a unique dataset to shed light on the economics of cross-border drug smuggling. Our results reveal that loads are generally quite large (mean 56 Kg) and of high wholesale value (mean $73,348). We also find that mule compensation is substantial (mean $1,601), and most interestingly, that mules appear to be paid compensating wage differentials for loads that carry a higher sentencing risk if detected and for loads that carry an arguably higher likelihood of detection. This suggests that this underground and unregulated labor market generally acts like a competitive labor market, with an equilibrium in which risk-sensitive, reasonably well informed workers are compensated for taking on higher risk tasks.
I – Introduction

Every year, roughly three thousand people are arrested while working as “mules” smuggling drugs through the ports of entry along the U.S.-Mexico border in California, Arizona, New Mexico, and Texas. For every mule caught, many more get through. Despite the great public concern over cross-border drug smuggling, and the enormous expenditures devoted to stopping it, little is known about this activity. A number of journalistic and scholarly accounts are available (Decker and Chapman 2008; Campbell 2009; Caulkins et al 2009; Green et al 1994), but no large-scale empirical analysis of the economics of border smuggling into the United States has yet been attempted. Yet the economics of border smuggling are vitally important to any assessment of border interdiction and prosecution strategies, and of domestic drug policy. In this study we use a unique dataset containing information we have collected directly from the probable cause narratives filed by federal agents after each smuggling arrest to shed light on this underground economy.

We have extracted our data directly from the statements of probable cause filed following federal smuggling arrests at California ports of entry along the Mexican border from September 2006 to the end of 2010. These narratives give the factual details of each smuggling event---time, place, what kind of drug, how much, how it was smuggled, the citizenship of the driver, etc.---allowing us to thoroughly describe many of the details of drug mules and their cargo along the U.S.- Mexico border.

Additionally, these narratives include information from the post-arrest interrogation of the mule by the responding ICE agent. One of the questions asked by the agent is how much money the mule was paid, or was promised that he would be paid, for carrying the load. While not all arrested mules make a statement, and not all statements include pay information, pay information exists for a little over half of all cases in our data.

These compensation data provide us with a key variable for analyzing the labor market for mules. While other papers have attempted to look empirically at issues regarding pay for those in the drug distribution business (Reuter and MacCoun 1992; Levitt and Venkatesh 2000), to our knowledge this paper is the first to directly evaluate
the extent to which pay responds to sentencing risk. In particular, our data allow us not only to examine the basic magnitudes and variance in mule pay, but also to examine whether compensating wage differentials as predicted by economic theory arise even in inherently unregulated and illegal labor markets such as this one. Specifically, all else equal, are mules paid more for carrying loads with higher expected sentencing risk?

This question is of interest not just as a test of economic theory, but also because it may help us better understand how border policing and sentencing policies can interact with the drug market. Specifically, while Rueter and Kleiman (1986) sought to understand how enforcement policy affected the drug market through altering the eventual price of drugs to consumers, this study pushes back one step to see how enforcement policy directly affects the cost of getting drugs to the market.

We focus on the data regarding California ports of entry, as this is where we have the richest data at this time and where the majority of smuggling cases arise. Among the drug mules caught at the California ports of entry, we find that on average, these mules are paid (or at least promised to be paid) quite well for a day of work. The mean reported compensation amount is $1,601 and the median is $1,272. Given this median wage, drug mules would have to complete only a little over two smuggling trips per month to earn the roughly $35,000 annual salary paid to American commercial truck drivers with 1-4 years of experience.1

There is also substantial variation in reported pay. While much of this variation is unexplained by the variables we have in our data, our results reveal that even in an inherently unregulated labor market such as this, compensating wage differentials for higher risk do arise. In particular, we estimate the expected sentence imposed if caught for each drug mule in our data (hereafter referred to as expected sentence exposure) using the actual distribution of sentences imposed on mules caught bringing similar loads of drugs through California ports of entry.2 We find that an additional year of expected sentence exposure translates into well over $600 more pay on average. Given we suspect

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1 This is according to payscale.com.
2 As stated above, “expected sentence exposure” refers to the expected sentence that will be imposed if caught, not the overall “expected sentence” associated with attempting to smuggle the load, which would be the expectation taken over the probability of being caught times the sentence imposed if caught. However, we use the term the term expected in “expected sentence exposure” as one must still take the expectation over the distribution of possible sentences associated with being caught for a given load when calculating this term.
the likelihood of capture at the border is on the order of 5%, this finding crudely suggests that drug mules would need to be compensated $12,000 for each additional year of sentencing with certainty (i.e., $600/0.05), a finding that bears out Reuter’s (1990) speculation that compensation for incarceration risk was likely driven largely by opportunity cost of lost wages.

Our results also show that there is a hierarchy of compensation by drug type: in ascending order, heroin, marijuana, meth, and cocaine. However, conditional on sentencing risk upon being caught, mules carrying marijuana are paid—perhaps counter intuitively—significantly more than those carrying cocaine, who in turn are paid significantly more than those carrying methamphetamine or heroin. For example, mules carrying marijuana loads with an *expected sentence exposure* of one to two years are paid more on average than mules carrying cocaine or heroin loads with an *expected sentence exposure* of up to three years and meth loads with *expected sentence exposure* up to four years. We argue that the primary reason for this is that the likelihood of detection is strongly positively correlated with load size, and the marijuana loads with *expected sentence exposure* of two years are on the order of 100 times larger than cocaine and heroin loads with an expected sentence exposure of three years, or meth loads with an *expected sentence exposure* of four years. Therefore, the pay premium for marijuana loads conditional on sentencing exposure arguably reflects a compensating differential for the higher likelihood of detection associated with smuggling such loads.

Finally, we do not find evidence linking compensation to other obvious characteristics of the mule. For example, in both absolute terms, and conditional on the expected sentence associated with the load, and amount and type of drug being carried, there is no statistically significant difference between female and male compensation, or between U.S.-citizen and non-citizen compensation.³

**II - Description of Data**

The data used for our analysis are collected directly from the statements of probable cause filed in every federal border-smuggling case, or “border bust.” Our study examines the busts made at California ports-of-entry between the latter half of 2006

³ All the mules were either U.S. citizens (45%) or Mexican citizens (55%).
To our knowledge, this is the first systematic collection and study of this data.

To describe where this data comes from, it will be helpful to describe the typical way in which a border bust proceeds. People wishing to cross through a port of entry from Mexico to the United States (either by car or on foot) go through three stages of inspection: pre-primary (lining up to get to the inspection booth), primary (presentation of documents at the inspection booth), and secondary (intensive inspection if referred from primary). The physical border line is south of the inspection booths, so as cars line up and wait they are already in the United States, and inspection, usually dog sweeps, may occur there. Officers from Customs and Border Protection (CBP) may develop suspicion at any point before entry, and no initial quantum of suspicion is required for a search.\(^4\) At pre-primary, as cars (and pedestrians—though the vast majority of smuggling is done with cars) line up, officers walk with drug-sniffing dogs in random sweeps through the lanes. If a dog alerts to a vehicle, the vehicle is immediately sent to secondary inspection, where the car will be more closely inspected.

Officers may also refer a vehicle to secondary after the primary inspection at the booth. These referrals may be because of the driver’s demeanor, or responses, or documents. They may also be based on tips from informants, or they may be purely random (at random intervals, the computer system will direct inspectors to refer cars to secondary).

When a vehicle is referred to secondary, the officers will remove the driver from the vehicle and take him or her inside the station while the secondary inspection is conducted. At secondary, officers will look for drugs and signs of hidden compartments. If hidden packages are found, they are removed and weighed, and the contents field-tested for the presence of illegal drugs.

