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"The War on Drugs: An Analysis of the Effects of Supply Disruption on Prices and Purity"

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Abstract

Retail prices of illicit drugs have fallen despite rising supply disruption. This article presents and empirically tests a model which may explain the price puzzle. Supply disruption increases the cost of purity. Illicit drugs are experience goods, with demand depending on the seller's purity reputation. There is an equilibrium in which seizures decrease purity, reducing future demand and prices. These predictions are tested using monthly data for crack cocaine in Washington DC. Persistence of the series is exploited to handle endogeneity resulting from seizures mirroring supply. A 10% increase in seizures reduces purity by 4.7% and future prices by 2.3%.

JEL codes: L11, L14, K14, D22

Key words: Illicit drugs, seizures, seller reputation

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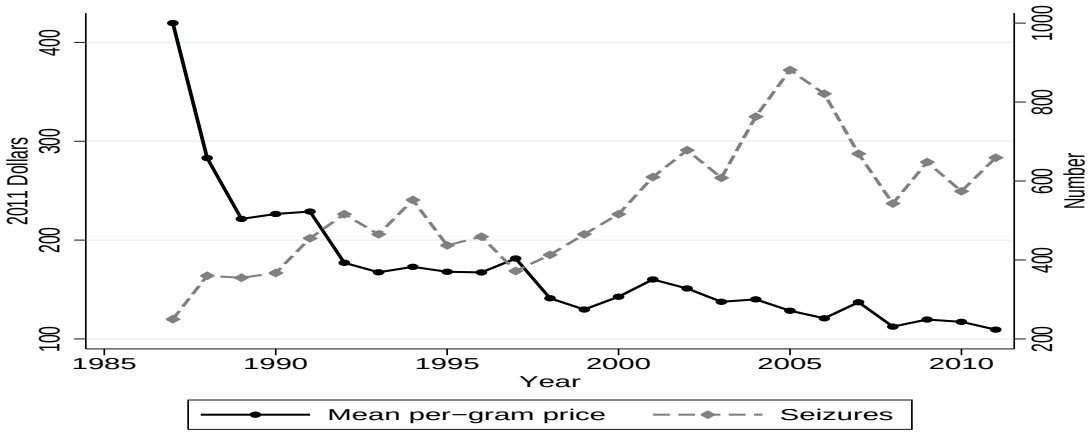
1 Introduction

Between 1987 and 2011 the Drug Enforcement Administration (DEA) seized more than 27 million kilograms of narcotics, equating to around 54 billion doses.[1] The intervention takes place under the supposition of a Walrasian market structure: the aim of high level disruptive policies is to increase wholesale costs, thereby raising retail prices and reducing consumption (Reuter & Kleiman 1986, Galenianos et al. 2012).[2] However, retail prices of powder cocaine, crack cocaine and heroin have declined markedly in recent decades, whilst seizures have increased substantially. Figure 1 illustrates these trends for powder cocaine.

Fig. 1 Per-gram price of retail powder cocaine & high level domestic cocaine seizures: US 1987-2011



Notes: Per-gram prices are constructed from STRIDE according to the method in the appendix. Following Caulkins et al. (2004), a retail purchase is of mass 0.1g-2g. High level domestic seizures are extracted from STRIDE, and are measured as the number of US cocaine seizures of mass in excess of 10 kilograms.

This essay establishes stylised facts on trends and market characteristics and makes two contributions to understanding the apparent price puzzle. First, the essay presents a theoretical model which uses empirically supported market characteristics to rationalise the trends in prices and seizures. The model incorporates dilution, moral hazard, repeated trade and seller reputation. There is a 'dilution' equilibrium in which seizures have no direct effect on prices and decrease purity. This causes future demand to fall, lowering future prices. The model is able to explain falling prices as a consequence of heightened supply disruption, and is also consistent with the observed declines in purity.

Second, the theoretical framework is used to motivate an empirical model, which is applied to monthly data for crack cocaine in Washington DC. Seizures mirror aggregate supply and are hence correlated with unobserved supply shocks, which also determine price and purity. Causal estimates

[1] For most drugs a typical dose is less than 0.5g.

[2] A Walrasian market is a centralised market with the elementary supply and demand curves and a market clearing price.

of the effects of seizures on purity and prices are obtained by exploiting persistence in the data to generate instrumental variables. Estimation results are consistent with dilution: month t seizures have no effect on the month t price and reduce month t purity, causing the month $t+1$ price to fall.

This essay is the first to conduct a theoretical and empirical analysis in which purity and the per-gram price are studied as separate outcomes, as opposed to an aggregate measure of affordability such as the per-pure-gram price.[3] This is important since moral hazard implies that consumption decisions are based on the per-gram price and buyers' purity expectations, and not on the per-pure-gram price which buyers do not observe prior to consumption. Moreover, the per-pure-gram price masks variation in per-gram prices and purity, which have different consequences for buyers and sellers.[4] Finally, repeated trade and moral hazard generate dynamic relationships between seizures, purity and per-gram prices which are not captured by the existing literature.

The primary source of data is the DEA's System to Retrieve Information from Drug Evidence (STRIDE).[5] STRIDE is an administrative catalogue of undercover purchases and seizures made by the DEA and local enforcement agencies, and may be used to construct measures of per-gram prices, purity and seizures for any spatio-temporal unit. This essay uses STRIDE to document falling per-gram prices, falling purity and rising supply disruption in the US cocaine and heroin markets, to provide empirical evidence of market characteristics which may explain these trends, and to estimate the causal effect of seizures on purity and the per-gram price. The remainder of this section summarises this essay's contribution in more detail and relates it to the existing literature.

This essay's theoretical contribution is to present a model incorporating three empirically supported features of the drugs market; dilution, moral hazard, and repeated trade. The model is able to rationalise the observed trends in purity, per-gram prices and seizures. Seizures increase the cost of wholesale narcotics, incentivising dilution. For powder cocaine and heroin, the wholesale purity distribution first order stochastically dominates the retail purity distribution, providing strong evidence of dilution.

Trade is subject to moral hazard since buyers do not observe purity prior to consumption. Moral hazard is evident from zero purity mass points in the retail purity distributions, with prices comparable to standard purity transactions. These 'rip-offs' are difficult to explain if dilution is observed by buyers (Galenianos et al. 2012). Moreover, rip-offs are substantially less prevalent at the wholesale level, where moral hazard is less acute (Reuter & Caulkins 2004).

[3]The per-gram price is the amount paid in 2011 dollars divided by the mass in grams. The per-pure-gram price is the amount paid in 2011 dollars divided by the product of mass (in grams) and purity (0-1).

[4]For example, fluctuations in purity and per-gram prices are likely to have different implications for user health.

[5]The author accepts sole responsibility for any conclusions drawn from the STRIDE data, which are unvalidated data provided by the Drug Enforcement Administration.

The theoretical framework comprises a representative local monopoly in which trade is infinitely repeated and demand is increasing in buyers' purity expectations. If buyers observe purity prior to trade, seizures may either increase the per-gram price, or decrease purity and ambiguously effect the per-gram price. The Walrasian model describes the former, whilst the latter arises through dilution. Dilution causes both costs and demand to fall, resulting in an ambiguous effect on per-gram prices. For two benchmark models, one with linear demand and another where demand is for pure drugs, the price effect is unambiguously negative. The theoretical model is able to explain falling purity and per-gram prices as a direct consequence of rising supply disruption.

If buyers do not observe purity prior to trade there must be some link between current purity and current or future profits in order to sustain non-trivial equilibria.[6] The mechanism proposed in this essay is seller reputation, which has not been previously applied to drug policy evaluation.[7] Seller hetereogeneity gives rise to reputation equilibria in which the seller incurs the cost of high purity so as to convince buyers that his type is 'good' and hence that he is more likely to offer high purity in the future.

In the model with moral hazard and seller heterogeneity, seizures may either increase per-gram prices and decrease consumption, or decrease current purity and ambiguously effect future per-gram prices and consumption. In the latter case, a seizure today incentivises dilution, leading purity to be low today and harming the seller's reputation for purity. This causes future demand to fall. In the benchmark models of linear demand and demand for pure drugs, future per-gram prices fall and future consumption rises.

This essay's empirical contribution is to estimate the causal effect of seizures on purity and the per-gram price. The theoretical model's predictions are evaluated using monthly time series data for per-gram prices and purity of retail crack cocaine and cocaine seizures in Washington DC.[8] This essay contributes to the empirical literature through being the first to specify a theoretically motivated empirical model and the first to account for endogeneity of supply disruption. The theoretical model generates persistence in seizures, purity and per-gram prices. The empirical counterparts also exhibit strong persistence, which is exploited to generate instrumental variables.

Baseline results indicate that a 10% increase in the total number of month t seizures decreases mean

[6] Otherwise moral hazard precludes trade in high purity such that the unique equilibrium is one in which purity is low in every period.

[7] Another mechanism which yields qualitatively similar results is rational addiction as studied by Becker & Murphy (1988).