Whenever concealed loads of drugs are discovered, the CBP officers contact Immigration and Customs Enforcement (ICE) agents, who respond to the port, take over the case, and interview the suspects. The probable cause statements we use for this study are drafted by the responding ICE agents, and then filed with the court when the suspects are charged. To obtain these probable cause statements, we first used Westlaw to identify

drug importation cases charged in the Southern District of California. We then used the
PACER system (Public Access to Court Electronic Records) maintained by the federal
judiciary, to access the docket filings for each case. For each case, we accessed the
docket, then downloaded a pdf image of the complaint, from which we obtained our
data.\(^5\)

For each case, we coded for the following data: case number, port of entry, date, day of the week, time, mule name, mule gender, drug type(s), drug weight(s), compensation, vehicle make, vehicle year, location of compartment, dog alert, nervousness, interview response (confessed to the charges/denied the charges/invoked right to silence), type of identification presented, citizenship, sole or not sole, gender, outcome of case, sentence imposed, and amount of time actually incarcerated.\(^6\)

We classified citizenship based on what could be inferred from the type of identification presented, with U.S. passports and birth certificates being coded as U.S. citizens and visas of any kind (mostly I-551s (legal permanent resident visas) or B1/B2s (Border Crossing Cards) coded as non-U.S. citizens. All told, we obtained citizenship data for about half of the cases in our dataset.\(^7\)

When calculating pay for each load, we used the total amount paid for each load, regardless of whether it went to one person or more than one person (e.g., a case in which $1000 went to the driver and $500 went to the passenger was coded as $1500). When payment was in pesos, we converted to dollars for coding. In a handful of cases, the payment was the car itself or a certain amount of the drugs. In those cases we used the Kelly Blue Book value for the year, make and model of car, using the “private party sale”

\(^5\) By the middle of 2006 all complaints were scanned and filed electronically as pdf documents.
\(^6\) Some sentences are reported as “time served,” and we translated these into months by calculating from the docket the total amount of time between arrest and judgment, subtracting any time out on bail. And many marijuana sentences are probation. Rather than code these as if no time were spent behind bars, we calculated from the dockets the amount of time spent incarcerated prior to imposition of the sentence. We employed the same method for dismissals and acquittals: we code them based on the amount of time incarcerated prior to judgment.
\(^7\) When the identification presented was a state i.d. or driver’s license, we coded citizenship as U.S., because all foreign citizens have always had to present immigration documents, while prior to 2009, U.S. citizens could enter with a state i.d. or driver’s license. (Since 2009, U.S. citizens have had to present passports.) In some cases, the report simply stated the defendant’s citizenship, which we coded accordingly. While we can’t be certain that it never happens, we have good reason to believe that cartels would not use mules with fake documents because any irregularities in documents mean a guaranteed trip to secondary. Fake and stolen documents are of course endemic to the other main underground border industry, facilitating illegal entry, and thus entry documents are closely examined.
figure for a car in “good” condition and 50,000 miles. When payment was in drugs, we used regional retail Office of National Drug Control Policy (ONDCP 2007) price data to convert to dollars. All payments are calculated to be in 2010 dollars. However, these types of non-cash payments were less than 10% of the cases for which we have compensation data.

We excluded any cases in which 21 U.S.C. 952, the importation offense, was charged for personal-use amounts (e.g., a gram of cocaine in someone’s pocket). We also excluded cases in which Section 952 was charged as part of a broader conspiracy---cases, in other words, in which there was not a specific smuggling event within our time range recorded in the complaint. Finally, we excluded cases that were not port-of-entry cases (e.g., stash house, tunnel, boat or plane cases) as they seemed to be of a fundamentally different nature. We have pay information available for fifty-one percent of our observations. Sixty-four percent of the suspects in our dataset confess to smuggling at the time of arrest. Of these, seventy-nine percent provide information regarding their compensation or promised compensation.

One obvious concern about this data is the reliability of the defendants’ answers regarding their pay, or promised pay, as there is no direct way to verify whether they are telling the truth absent discovery of cartel accounting books. Given that punishment is not affected by what a mule reports regarding his pay or promised pay, there is no objective incentive for any defendant to over-report, under-report, or conceal his promised pay once he has made the initial decision to confess. However, one can think of reasons why captured mules may still mis-report. For example, they may not believe their punishment is unaffected by what they report, or they may believe their interrogators may try to solicit bribes if higher pay is reported (one could imagine this to be a consideration for Mexican mules who may have had interactions with corrupt law-enforcement officials).

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8 Sentences are determined by drug type and load size. There is a guidelines adjustment for “minor role,” which is available to mules, though not always granted by the sentencing court. It is possible to envision a case in which a sentencing court would rule that a mule’s role was not minor based inter alia on a high reported wage. However, we are aware of no such cases. Furthermore, close to 99% of smuggling cases are resolved by plea agreement, in which the parties agree on either a sentence recommendation or a range. We are aware of no evidence that plea offers are affected by reported mule wage. Thus, while it is theoretically possible that a mule might lowball his wage in hopes of maintaining a minor role claim or getting a better plea deal, the possibility is so speculative and remote that we see no need to address it further.
On the other hand, a mule might overstate his true pay in an attempt to aggrandize his role in the operation, perhaps to make himself appear a better candidate for a cooperation deal. To the extent there is mis-reporting, this could potentially bias our results (if defendants systematically over- or under-report) or render our results too imprecise to be informative. The results below suggest the latter is not too large an issue. Regarding potential bias, there is not a whole lot we can say with much confidence. However, our data suggests that it is unlikely that Mexican mules systematically under-report their pay relative to U.S. mules because of a fear of official solicitation of bribes. In particular, if this were true, then we would see higher wages, controlling for other factors, for U.S.-citizen mules than for Mexican-citizen mules. But, as we will show later, we find that mule citizenship actually has no significant relationship to reported pay. This at least suggests the Mexican drug mules were not more likely to attempt to conceal earnings due to fear that higher reported earnings would translate to higher bribe requests.

Finally, because our data is from federal prosecutions, we do not have complaints for cases that were prosecuted instead by state authorities. While this is certainly an issue for further study, for reasons we discuss in the Data Appendix, we do not think it undermines the validity of our results here.

III - Analyzing the Data

Figure 1 shows the number of federal smuggling cases at the California border ports of entry for 2007-2010, by drug. Marijuana arrests are by far the most prevalent. However, this has been changing recently, with arrests for cocaine and methamphetamine increasing dramatically between 2009 and 2010, and arrests for marijuana falling over this time period. While heroin arrests increased substantially between 2009 and 2010, they still remain comparatively rare.

III(a) - Quantity

Generally, the load sizes are quite large, with a mean size of 56 kilograms. However, there is substantial variation. The median load size is 28 kilograms, while the 90th and 10th percentiles are 74 kilograms and 4 kilograms respectively. Not surprisingly, there is substantial variation in load size by drug type. Table 1 gives information about the distribution of load sizes by drug type. Notably, methamphetamine (median 8 kg) and
especially heroin (median 4 kg) loads are generally much smaller than cocaine loads (median 21 kg). However, marijuana (median 41 kg) loads are generally much larger than even cocaine. Specifically, while the 10th and 90th percentiles of the cocaine loads are 36 kilograms and 6 kilograms respectively, the analogous measures for marijuana loads are 100 and 15 kilograms respectively. Moreover, the right tail of the quantity distribution for marijuana is very large, with the ninety-ninth percentile being 959 kg and the four largest marijuana loads all totaling over 4000 kg.

III(b) – Value

Besides type and quantity of drugs being smuggled by mules, it is also interesting to note the value of each load, as drugs vary quite dramatically in their value by weight. However, calculating the value of each load is no easy task. While there are some data on drug prices at different points in the distribution chain, such data are quite limited for the wholesale sized loads in our data set. Drug prices also generally reflect purity, which we do not have data on. Finally, drug prices are also generally not linear with respect to quantity, meaning it is not appropriate to calculate load values for each of the loads in our data by simply extrapolating out linearly from one price/quantity observation from other sources.

While there is no unimpeachable way to calculate load values given the limitations of our data, we choose to employ the Caulkins and Padman (1993) and Caulkins et al. (2009) model describing drug pricing according to a power law: \( P(Q) = \alpha Q^\beta \). To implement this model, we used a different parameterization for each drug where the \( \beta \) for each drug was taken from the "mid-level" estimates from the U.S. drug market in Arkes et al. (2004) (via Table 3 from Caulkins et al. (2009)). We then used the "mid-level" prices per ounce of each drug as stated in the National Illicit Drug Prices report put out by the U.S. Department of Justice (USDOJ 2008) and the \( \beta \)'s discussed above to back out the implied value for \( \alpha \) associated with each drug. Once we know \( \alpha \) and \( \beta \) for each drug, we can then calculate a load value for each load in our data set given its type and size.

\[ \alpha = P/Q^\beta, \]  
\text{where } \beta = 1 - \ln(\delta)/\ln(\phi). 

Specifically, if drugs are marked up by 100(\( \delta - 1 \))% as they move through each transaction layer with a branching factor of \( \phi \), then to price of a transaction of quantity \( Q \) will be captured by the equation \( P(Q) = \alpha Q^\beta \).
As Caulkins and Padman (1993) make clear, there is undoubtedly mis-measurement implicit in calculating load value this way. However, we feel this method is likely to be more accurate, and arguably quite a bit more conservative, than other potential methods such as using the prices per ounce from the National Illicit Drug Prices report and assuming a simple linear growth rate in load value with respect to quantity.

Using the procedure described above, the wholesale value of the loads intercepted at the border crossings generally appears to be moderately high, with a mean value of $73,348. It is also important to note that given the substantial variation in load size, as well as the different values for different types of drugs, there is substantial variation in load value as well. The median value is $39,364, while the 90th and 10th percentiles are $159,229 and $15,445 respectively.

The lower panel of Table 1 shows how the distributions of load values differ by type of drug (shown in thousands of dollars). As can be seen, it is generally the cocaine and meth loads that are most valuable. While very small fractions of the marijuana and heroin loads have a wholesale value of more than $110,000, more than half of the meth and cocaine loads have a wholesale value of more than $110,000.

**III(c) – Other Characteristics**

A little under one quarter of the apprehended mules were female. As shown in Figure 2, this fraction was relatively constant by type of drug smuggled. Similarly, a little under fifty percent of apprehended mules are U.S. citizens. Again, as shown in Figure 3, this fraction is relatively constant across drug type, though mules apprehended for smuggling cocaine and heroin appear slightly less likely to be U.S. citizens than those smuggling marijuana and meth.

Figure 4 shows that mule apprehensions increase over the beginning of each week, peaking on Wednesday and then slowing over the remainder of the week, though differences across days of the week are relatively minor. Finally, the vast majority of apprehensions occur between 7AM and 10PM, with only a little over 10 percent happening during the night hours of 10PM to 7AM.

**IV - The Relationship Between Pay and Load**
One of the novel contributions of this dataset is what it can say about the labor market for mules. In particular, as discussed above, for a majority of our observations, we have data on the pay apprehended mules reported receiving or being promised for attempting to smuggle their loads into the United States.

Mule compensation is interesting for several reasons. First, understanding the magnitudes in question is important for understanding who might be getting involved in this activity. Is pay sufficiently low that it is really only the truly desperate who find such work worthwhile, or is pay high enough relative to the local labor markets that it is an attractive option to a broad swath of potential workers?

Second, understanding what is correlated with compensation can tell us something about the workings of an inherently unregulated and illegal labor market. For example, is there discrimination? Do females get paid differently from males for similar loads? Do U.S. citizens get paid differently than non-U.S. citizens? And what factors drive pay? Can standard models of competitive labor markets help us understand illegal underground markets such as this?

In particular, basic economic theory suggests that even in the absence of regulation, a competitive labor market should mean that workers are generally cognizant of the risks they take on in performing a particular job, and those taking on a higher risk of a negative outcome should earn a higher wage all else equal---i.e., a compensating wage differential should arise (Rosen 1986). The labor market for mules offers a perfect test of this theory because while the risk of carrying different loads across the border will depend on load characteristics (type of drug, quantity), the actual labor involved (driving the car across) will not. Our data allow us to examine whether differences in detection and sentencing risk across loads do in fact translate into compensating pay differentials.11

While economic theory predicts that compensating wage differentials will arise in a context such as this, we can identify a few plausible reasons why they might not.

First, it is possible that the labor market for drug mules may be "thin," with little systematic organization, causing compensation to be determined on a case-by-case basis. Under this model mule pay would primarily be determined by the particular interactions

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11 Caulkins, Gurga, and Leslie (2009) emphasize the paucity of data in this area: “There is no way to know how much compensation dealers would, could or should demand per year of incarceration. Probably few think about the calculus in such terms.”
and negotiations between a given mule and recruiter, and we would not necessarily expect a strong systematic relationship between compensation and the nature of the cargo.

A second possibility is that the cartels are able to utilize such a desperate labor pool of potential mules that they can simply offer a minimal fixed rate per load. Under this model, the mules may care very much about differential sentencing risk, but their concern will not be reflected in compensation because of their more primary concern of obtaining paying work. Indeed, mules may be sufficiently desperate that they do not even demand to be informed about the exact nature of what they are carrying.\(^\text{12}\)

Finally, it may be that the likelihood of being caught carrying drug cargo through border crossings is sufficiently small that mules do not have a meaningful incentive to care about what they are carrying. Under this model, the labor market for mules would operate much like the market for couriers of legal goods, with pay simply compensating the mule for his or her time and labor, without variation based on cargo type.

While it is very difficult if not impossible to precisely ascertain mules’ perceived risk of being caught bringing in a load of drugs, available evidence does suggest that being caught is quite unlikely. In particular, we can at least do a “back of the envelope” calculation for the fraction of cocaine that is being intercepted. The Office of National Drug Control Policy (ONDCP) estimates that in 2007 (the most recent year for which data is published) cocaine shipments from South America (where almost all of the world’s coca crops are cultivated) to the United States totaled between 545 and 707 metric tons, with a best estimate of 626 metric tons that “departed from South America toward the United States” (ONDCP 2007). The ONDCP estimates that 90% of the cocaine coming to the U.S. comes through the Mexican corridor, either up the Pacific coast of Mexico or the Caribbean coast of Mexico, with the other 10% going through the Caribbean Islands to Miami. Both of the major routes through Mexico include crossing points on the Southwest border: the Pacific route terminates in Tijuana and Mexicali and crosses through the California ports of entry, and the Caribbean route terminates in Juarez.

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\(^{12}\) The claim of ignorance of cargo is commonly made in smuggling cases. See for example, United States v. Sepulveda-Barraza, 645 F.3d 1066 (9th Cir. 2011); Gomez-Granillo v. Holder, 654 F.3d 826 (9th Cir. 2011); United States v. Cordoba, 104 F.3d 225 (9th Cir. 1997); United States v. Mendoza, 121 F.3d 510 (9th Cir. 1997); United States v. Beltran-Lopez, No. 95-50104 (9th Cir. 1995),
and Tamaulipas and crosses through the Texas ports of entry. Thus we would estimate 563 tons (626 * 0.9) of the cocaine headed to the U.S. will come via routes headed toward the Southwest border.

However, in 2007, 209 metric tons were seized in all transit zones before reaching the U.S. border, so we estimate that 188 tons (209 * 0.9) of the cocaine en route to the Southwest border was seized before reaching the border. Therefore, our best estimate of the amount of cocaine arriving at the Southwest border region in 2007 is roughly 375 tons (563 – 188). Finally, in 2007, another 27 tons of cocaine was seized at all “arrival zone” areas (areas including both the border crossing areas and areas just before the U.S. border, including both areas near the border and in the oceans off the coasts).

If we again assume that 90% of these arrival zone seizures took place in the Southwest Border region, this means a total of 24.3 tons were seized at the “arrival zone” areas at or near the southwestern United States borders. Since only 11 tons of cocaine were actually seized at the southwest border crossings in 2007 (NDIC 2008), roughly 13.3 tons of the arrival zone seizures must have taken place prior to crossing the border. Therefore, our best estimate is that about 362 tons of cocaine (375 – 13.3) made it as far as the border itself. Of that 362 tons, 11 tons were seized at the border, meaning only about 3% of the cocaine that made it to the U.S. –Mexico border was intercepted.13

Caveats, of course, abound: the seizure data does not specify type of importation modality, and includes all seizures made within 150 miles of the border. So the amount actually seized in port-of-entry vehicle smuggling will be somewhat less than the total reported seizure amount. This would mean that the detection rate for port-of-entry vehicle loads will be lower than the figure calculated above. Moreover, the use of other importation modalities (e.g. tunnels and planes) lowers the total amount imported via port-of-entry vehicle smuggling, which would mean that the detection rate for port-of-entry vehicle loads would be higher.

Nonetheless, the production-based and consumption-based estimates are close enough that we feel reasonably confident in asserting that the likelihood of detection for

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13 Using a consumption based measure, Kilmer et al (2010) estimate 252 metric tons of import-quality cocaine make it into the United States. Taking this estimate and including the 11 tons seized at the border, then about 4% of the cocaine coming through the U.S.-Mexico border was intercepted.
drug smugglers coming through ports of entry is certainly less than one in ten and probably closer to one in twenty or less.