[8] The market for crack cocaine in Washington DC is selected due to data constraints: the number of observations is considerably larger than for any other city or any other drug. This owes to the fact that both the DEA and the DC Metropolitan Police (MPDC) submit samples to STRIDE, whereas in other cities only the DEA makes a significant contribution. A lack of reliable consumption data precludes empirical analysis of the consumption effect.

month t purity by 4.7% and has no effect on the mean month t per-gram price.[9] The 4.7% decrease in mean month t purity leads the mean period $t+1$ per-gram price to fall by 2.3%. Consequentially, month t seizures have no effect on month t per-gram prices, and reduce month $t+1$ per-gram prices. The estimated elasticities are statistically significant. The empirical results reject the equilibrium in which seizures increase per-gram prices in favour of one in which seizures incentivise dilution. Endogeneity of seizures causes OLS estimates to be incorrectly signed.

Empirical evaluation of the effect of seizures on consumption is precluded by absence of detailed consumption data. Theoretical ambiguity of the consumption effect arises due to the impact of seizures on sellers' purity incentives, and suggests that policies aimed at increasing costs uniformly over purity are likely to be more effective. For example, the model predicts that an increase in the arrest rate of retailers raises per-gram prices and decreases consumption. This is supported empirically by Kuziemko & Levitt (2004), who show that incarceration of suppliers increases the per-pure gram price of cocaine. The remainder of this section places this essay in the literature.

1.1 Related Literature

This essay relates the literature on market structure with experience goods to the theoretical and empirical literatures on drug policy. The literature on experience goods has primarily focused on the capacity for reputation effects to sustain high quality equilibria in repeated games. Reputation effects occur either through dynamic strategies in which buyers' future actions reward the sellers' past good performance, or through seller heterogeneity in the capacity for high quality, in which sellers incur the cost of good performance in order to convince buyers that their type is 'good' so as to separate themselves from the 'bad' type. The majority of the recent literature focuses on the latter, which forms the basis for seller reputation in Holmström (1999), Hörner (2002), Liu (2011) and Mailath & Samuelson (2001). The model in this essay is most closely related to Mailath & Samuelson (2001), which is modified to allow supply disruption to increase the cost of high quality.

The most closely related applied theory paper is Galenianos et al. (2012), which characterises the drugs market as one with search frictions and moral hazard. The model explains purity dispersion and the presence of rip-offs as a consequence of search frictions in a market with many competing sellers. The per-gram price is fixed across all buyer-seller matches and the within-match purity and per-pure-gram price are also fixed. Moral hazard is overcome through formation of long run relationships. The framework suits comparative statics for policies related to search costs and the match destruction rate, such as the arrest rates of buyers and sellers. Galenianos et al. (2012) show that some types of

[9] Results are robust to alternative measures of seizures such as total mass seized.

enforcement may reinforce long run relationships by making search more costly. This alleviates moral hazard and increases affordability.

Relative to Galenianos et al. (2012), this essay contributes through permitting the seller to choose purity and the per-gram price in each period: per-gram prices are not fixed, and the seller need not commit to future purity. This allows for unrestricted, potentially dynamic responses to supply disruption. This gain comes at the expense of search frictions and competition between sellers, which are not considered. In this sense, the focus of this essay is on the within-match interaction, taking the match as exogenous.

The empirical literature has focused on quantifying the effects of policy interventions on outcomes including the per-pure-gram price (DiNardo 1993, Caulkins & Yuan 1998, Miron 2003, Kuziemko & Levitt 2004, Dobkin & Nicosia 2009), purity (Dobkin & Nicosia 2009), hospital admissions (Dobkin & Nicosia 2009, Dobkin et al. 2014, Kelly & Rasul 2014) and crime (Kuziemko & Levitt 2004, Dobkin & Nicosia 2009, Dobkin et al. 2014). The most closely related papers are DiNardo (1993), Caulkins & Yuan (1998), Miron (2003) and Dobkin & Nicosia (2009), which use the STRIDE data and focus on the impact of supply disruption on prices and purity.

DiNardo (1993) uses STRIDE to construct a state-year panel, and finds a small, statistically insignificant, positive association between seizures and the per-pure-gram price of cocaine, and no impact on consumption. This paper does not address endogeneity of seizures beyond incorporation of the usual state and year fixed effects. Moreover, localised effects may be masked by aggregation of the data over space and time. Temporal aggregation also rules out dynamic effects, which are likely to be important in the presence of moral hazard.

Caulkins & Yuan (1998) use STRIDE to construct a monthly time series at the national level, and conclude that seizures do not Granger cause the per-pure-gram price of cocaine, and have a negative association with the per-pure-gram price of heroin. The authors argue that the negative impact on heroin prices may be attributed to six factors related to the timing of the empirical model, heightened risk of storage during periods of heavy enforcement, the effects of enforcement on competition between sellers, quantity/quality trade-offs in enforcement, endogeneity of enforcement and the deterrence effect of enforcement on demand. The empirical specification does not permit seizures to have a same month impact on per-pure-gram prices, does not account for endogeneity of seizures, and aggregates the data heavily over space.