Similar estimates for the other drugs are somewhat more speculative because their sources are more diffuse, so that we lack a reliable “total volume headed to the U.S.” estimate. However, Kilmer et al (2010) attempted to estimate the share of U.S.-consumed marijuana that is imported from Mexico. They estimate that Mexican-grown marijuana accounts for between 40 and 67% of annual U.S. consumption, which they estimate at approximately 3,300,000 kilos. At the observed mean marijuana load size of around 80 kilos, that would be around 42,000 marijuana trips a year. We know, though, that vehicle smuggling is not the only modality for marijuana smuggling. Tunnels and backpack loads (and ultralights and pangas) are also common importation modalities, and we simply lack data on the relative distribution of the various methods. The 2011 National Drug Threat Assessment states that backpack loads brought across the desert in Arizona may be the primary marijuana importation modality. While we simply cannot definitively say how much marijuana comes in through official border crossings relative to these other methods, for purely illustrative purposes let us use a relatively conservative estimate that one-quarter of total Mexican marijuana importation was done by vehicles through California ports of entry. That would be some 10,000 smuggling trips in a given year. There are around 500 federal marijuana smuggling cases brought each year arising from California POEs, and again using a conservative estimate that another 500 cases that result in state charges or apprehensions followed by declinations (for small Imperial County loads, for example). These conservative calculations would still only then translate to a roughly 10% detection rate, which is higher than the predicted cocaine detection rate calculated above, but still arguably quite low.

Kilmer et al (2010) have also attempted consumption estimates for heroin and meth. They estimate total consumption of 101 metric tons of heroin (of import-level purity), of which they estimate roughly 60% is imported from Mexico. That would mean 60.6 tons imported through the Southwest border. Given the 2011 National Drug Threat Assessment reports that 0.905 metric tons were seized on and around the border in 2010, which would imply a detection rate of around 1.5%.
We are unable to perform a similar calculation for meth, however, because meth is produced in the U.S. as well as in Mexico, and the NDTA includes in its “border area” seizures report all drugs seized within 150 miles of the border—namely, all of Southern California, and much of Arizona, New Mexico, and Texas. The NDTA figure thus includes all domestic meth-lab seizures as well as border seizures. Better data may help us to refine our estimate.

In general, we doubt the seizure rates are higher for meth and heroin than for cocaine because meth and heroin loads are generally smaller than cocaine loads. Further, a significant portion of border seizures are random, “pre-primary” sweeps, in which the drug dog is simply walked through the line of cars awaiting inspection. We do think it likely that detection rates for marijuana are significantly higher than for the other drugs, given the much larger load sizes and stronger smell, which we will return to again below. Conservatively, though, we feel safe in saying that detection rates are less than less than 10% for all drug mules crossing U.S.-Mexico ports-of-entry, and likely more on the order of 5% or less.

Given such a low real or even perceived chance of detection, it is certainly possible that the large differences in sentence risk by size of load and type of drug are sufficiently discounted so as to not translate into any notable differences in compensation. On the other hand, there is a substantial body of evidence that such “low-probability, high-consequence” events are actually over-valued in many contexts, because people have difficulty rationally discounting them (Slovic 2000).

In general, while one could argue that markets in the drug trade should generally work according to the standard models of economic theory, as it is essentially a market for semi-refined agricultural crops (or easily manufactured chemicals in the case of meth), sold and transported by an easily substitutable low-skilled labor force, those researchers who have examined this market for many years have often found numerous market irregularities and puzzles (see for example Caulkins and Rueter 2006; Caulkins and MacCoun 2003).

The extent to which changes in sentencing risk produce compensating wage differentials in the market for mules is an interesting one in its own right. On a purely academic level, this market provides an interesting and understudied environment to
examine the implications of economic theory---much in the spirit of Levitt and Vankatesh’s (2000) analysis of an urban street gang’s finances. It will also allow us to compare the compensation structures in different segments of the underground drug economy: an interesting subject for further research would be a comparison between the labor market for couriers and the labor market for retail dealers, as modeled, for example, by Reuter (1990).

Second, there are important policy implications. The United States spends large sums of money detecting, prosecuting and incarcerating individuals caught transporting drugs through its borders. It is therefore an important question what effect such enforcement policies have on the economics of the illegal drug importation industry. Specifically, if cartels generally do not have to compensate mules (or compensate them much) for the extra incarceration risk they incur for smuggling different types and sizes of drug loads, then border policing and incarceration policy would have little effect on the supply of willing mules and thus on the bottom line of the cartels. On the other hand, if cartels do in fact generally have to compensate mules for the differential incarceration risk associated with different loads, then we can infer that detection and sentencing policies do affect cartel labor costs, and thus, the profits for cartels (at least to some extent).

**IV(a) – Summary of Mule Compensation**

As discussed above, in analyzing mule compensation, we focus here on the California data because the majority of port-of-entry drug smuggling arrests occur at the California ports of entry and because that is where we have collected full data at this point. Furthermore, we focus on those carrying only one type of drug through the border. This restriction is not very limiting, however, as fewer than 4% of our observations were carrying more than one type of drug. Moreover, this group of individuals caught carrying more than one drug is extremely heterogeneous, carrying numerous different combinations of drugs of various sized loads, and in some cases it appears that one of the drugs they are caught with are in quantities that suggest it is for personal use rather than distribution. Therefore, we feel making any statistical inferences from this group would not be warranted.
For those mules arrested carrying only one drug coming through one of the California ports of entry, the mean reported pay is $1,601. However, there is substantial variation, as the median of the distribution is $1,256, with a tenth percentile of $500 and a ninetieth percentile of $3,030. Even with a $1,256 median, though, this compensation seems to be substantial. As alluded to in the introduction, the website payscale.com reports that American commercial truck drivers with 1 – 4 years of experience earn roughly $35,000 per year, meaning at this median amount for mule pay, a mule would only have to make about two trips per month to earn this much money.

Another point of comparison is to compare this median mule earnings amount to measures of average earnings in the border regions. One such measure is the Per Capita Gross Regional Revenue, which is the regional equivalent of Per Capita Gross National Product. Using data for 2000, Anderson and Gerber (2008) report a Per Capita GRR for the border counties of the United States to be $25,067, which translates to $32,164 in 2010 dollars. For the border counties on the Mexico side of the border, Anderson and Gerber (2008) report Per Capita GRR in 2000 to be only $10,458, which translates to only $13,419 in 2010 dollars. Hence, at the median pay level, a mule will surpass the average annual earnings for other residents of the U.S.-Mexico border region in between 10 and 20 trips over the course of a year. This is arguably quite high pay given the relatively little amount of specific skill required and the likely well less than 1 in 10 chance of actually being caught each time.

Pay also appears to differ substantially by type of load. As can be seen in the top panel of Table 2, mules carrying cocaine loads generally appear to be paid the most, followed by mules carrying meth loads, with mules carrying marijuana and heroin loads reporting being paid almost fifty percent less than cocaine mules on average. We will explore such differences in more depth in the following subsection.

IV(b) – The Relationship Between Compensation and Sentencing Risk

As discussed above, if pay for mules is at least partly compensating them for expected jail time, mean pay should respond to both the perceived likelihood of detection, and to the expected sentence to be served if caught (expected sentence exposure). In this section we attempt to evaluate these hypotheses.
In doing this analysis we first had to deal with outliers. Two types of outliers concerned us: quantity outliers and pay outliers. We attempted to deal with both types of outliers them as conservatively as possible.

With respect to quantity outliers, as will be seen below, much of what we are interested in is how pay responds to increased expected sentence exposure, which in turn depends on drug type and quantity. Therefore, in order to make plausible statistical inference, we need multiple observations by drug within a relatively narrow quantity range. This in turn necessitated some trimming of the sample to exclude loads with few or no other observations “nearby.” The exclusion rule that we used was the following. For Cocaine, Meth, and Heroin, we excluded any observation with less than five other observations with pay data within 5 kilos. Similarly, for Marijuana, we excluded any observation with less than five other observations with pay data within 20 kilos. This procedure excluded 4 observations for cocaine, 2 observations for Meth, 42 observations for Marijuana, and 4 observations for Heroin. While keeping these outliers in the sample does not change our results dramatically, it does substantially decrease the precision of our estimates, and indeed we would argue that making statistical inference near such observations is likely to be misleading.

The second type of outliers is pay outliers. The concern here is that there might be substantial measurement error in reported pay, and while under-reporting of pay is bounded from below at zero, over-reporting of pay is unbounded. Indeed, we have a couple of pay observations that are over 10 standard deviations from the median. To deal with these outliers we do a type of “winsorizing” of the data. Specifically, we first find any observations that have reported pay greater than five standard deviations away from the 90th percentile of that drug. We found two such observations for cocaine, two such observations for marijuana, and zero such observations for meth and heroin. We then replace those two extreme pay amounts for cocaine and marijuana, as well as the two smallest pay amounts for cocaine and marijuana, with the third largest and third smallest pay observations for each drug respectively. As discussed by Rivest (1994), such a procedure can lead to large efficiency gains with minimal bias. Again, while our basic results do not change qualitatively when we do not use this procedure, the precision of some of our estimates decreases.
The lower panel of Table 2 summarizes how using this “trimmed” sample alters the pay distribution in the data. As can be seen, our trimming procedures do not lead to large changes in the basic summary statistics.

Let us now consider the relationship between expected sentence exposure and pay. Obviously it is not possible to directly measure mules' ex-ante perception of sentencing risk for being caught with a given load. However, in lieu of direct a measure, we make the assumption that potential mules' expectations of sentencing exposure are determined by the sentences received by individuals caught trying to smuggle similar loads. In order to place minimal assumptions on how the actual sentencing process works in practice, we estimate the expected sentence exposure function non-parametrically. Specifically, we collected data on the actual sentence received by each of the individuals in our dataset.\textsuperscript{14} We then set the expected sentence exposure for each quantity observation for each drug equal to the locally weighted mean sentence for quantities "near" that observation, where closer observations receive higher weight.\textsuperscript{15}

Figure 5 shows scatterplots along with the estimated expected sentence exposure functions for each drug (solid lines). As can be seen, for all drugs, expected sentence exposure rises with quantity before asymptoting at some maximal level. However, the quickness with which the function asymptotes, as well as the maximal level at which it asymptotes, differ by drug. For example, for both meth and heroin, the expected sentence exposure function asymptotes very quickly (e.g., less than 5 kilos), while for cocaine the function does not asymptote until almost 20 kilos and marijuana not until roughly 100 kilos. As for the maximal expected sentence exposure, again this ranges from about 2 years for marijuana to around 5 years for meth.\textsuperscript{16}

\textsuperscript{14} As noted previously, for those defendants eventually acquitted, had their charges dismissed, or were sentenced to "time served" we calculated the sentence based on the actual number of days spent in jail waiting for trial.
\textsuperscript{15} Specifically, we use the “lowess” command in Stata, with an Epinechnikov weighting kernel and a bandwith of 0.5 (i.e., half of the observations within a drug were used to calculate each expectation).
\textsuperscript{16} It is notable that the observed asymptote is nowhere near the statutory maximum, which is life imprisonment for almost all the hard-drug loads, and 20 or 40 years for almost all the marijuana loads (for the biggest marijuana loads, it’s life). The longest sentence in our California data is 188 months, or 15 years and eight months. And there are only 11 sentences, out of more than 4000 in the data, above 120 months. Clearly, it would be a mistake to model the economics of sentencing risk using statutory maximums.
One factor that normally has a significant effect on federal sentencing is criminal history. For example, a median marijuana load of around 50 kilos has a base offense level of 20 under the Guidelines, which would mean a sentence of 33-41 months, if no adjustments are applied and the defendant has no criminal history. But the level 20 sentence increases significantly with prior convictions; a defendant with three priors would likely be looking at 63-71 months. However, we can tell from the data that virtually none of the defendants had any criminal history, because almost all of the sentences imposed on the individuals in our data were below the statutory mandatory minimum. There is a statute that specifically provides for below mandatory minimum sentencing in drug cases, but only if several prerequisites are met, most importantly that the defendant have no (or only minimal) criminal history.17

Interestingly, Table 3 shows that if we compare our expected sentence exposure measures for different drug and quantity levels to the both the federal Sentence Guidelines and the package of guideline reductions associated with "Fast-track" sentencing (a plea deal available to those who plead quickly and have no prior criminal history), our expected sentence exposure measure appears to line up quite well with the "Fast-track" guidelines, suggesting that most of these cases follow those guidelines (and again suggesting few of the mules in our data have a criminal history). One does not need to hypothesize that cartels do background checks on potential mules (though we see no reason why cartels could not perform them); we think it plausible that potential mules with criminal history are aware of the greater sentencing risk and self-select out of the labor market.

Figure 6 shows how pay relates to expected sentencing exposure in the pooled sample of all drugs. In order to place minimal structural assumptions on the data, we again calculated the relationship between pay and expected sentence exposure completely non-parametrically. In particular, Figure 6 again shows the results of calculating locally

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17 There is a 10-year man-min for 0.5 kilos of meth, 5 kilos of coke, and 1 kilo of heroin, and a 5-year man-min for 100 kilos of marijuana (21 U.S.C. 952). However, there is a special “safety valve” provision of sentencing law, 18 U.S.C. 3553(f), which allows for sentences under the man-min in drug cases, but only if certain conditions are met—chief among these is lack of criminal history (zero or one criminal history points). Without safety valve, mandatory minimums are indeed mandatory. We do have a small number of 120-month sentences (42 cocaine cases, 40 meth cases, 2 heroin cases). While these defendants may have had a criminal history, another possibility is that they refused to make a statement, which is another condition of safety valve.
weighted average pay by expected sentence exposure. As can be seen, pay does appear to generally rise with expected sentence exposure, but only relatively modestly, and notably, it actually falls between about 1.5 years of expected exposure and a little over two years of expected exposure. If were to assume a linear relationship and run a simple OLS regression of pay on expected sentence exposure we get an estimated intercept of 1170 (s.e. 33.3) and an estimated slope coefficient of 206 (s.e. 19.4), both of which are statistically different from zero at well over the 99% confidence level. So, when we aggregate all drugs together, a year of additional sentencing risk if caught appears to be correlated with roughly $206 more in compensation.

This simple parameter is obviously quite misleading however; as Figure 6 shows, this relationship between expected sentence exposure and pay is not even monotonic. As we explain below, this non-monotonicity is due to the fact that there is hardly any overlap in expected sentence exposure between marijuana loads and the other drugs. Essentially, almost all the marijuana loads carry expected sentence exposure of 2 years or less, while the expected sentence exposure for all of the loads for the other drugs exceeds 2 years. So to accurately model the relationship between pay and sentencing risk, we must take into account this heterogeneity across drug types.

Figure 7 is the same as Figure 6, but shows the relationship between mean pay and expected sentence exposure separately by drug. As can be seen directly, the expected sentence exposure range for the marijuana loads in our data hardly overlaps with the expected sentence exposure range for the other drugs. Also, it is worth noting that the expected sentence exposure range for cocaine and heroin loads only slightly overlap with the expected sentence exposure range for meth among the individuals in our dataset.

Figure 7 reveals several things. First, within drug, pay does appear to be positively and monotonically associated with expected sentence exposure. Second, the strength of the relationship between pay and expected sentence exposure appears to be stronger for cocaine, meth, and heroin than for marijuana.

Table 4a tells a similar story to Figure 7 in a different way. In particular, Table 4a shows the results of using OLS to regress pay on expected sentence exposure separately

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18 In order to obtain standard error bounds, we used the Stata procedure "lpoly", using the default first degree locally weighted polynomial, or in other words the locally weighted mean. Again, we also used an Epanechnikov weighting kernel.
by drug. While the non-parametric results in Figure 7 reveal that the relationship between pay and expected sentence exposure is not perfectly linear for any of the drugs, they also reveal that the linear approximation associated with OLS will not be dramatically off base. Moreover, the OLS results can give us monetary values associated with a marginal year of expected sentence exposure. As can be seen, in all cases, the coefficient on expected sentence exposure is positive and highly statistically significant. Moreover, the coefficients on expected sentence exposure are largest for heroin and meth, followed by cocaine, then marijuana. Indeed, for heroin, an extra year of expected sentence if caught is correlated with $1,364 more in compensation, while for marijuana, an extra year of expected sentence if caught is only associated with only $600 more in compensation.