Miron (2003) finds that the ratio of farmgate to retail per-pure-gram prices of cocaine and heroin are greater than for similar legal products such as coffee and beer, suggesting that prohibition decreases affordability. Up to the validity of the comparison with legal goods, this paper provides strong evidence

that prohibition decreases affordability. The empirical strategy is well suited to a long run analysis of prohibition, but is less well suited to studying the short run effects of its component interventions such as seizures.

Dobkin & Nicosia (2009) study a natural experiment. In 1995, legislators removed administrative exemptions for distributors of ephedrine (a common methamphetamine precursor) based products and permitted the DEA to revoke their license without proof of criminal intent. The authors argue that the sudden policy change is plausibly exogenous, and had a significant impact on the production of methamphetamine. Using monthly data for California, this paper finds that the precursor restrictions raised per-gram prices, reduced purity and reduced methamphetamine related hospital admissions and methamphetamine use among arrestees, but had no effect on violent or property crimes. The effects were temporary, with all of the indicators returning to pre intervention levels within 18 months.

This essay makes three contributions to the empirical literature. First, the empirical model is theoretically motivated, dynamic, and purity and the per-gram price are studied as separate outcomes. This is important since moral hazard and repeated trade generate dynamic relationships between per-gram prices, purity and seizures. Second, the identification strategy accounts for endogeneity of supply disruption, implying that estimation results have a causal interpretation and are hence useful for policy purposes. Finally, the monthly city level time series in this paper is less susceptible to aggregation effects than DiNardo (1993), Caulkins & Yuan (1998) and Dobkin & Nicosia (2009).

2 Stylised Facts

This section presents stylised facts regarding trends in per-gram prices, purity and seizures and empirically motivates the core components of the theoretical framework. At the national-annual level there are sufficient data to study powder cocaine, crack cocaine and heroin, hence all three are considered in this section. This is not the case when focusing on disaggregated data, hence the causal analysis in section 4 focuses on crack cocaine, for which there are sufficient data to construct monthly series for Washington DC.

2.1 Data

This essay uses a subsample of STRIDE between 1987 and 2011, as prior to this there are not enough purchases to construct measures of purity and per-gram-prices which are not heavily aggregated over time and/or space. Metrics for per-gram prices, purity and seizures are constructed from STRIDE using the method described in the appendix. Table A1 in the appendix summarises the 1987-2011

subsample used in this section.

STRIDE is the most reliable source of data on the illicit drugs and is used in several studies, including but not limited to DiNardo (1993), Caulkins & Yuan (1998), Dobkin & Nicosia (2009) and Galenianos et al. (2012). The main limitation is that STRIDE is a convenience sample: observations are collected as a direct consequence of enforcement activity, and variation in the acquisition process may generate spurious variation in the constructed series. These concerns are described in detail in Manski et al. (2001) and Horowitz (2001). Arkes et al. (2008) provide a comprehensive appraisal of STRIDE, showing that many of the issues can be addressed through appropriate use of the data. In particular, aggregation over space, time, drug type and purchase mass should be avoided (Arkes et al. 2008). This paper follows these recommendations.

The National Survey on Drug Use and Health (NSDUH) and Census data are used to estimate the number of users of cocaine and heroin.[10] The NSDUH is a large, representative national survey containing information on drug abuse, health and sociodemographic characteristics. The survey provides useful information the extensive margin of drug consumption but not on the intensive margin, implying that accurate consumption data cannot be extracted. Moreover, no geographic identifiers are provided in the public use data, hence the survey is useful only for documenting national trends and cannot be used in the Washington DC time series analysis.

2.2 Trends in Per-gram Prices, Purity, Seizures & Drug Use

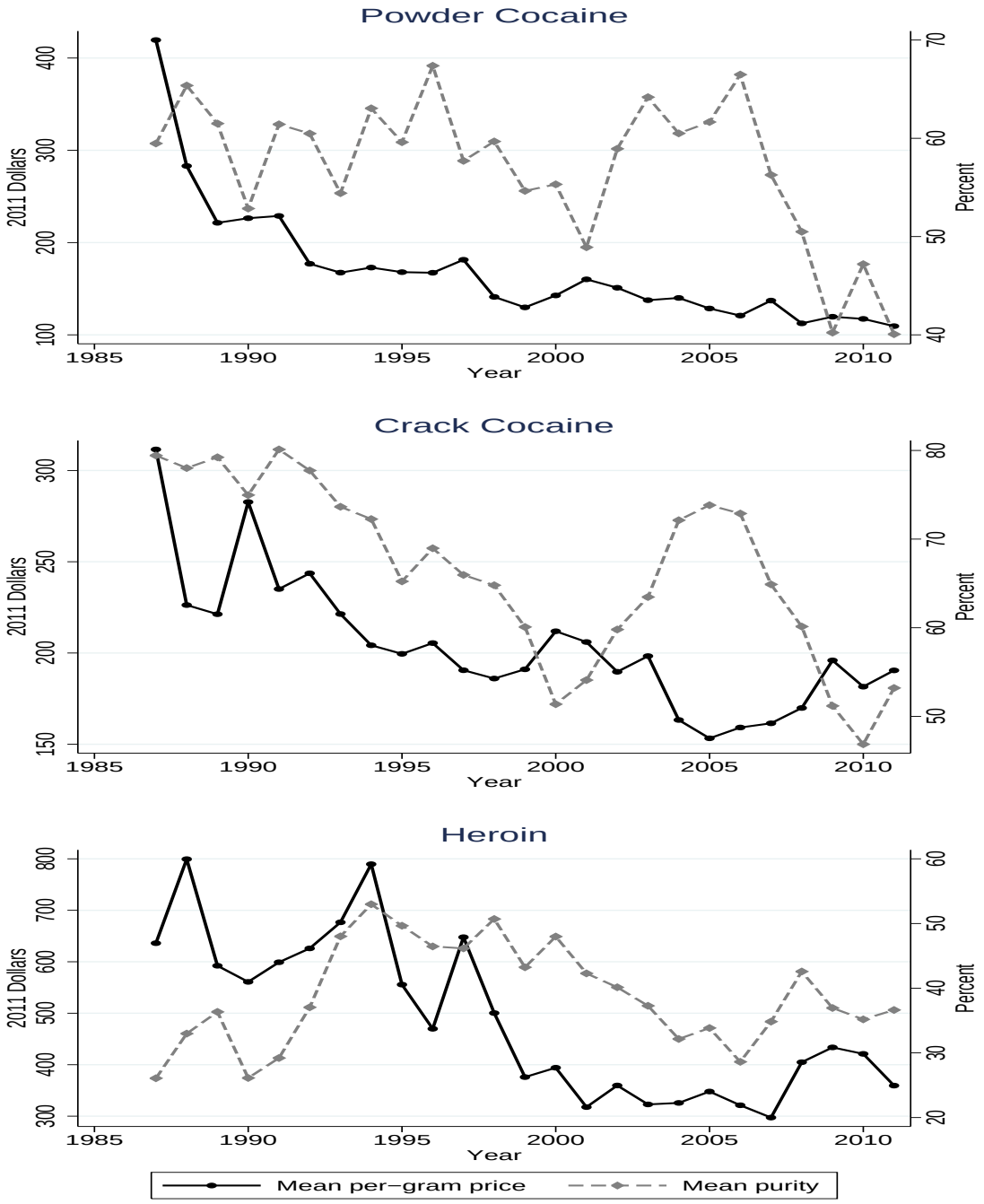
In recent decades, US retail prices of crack cocaine, powder cocaine and heroin have declined substantially, whilst, despite some volatility, purity has fallen gradually. Figure 2 illustrates these trends.[11] The mean per-gram price of powder cocaine has fallen from \$421 in 1987 to \$110 in 2011, whilst from its 67% peak in 1996, mean purity has fallen to 40%. The mean per-gram price of crack cocaine has declined from \$305 in 1987 to \$187, with mean purity dropping from its 1991 peak of 82% to 53% by 2011. The mean per-gram price of heroin has fallen sharply from \$815 in 1988 to \$365 in 2011, with purity dropping steadily from its 1994 peak of 53%.

Over the same period, supply disruption has increased markedly. Figure 3 shows that the DEA's real annual budget more than doubled from 1987 to 2011, rising from around 0.7 billion dollars in 1987 to 2.5 billion dollars in 2009, before falling to just under 2 billion dollars by 2011. Over the

[10] An individual is a user if they report having used cocaine or heroin in the past month.

[11] Following Caulkins et al. (2004), a retail purchase is defined as one of mass greater than 0.1g and less than or equal to 1g for crack cocaine and heroin, and greater than 0.1g and less than or equal to 2g for powder cocaine. Purchases of less than 0.1g are excluded as purity testing is unreliable for specimens of small mass. Due to an unfortunate coding practice in STRIDE, purity is recorded as zero in these cases, making it impossible to distinguish between low purity specimens and untestable specimens.