Table 4b attempts to provide an overall estimate of the pay premium associated with a marginal year of expected sentence exposure. It takes a weighted average of the slope coefficients from the OLS regressions shown in Table 4a, where the weights correspond to the fraction of the data corresponding to each drug type. This procedure suggests that every marginal year of expected sentence exposure is associated with about $682 in additional compensation.

The other notable feature in Figure 7 is that, conditional on expected sentence exposure, wages vary by drug. For example, for loads associated with around 3 years in prison if caught, cocaine loads appear to be compensated at over twice the rate of meth loads (a little over $2,000 versus a little under $1,000). Or, just as notably, a marijuana load with an expected sentence exposure of one year is compensated on average at the same level as a cocaine load with an expected sentence exposure of two and a half years, or a meth load with an expected sentence exposure of three and a half years.

One explanation for this variation is differences in the likelihood of apprehension. The likelihood of getting caught at the border is arguably an increasing function of how much contraband the individual is attempting to smuggle. After all, more contraband would require more or larger hidden compartments, which would presumably be harder to conceal, and would likely have a stronger odor, and the different drugs carry very different expected sentences for similar weights.

Figure 8 illustrates this explicitly, showing the relationship between expected sentence exposure and quantity, by drug. As can be seen, for loads carrying similar
expected sentences if caught, the meth loads are much smaller than the heroin loads, or especially the cocaine loads. For example, the mean size of the meth loads carrying an expected sentence if caught of 3 years is about 1.5 kilos, while cocaine loads with similar sentencing exposure average almost 10 kilos. Even more notably, loads of marijuana with expected sentence exposure of only 2 years are extremely large, averaging around 100 kilos. Since overall sentencing risk is a function of both expected sentencing exposure if caught and likelihood of detection, it certainly seems plausible that the pay premiums for some drugs relative to others conditional on expected sentencing if caught is consistent with a compensating wage differential for higher sentencing risk, due to the higher likelihood of detection associated with larger loads.

While the results discussed above are consistent with a significant wage premium being paid for carrying higher sentencing risk loads, another hypothesis is that mule compensation is generally determined as a fixed percentage of load value. This hypothesis is difficult to rule out for two reasons. First, both sentencing and load value are increasing functions of load size within drug. Such co-variation will make it difficult to separately identify sentencing effects from value effects. Second, as we discussed above, valuing loads is quite complicated. While we attempted to use the best methods available for valuing drug loads, clearly we likely still have substantial measurement error.

Keeping in mind the caveats above, we can still look at the relationship between pay and load value. Figure 9 again estimates this relationship between pay and load value non-parametrically, via the locally weighted average procedure used previously. As can be seen, for each drug, pay and load values initially have a positive relationship, but pay eventually becomes roughly constant in load value. If mules were generally being paid a fixed fraction of load value, we would expect the estimated functions shown in Figure 9 to be monotonically increasing, and perhaps even increasing at a constant rate. In general, we would argue that pay responding to sentencing risk appears to fit the data better than pay responding simply to load value.

**IV(c) – The Relationship Between Compensation and Other Mule Characteristics**

Finally, we can look at whether other mule attributes are correlated with pay. Specification 1 in Table 5 shows the results from regressing reported pay on expected
sentencing exposure and a variety of mule attributes, including indicator variables for
gender, citizenship, whether the mule crossed the border in the car, whether the mule
crossed the border on the weekend, and dummies for time of day, for all drugs combined.
As can be seen, of the coefficients on these other variables, only the coefficient on the car
indicator is statistically significant at even the ten percent level. Specifications (2)
through (5) show that not much changes when we do separate regressions by drug type.
Notably, the coefficients on the indicator variables for gender and citizenship are not
statistically significant in any of the specifications, suggesting pay is not strongly
correlated with obvious attributes of the mule.

In sum, while mule compensation appears to be correlated with expected
sentencing exposure and total quantity—the factors that could impact the expected
sentencing risk of attempting to smuggle the load—compensation does not appear to be
strongly related to other mule characteristics.

IV(d) - Sample Selection Concerns

The findings discussed above, of course, are based on a subsample of the total
population of drug mules—namely, only the mules who got caught. Moreover, our
findings regarding mule pay are based on even a smaller subsample—the mules who got
caught and were willing to say something about their compensation. Do these constraints
on the data undermine the validity of our results?

As to the first constraint, we cannot absolutely rule out the possibility that the
mules who get caught differ systematically in some ways from those who don’t.
However, we think that the possibility is unlikely. To be sure, mules who act suspiciously
at the primary screening area are probably more likely to get caught. But pre-primary
dog sweeps are random, so mule competence is irrelevant in those cases. While our data
does not tell us the relative distribution of pre-primary sweeps vs. booth interviews as the
basis for secondary inspections, anecdotal evidence from prosecutors at the United States
Attorney's office that handle these cases in the Southern District of California suggests
that the former is quite common. We have heard anecdotal accounts of mule-smuggling
tactics involving a “sacrificial” mule with a small load followed by a mule with a larger
load who is thought to have a greater chance of getting through while the inspectors are
processing the sacrificial mule. To the extent that this strategy is in wide use on the
Southwest border (a question we have no data on), then our findings would tend to underestimate the size and value of the loads. This is certainly an area for interesting further examination.

As to the second concern—whether there are systematic differences between the arrested mules who talk and the ones who remain silent—our data do show some differences. In particular, Table 6 shows how certain characteristics of the loads differ between those with valid pay data and those without. More specifically, those without pay data are divided into two categories: (i) those who confessed but did not give pay information, (ii) those who denied the charge or invoked their right to silence (and thus did not give pay data). As can be seen in Table 6, there are no statistical differences between load type, or load size conditional on type, between those with valid pay data and those who confessed but did not provide pay data. However, those who denied the charge or invoked their right to silence appear to have been more likely to be carrying harder drugs (cocaine, meth) and larger loads conditional on type of drug.\footnote{This is a significant finding insofar as it is evidence that, on the whole, mules do have knowledge of the size and nature of their cargo. Such knowledge is obviously a necessary condition for the existence of a market-driven risk compensation model of the sort we argue for herein.}

As explained above, sentencing exposure risk is much greater for hard drugs, and conditional on drug type, sentencing risk is increasing in quantity. Thus, Table 6 shows that there is an inverse relationship between sentencing risk and likelihood of confession: the riskier a mule’s load is the less likely he or she is to confess. Indeed, running a simple probit regression of an indicator variable for whether or not an individual confessed on the expected sentence exposure associated with his load suggests that being caught with a load carrying an extra year of expected sentencing exposure beyond the mean is associated with an over three percentage point decrease in the likelihood of confessing (based on a mean of about 66 percent)—a result that is statistically significant at well beyond the 99\% confidence level.

Therefore, while we think our results are representative of all of those who confess, we also think that if anything, they may understate the average compensation for mules overall. Because those mules who deny or invoke their right to silence are on average carrying loads with higher sentencing risk, and among the mules for whom we have valid pay data for those carrying loads with higher sentencing risk are on average
paid more, we suspect that those who deny the charges or invoke their right to silence are paid more than those for whom we have pay data.

Finally, we would argue that the negative correlation between the expected sentence exposure and confession strengthens our conclusion that mules in most cases know roughly what the cargo is. If mules did not have this knowledge in most cases, then the observed correlation between load type and size, and willingness to talk, should not arise.20

V - Summary and Conclusions

This paper uses a novel dataset to explore the underground economy of smuggling drugs into the U.S. from Mexico. Our findings show that the drug loads these mules carry are on average large and very valuable on the street, often on the order of a hundred thousand dollars or more wholesale. Moreover, we find that mules are arguably quite well paid for their courier work, generally being paid between one and two thousand dollars for a day's work—a wage far in excess of the average wage rates on either side of the border.