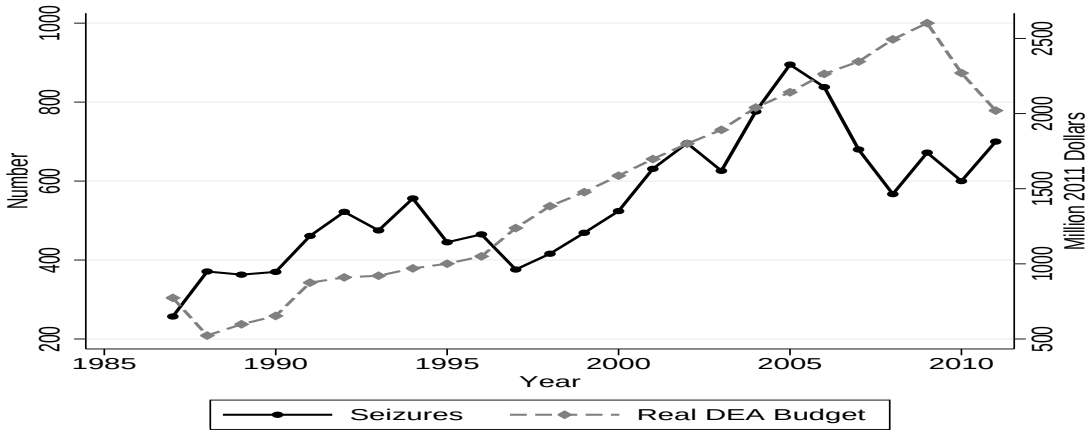
Fig. 2 Purity & per-gram price of retail drugs: US 1987-2011



Notes: Per-gram prices and purity are constructed from STRIDE according to the method in the appendix. Following Caulkins et al. (2004), a retail purchase is of mass 0.1g-1g for crack cocaine and heroin, and 0.1g-2g for powder cocaine.

same period, the combined incidence of high level cocaine and heroin seizures have more than doubled between 1987 and 2011, rising from around 250 in 1987 to 900 in 2005, and then dropping off to around 700 by 2011. Kuziemko & Levitt (2004) document similar trends in the incarceration rate. The remainder of this section establishes empirical evidence of the market characteristics which form the basis for the theoretical model.

Fig. 3 Real DEA budget & high level domestic seizures: US 1987-2011



Notes: Budget information is obtained from the DEA website, and deflated using the CPI for urban consumers obtained from the Bureau of Labor Statistics. High level domestic seizures are extracted from STRIDE, and are measured as the number of US seizures of cocaine and heroin of mass in excess of 10 kilograms.

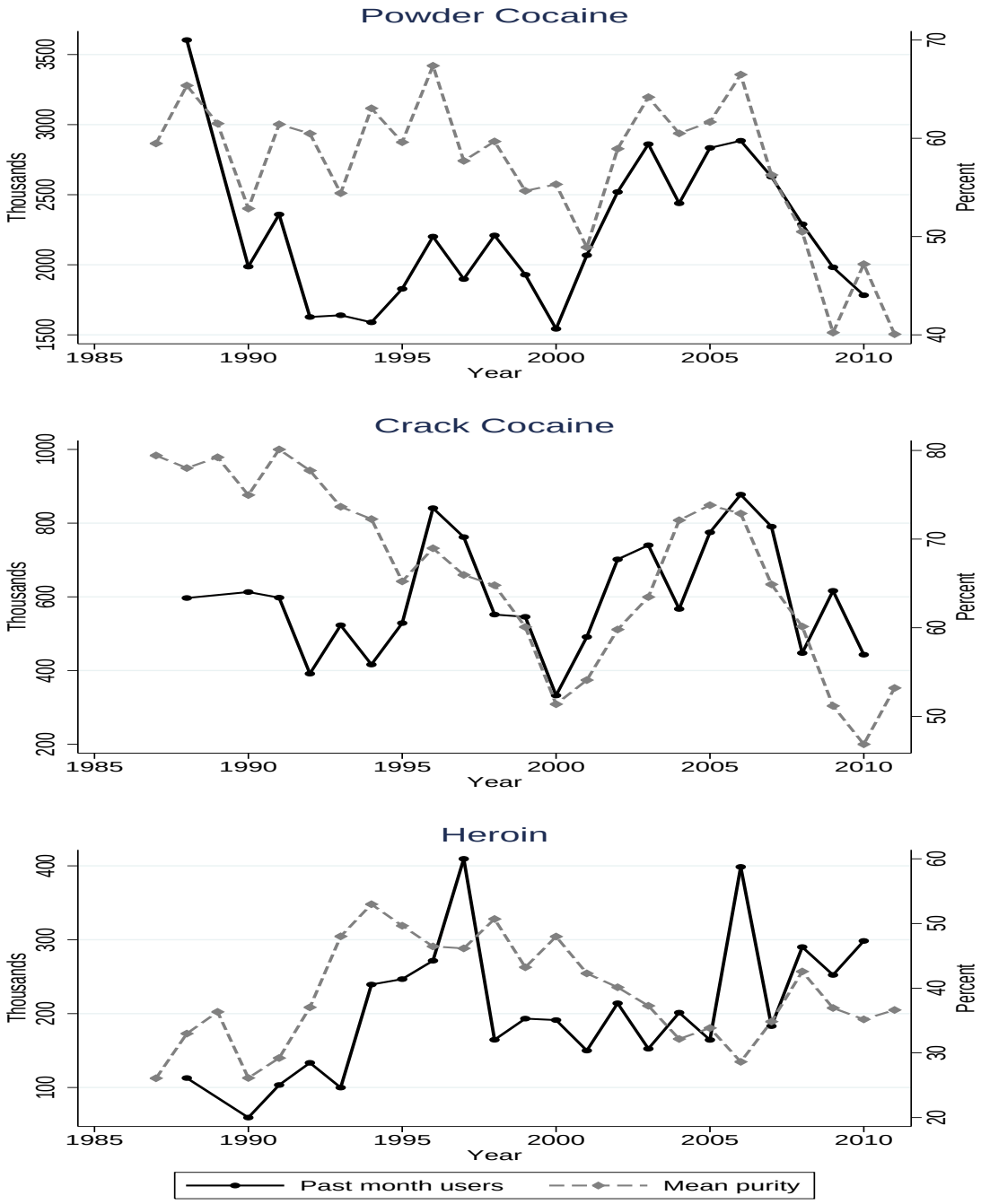
Figure 4 plots mean purity and the number of past month users of crack cocaine, powder cocaine and heroin. There is a positive association between the number of past month users and mean purity: the correlation coefficient is 0.45 for powder cocaine, 0.26 for crack cocaine and 0.20 for heroin. Combined with the evidence of moral hazard, this suggests that the extensive margin of consumption is positively associated with buyers' (accurate) purity expectations. It is not possible to make precise statements regarding aggregate consumption since there is no reliable source of data for the intensive margin. Nevertheless, from the evidence in figure 4 it is likely that aggregate consumption and mean purity are positively associated, such that demand is likely to depend on buyers' purity expectations.