We find that neither the characteristics of the mule (gender and citizenship), nor the timing of when the mule attempts to cross the border, have significant impacts on mule compensation. However, we do find evidence that suggests that even this illegal unregulated labor market behaves in a manner consistent with basic economic theory. Namely, compensating wage differentials appear to arise for otherwise similar work that involves higher risk—in this case longer expected incarceration associated with the load carried. In particular, we find that after conditioning on drug type and load size, mules are paid on average on the order of $682 more for an additional year of sentencing risk if caught. We also find that after controlling for sentencing risk if caught, larger loads are associated with higher compensation, again a finding consistent with a compensating

20 We reject the other possible explanation, which is that agents systematically tell mules what the cargo type and size was, before reading them their rights and getting the invocation/confession/denial response. We can say as a matter of personal experience with these interviews that that is not the standard practice of ICE agents in California; more importantly, as a legal matter, such a practice would likely violate Miranda and render any subsequent confession inadmissible (because telling the mule the nature of the cargo would constitute “interrogation” under Rhode Island v. Innis, and per Miranda, custodial interrogation must be preceded by a valid waiver). We’re not saying it has never happened; rather, it is not policy, it does not happen systematically, and if it did occur, it would undermine the prosecution’s case.
differential for higher expected sentencing risk if, as is likely, one believes larger loads are more likely to be detected.

The extent to which $682 for an additional year of sentencing risk if caught is a large or small wage premium is a matter of opinion. One admittedly tenuous way to interpret this finding is to consider what it might imply about how mules value the utility cost of a year in prison. Specifically, if we consider risk-neutral drug mules, and suppose the likelihood of detection at the border is roughly 5% (consistent with our argument above), this would imply mules would need to be compensated about $13,000 for spending an additional year in jail with certainty. While one could argue that this seems quite low, if we consider it as the opportunity cost of lost wages, this arguably seems somewhat reasonable for this population. However, if we use a higher estimate of the likelihood of detection at the border, say 10%, our findings would suggest a much lower $6,820 in compensation necessary for spending an additional year in jail with certainty.

In general, our findings reveal that even in an unregulated and illegal market such as the one for drug mules, basic predictions of competitive labor markets seem to hold---on average, mules appear to be knowledgeable of what they are carrying and competitive forces lead to a compensating wage premium being paid to those carrying higher expected sentencing risk loads. This suggests that efforts to increase drug detection at border crossings can affect the revenue stream going to drug cartels not only through lessening their ability to get drugs into the U.S., but also by increasing their labor cost for couriers.
Data Appendix

In the Southern District of California, all hard-narcotics importation cases (that is, coke, meth, and heroin) are taken by federal prosecutors, so our dataset contains the full universe of cocaine, meth, and heroin border busts in California. In addition, our data contains the full universe of marijuana border busts for the ports in Imperial County (Andrade and the two Calexico ports) because the Imperial County District Attorney does not accept border-bust cases. However, our dataset is missing some marijuana border-busts from San Diego County ports (San Ysidro, Otay, and Tecate), because the San Diego County District Attorney prosecutes some marijuana border busts.

Without obtaining similar data from the San Diego District Attorney’s office (unavailable at the time of this manuscript), we have no direct evidence as to whether the mules prosecuted in state court for San Diego County busts differ systematically from those busted in Imperial County or the other states. If state sentencing for marijuana importation differed dramatically from federal sentencing, then we might expect to see some differences. But it does not differ dramatically. The San Diego DA’s standard offer is one day of incarceration per pound. Our data shows us how the day-a-pound regime compares to observed federal sentencing. For example, 930 of our California marijuana mules got federal sentences of less than 6 months, which is around 40% of the federal marijuana cases in the district. The mean sentence for that group, excluding four tractor-trailer acquittals, with load sizes in the thousands of kilos, was 4.61 months (140 days), and the mean load size was 34.7 kilos (76.5 pounds). The top quintile (by sentence) of that set had a mean sentence of 5.05 months (154 days) and a mean load size of 35.4 kilos (78.04 pounds). For them, in other words, federal sentences are longer by around 76 days than a day-a-pound sentence would be. By comparison, for the bottom quintile of cases in which the defendant received a prison sentence, the mean sentence was 1.37 months (42 days), and the mean load size was 18.64 kilos (41.1 pounds)—which is almost exactly a day a pound. And another 200 cases got probation—though in most of those, the defendant remained in jail between arrest and sentencing.
Bibliography


Fig 1: Federal Smuggling Charges Filed in Arrests at CA-Mexico Ports of Entry (by Year and Drug Type)
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<th>Table 1 - Load Size and Value by Drug</th>
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### Table 2 - Average Pay Overall and by Drug (CA)

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<th>Marijuana</th>
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Fig 5: Calculating Expected Sentence Exposure - CA

Cocaine

Meth

Marijuana

Heroin

bandwidth = .5
### Table 3: United States Sentencing Guidelines Recommended Sentences and calculated "Expected Sentence Exposure"

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<td>(months)</td>
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<td>27-33</td>
<td>6-12</td>
<td>7.7</td>
</tr>
<tr>
<td>40-60 Kilos</td>
<td>33-41</td>
<td>8-14</td>
<td>10.3</td>
</tr>
<tr>
<td>60-80 Kilos</td>
<td>41-51</td>
<td>12-18</td>
<td>14.9</td>
</tr>
<tr>
<td>80-100 Kilos</td>
<td>51-63</td>
<td>18-24</td>
<td>16.0</td>
</tr>
<tr>
<td>100-400 Kilos</td>
<td>63-78</td>
<td>24-30</td>
<td>17.2</td>
</tr>
<tr>
<td>400-700 Kilos</td>
<td>78-97</td>
<td>30-37</td>
<td>no obs</td>
</tr>
<tr>
<td>700-1000 Kilos</td>
<td>97-121</td>
<td>37-46</td>
<td>no obs</td>
</tr>
<tr>
<td>1000-3000 Kilos</td>
<td>121-151</td>
<td>37-46</td>
<td>no obs</td>
</tr>
<tr>
<td>3000-10000 Kilos</td>
<td>151-188</td>
<td>41-51</td>
<td>no obs</td>
</tr>
<tr>
<td>Cocaine</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-5 Kilos</td>
<td>97-121</td>
<td>37-46</td>
<td>28.9</td>
</tr>
<tr>
<td>5-15 Kilos</td>
<td>121-151</td>
<td>37-46</td>
<td>43.1</td>
</tr>
<tr>
<td>15-50 Kilos</td>
<td>151-188</td>
<td>41-51</td>
<td>48.3</td>
</tr>
<tr>
<td>Methamphetamine</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-1.5 Kilos</td>
<td>151-188</td>
<td>51-63</td>
<td>39.3</td>
</tr>
<tr>
<td>1.5-5 Kilos</td>
<td>188-235</td>
<td>57-71</td>
<td>50.0</td>
</tr>
<tr>
<td>5-15 Kilos</td>
<td>235-293</td>
<td>57-71</td>
<td>55.9</td>
</tr>
<tr>
<td>&gt; 15 Kilos</td>
<td>292-365</td>
<td>57-71</td>
<td>58.1</td>
</tr>
<tr>
<td>Heroin</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-3 Kilos</td>
<td>121-151</td>
<td>37-46</td>
<td>37.5</td>
</tr>
<tr>
<td>3-10 Kilos</td>
<td>151-188</td>
<td>41-51</td>
<td>43.4</td>
</tr>
<tr>
<td>10-30 Kilos</td>
<td>188-235</td>
<td>51-63</td>
<td>44.5</td>
</tr>
<tr>
<td>&gt; 30 Kilos</td>
<td>235-293</td>
<td>57-71</td>
<td>no obs</td>
</tr>
</tbody>
</table>

*For "Trimmed" Sample.
Figure 6: Pay and Sentencing Exposure All Drugs

Figure 7: Pay and Sentencing Exposure by Drug
Table 4a: OLS Regressions - Pay vs Expected Sentence Exposure by drug (CA only)

<table>
<thead>
<tr>
<th></th>
<th>Cocaine</th>
<th>Meth</th>
<th>Marijuana</th>
<th>Heroin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected Sentence Exposure</td>
<td>686.3***</td>
<td>898.1***</td>
<td>600.3***</td>
<td>1,364.0***</td>
</tr>
<tr>
<td></td>
<td>(150.1)</td>
<td>(108.6)</td>
<td>(85.7)</td>
<td>(345.6)</td>
</tr>
<tr>
<td>Constant</td>
<td>-391.2</td>
<td>-2,140***</td>
<td>877.8***</td>
<td>-3427.5***</td>
</tr>
<tr>
<td></td>
<td>(580.2)</td>
<td>(432.1)</td>
<td>(70.2)</td>
<td>(1,111.9)</td>
</tr>
<tr>
<td>Obs</td>
<td>319</td>
<td>281</td>
<td>1270</td>
<td>44</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.048</td>
<td>0.135</td>
<td>0.041</td>
<td>0.142</td>
</tr>
</tbody>
</table>

Note: Huber-White Robust standard errors in parentheses. One asterisk indicates significance at 10% level, two asterisks 5 % level, three asterisks 1% level.

Table 4b: Estimated Premium for Marginal Year of Sentence Exposure (CA only)

<table>
<thead>
<tr>
<th>Drug Type</th>
<th>coefficient</th>
<th>% of cases (those with pay data)</th>
<th>Weighted coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>cocaine</td>
<td>686.3</td>
<td>18</td>
<td>123.5</td>
</tr>
<tr>
<td>meth</td>
<td>898.1</td>
<td>17</td>
<td>152.7</td>
</tr>
<tr>
<td>marijuana</td>
<td>600.3</td>
<td>63</td>
<td>378.2</td>
</tr>
<tr>
<td>heroin</td>
<td>1364.0</td>
<td>2</td>
<td>27.3</td>
</tr>
</tbody>
</table>

Estimated pay premium for marginal year of sentencing exposure $682
Figure 8: Quantity and Expected Sentencing Exposure - by Drug

Cocaine

Meth

Marijuana

Heroin

kernel = epanechnikov, degree = 0, bandwidth = .15, pwidth

kernel = epanechnikov, degree = 0, bandwidth = .18, pwidth

kernel = epanechnikov, degree = 0, bandwidth = .05, pwidth

kernel = epanechnikov, degree = 0, bandwidth = .16, pwidth

95% CI Estimate

95% CI Estimate

95% CI Estimate

95% CI Estimate
Figure 9: Pay and Estimated Load Value - by Drug

Cocaine

Meth

Marijuana

Heroin

kernel = epanechnikov, degree = 0, bandwidth = 27.35, pwidth = 41.02

kernel = epanechnikov, degree = 0, bandwidth = 25.88, pwidth = 38.82

kernel = epanechnikov, degree = 0, bandwidth = 11.8, pwidth = 17.69

kernel = epanechnikov, degree = 0, bandwidth = 23.17, pwidth = 34.76
<table>
<thead>
<tr>
<th>Specification</th>
<th>(1) - All drugs</th>
<th>(2) - Cocaine</th>
<th>(3) - Meth</th>
<th>(4) - Marijuana</th>
<th>(5) - Heroin</th>
</tr>
</thead>
<tbody>
<tr>
<td>expected sentence exposure</td>
<td>201.8***</td>
<td>507.5**</td>
<td>676.8***</td>
<td>464.8***</td>
<td>615.8</td>
</tr>
<tr>
<td></td>
<td>(18.93)</td>
<td>(200.5)</td>
<td>(159.2)</td>
<td>(86.46)</td>
<td>(382.5)</td>
</tr>
<tr>
<td>female</td>
<td>26.33</td>
<td>178.1</td>
<td>-49.26</td>
<td>42.12</td>
<td>-136.0</td>
</tr>
<tr>
<td></td>
<td>(64.87)</td>
<td>(246.2)</td>
<td>(165.6)</td>
<td>(61.33)</td>
<td>(256.2)</td>
</tr>
<tr>
<td>citizen</td>
<td>-1.949</td>
<td>329.2</td>
<td>-191.6</td>
<td>93.58</td>
<td>-364.8</td>
</tr>
<tr>
<td></td>
<td>(100.4)</td>
<td>(503.5)</td>
<td>(251.6)</td>
<td>(97.27)</td>
<td>(366.9)</td>
</tr>
<tr>
<td>citizenship missing</td>
<td>-40.48</td>
<td>-247.9</td>
<td>22.24</td>
<td>29.76</td>
<td>-414.6</td>
</tr>
<tr>
<td></td>
<td>(69.27)</td>
<td>(218.8)</td>
<td>(232.5)</td>
<td>(64.09)</td>
<td>(319.8)</td>
</tr>
<tr>
<td>car</td>
<td>938.0****</td>
<td>719.0**</td>
<td>383.6*</td>
<td>762.0***</td>
<td>-64.60</td>
</tr>
<tr>
<td></td>
<td>(57.93)</td>
<td>(322.9)</td>
<td>(213.3)</td>
<td>(59.32)</td>
<td>(209.4)</td>
</tr>
<tr>
<td>weekend</td>
<td>-8.385</td>
<td>-153.9</td>
<td>40.80</td>
<td>15.68</td>
<td>392.6**</td>
</tr>
<tr>
<td></td>
<td>(50.28)</td>
<td>(178.9)</td>
<td>(159.0)</td>
<td>(48.16)</td>
<td>(191.2)</td>
</tr>
<tr>
<td>morning</td>
<td>-13.95</td>
<td>-219.6</td>
<td>218.8</td>
<td>-28.43</td>
<td>616.8**</td>
</tr>
<tr>
<td></td>
<td>(64.18)</td>
<td>(208.4)</td>
<td>(204.5)</td>
<td>(59.96)</td>
<td>(282.0)</td>
</tr>
<tr>
<td>evening</td>
<td>-41.29</td>
<td>-199.7</td>
<td>87.25</td>
<td>-5.553</td>
<td>285.8</td>
</tr>
<tr>
<td></td>
<td>(66.44)</td>
<td>(239.2)</td>
<td>(174.0)</td>
<td>(65.52)</td>
<td>(203.8)</td>
</tr>
<tr>
<td>night</td>
<td>60.42</td>
<td>-149.4</td>
<td>383.0</td>
<td>7.611</td>
<td>2,243*</td>
</tr>
<tr>
<td></td>
<td>(80.37)</td>
<td>(254.7)</td>
<td>(287.3)</td>
<td>(78.84)</td>
<td>(1,253)</td>
</tr>
<tr>
<td>Constant</td>
<td>357.2***</td>
<td>-113.7</td>
<td>1,613***</td>
<td>246.1***</td>
<td>-1,176</td>
</tr>
<tr>
<td></td>
<td>(93.22)</td>
<td>(720.1)</td>
<td>(610.0)</td>
<td>(91.40)</td>
<td>(1,226)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,914</td>
<td>319</td>
<td>281</td>
<td>1,270</td>
<td>44</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.130</td>
<td>0.076</td>
<td>0.153</td>
<td>0.094</td>
<td>0.456</td>
</tr>
</tbody>
</table>

Note: Huber-White Robust standard errors in parentheses. One asterisk indicates significance at 10% level, two asterisks 5% level, three asterisks 1% level.
<table>
<thead>
<tr>
<th></th>
<th>Valid Pay Data</th>
<th>No Pay Data Confessed</th>
<th>No Pay Data Denied/Invoked</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>cocaine</strong></td>
<td>0.17 (0.01)</td>
<td>0.19 (0.02)</td>
<td>0.22*** (0.02)</td>
</tr>
<tr>
<td><strong>meth</strong></td>
<td>0.16 (0.01)</td>
<td>0.14 (0.02)</td>
<td>0.21*** (0.02)</td>
</tr>
<tr>
<td><strong>marijuana</strong></td>
<td>0.64 (0.01)</td>
<td>0.64 (0.02)</td>
<td>0.55*** (0.02)</td>
</tr>
<tr>
<td><strong>heroin</strong></td>
<td>0.03 (0.00)</td>
<td>0.03 (0.01)</td>
<td>0.03 (0.01)</td>
</tr>
<tr>
<td><strong>total quantity (cocaine)</strong></td>
<td>20.72 (0.63)</td>
<td>22.57 (1.19)</td>
<td>23.12* (2.96)</td>
</tr>
<tr>
<td><strong>total quantity (meth)</strong></td>
<td>9.06 (0.47)</td>
<td>9.08 (1.34)</td>
<td>12.12*** (1.02)</td>
</tr>
<tr>
<td><strong>total quantity (marijuana)</strong></td>
<td>62.94 (4.41)</td>
<td>69.84 (15.33)</td>
<td>122.57*** (53.03)</td>
</tr>
<tr>
<td><strong>total quantity (heroin)</strong></td>
<td>6.30 (1.01)</td>
<td>8.46 (1.86)</td>
<td>11.60** (2.65)</td>
</tr>
</tbody>
</table>

Note: standard errors in parentheses. One asterisk indicates significance difference relative to valid pay data sample at 10% level, two asterisks 5% level, three asterisks 1% level.