2.3 Dilution & Moral Hazard

Figure 5 plots the estimated cumulative distribution functions for purity at the retail and first wholesale levels for powder cocaine, crack cocaine and heroin. For powder cocaine and heroin, the wholesale distribution approximately first order stochastically dominates the retail distribution, providing strong evidence of dilution. First order stochastic dominance does not hold for crack cocaine, though the comparison of retail and wholesale purities is potentially misleading since retail crack cocaine is often synthesised from wholesale powder cocaine. Regression analysis shows that conditional on year, state and month, the mean purities of powder cocaine, crack cocaine and heroin are 1.9, 2.5 and 3.3 percentage points lower at the retail level respectively. In each case the difference is statistically significant at the 1% level.

Moral hazard is present if buyers cannot detect dilution prior to consumption. Galenianos et al.

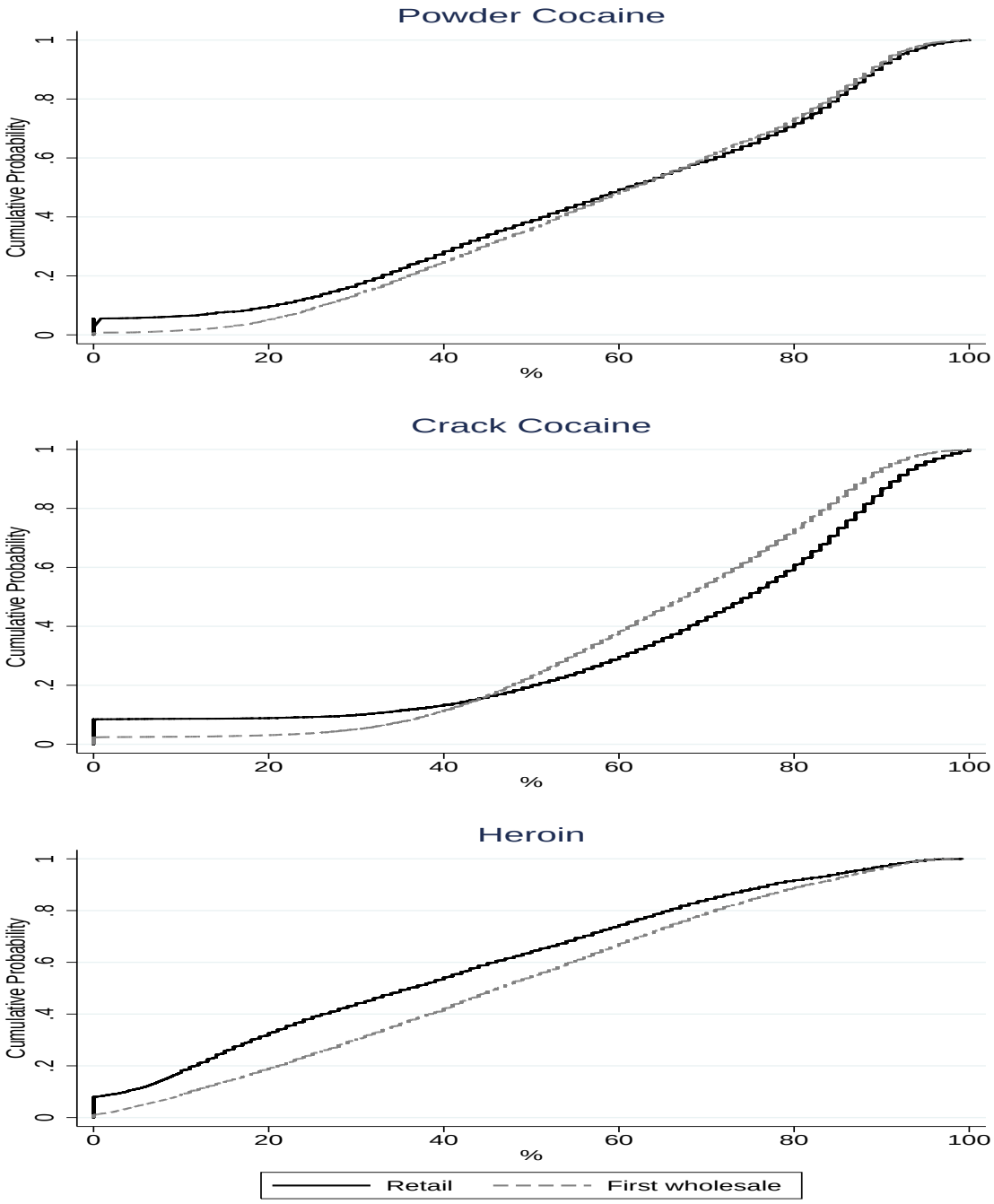
Fig. 4 Users & purity of retail drugs: US 1987-2011



Notes: Purity is constructed from STRIDE according to the method in the appendix. Following Caulkins et al. (2004), a retail purchase is of mass 0.1g-1g for crack cocaine and heroin, and 0.1g-2g for powder cocaine. The number of users is equal to the estimated proportion of the population with use in the last 30 days (NSDUH), multiplied by an estimate of the population (Census).

(2012) provide empirical evidence of moral hazard through showing that rip-off transactions are common. A rip-off occurs when a buyer receives very low purity drugs for a price comparable to that of high purity drugs, a transaction which is unlikely to occur in the absence of moral hazard. These transactions are evident from the mass points near zero in the distributions in figure 5, and are documented

Fig. 5 Retail & wholesale purity distributions: US 1987-2011



Notes: The retail and wholesale purity distributions are constructed from STRIDE according to the method in the appendix. The retail level corresponds to mass 0.1g-1g for crack cocaine and heroin, and 0.1g-2g for powder cocaine. The first wholesale level corresponds to 1g-15g for crack cocaine, 2g-10g for powder cocaine and 1g-10g for heroin. These values are taken from Caulkins et al. (2004).

in table 1.

Owing to the nature of STRIDE, the presence of rip-off transactions provides only weak evidence of moral hazard, since the purchasing objectives of undercover agents and genuine buyers may be different. Undercover agents may willingly purchase very low purity drugs in order to further the

Table 1 Rip-off retail transactions: US 1987-2011

Drug	Proportion of rip-offs (Purity <5%)	Mean per-gram price of rip-offs (std. dev.)	Mean per-gram price of non-rip-offs (std. dev.)
Powder Cocaine	5.8%	214.64	197.44
		(209.00)	(268.08)
Crack Cocaine	8.6%	227.27	203.29
		(133.35)	(117.02)
Heroin	11.4%	500.01	513.56
		(337.12)	(400.16)

Notes: The distributions of per-gram prices and purity are constructed from STRIDE according to the method in the appendix. Following Caulkins et al. (2004), a retail purchase is of mass 0.1g-1g for crack cocaine and heroin, and between 0.1g-2g for powder cocaine.

investigation, whilst genuine buyers may abstain. If the purchasing objectives of undercover agents are fixed across market levels, and since moral hazard is significantly more acute at the retail level than at the wholesale level (Reuter & Caulkins 2004), it is possible to infer the extent of moral hazard in the retail market through comparison of the retail and wholesale purity distributions.[12] If moral hazard is present one ought to observe rip-off transactions most frequently at the retail level. Figure 5 supports this: for each drug the mass points at zero are more pronounced at the retail level. Probit regressions confirm this difference is statistically significant at the 1% level for each drug, conditional on year, state and month.

2.4 Repeat Purchases

In a static environment, moral hazard may preclude high purity trade (Akerlof 1970). However, it is clear that this does not describe the majority of purchases. A sizeable literature shows that repeated interaction can overcome moral hazard through reputation effects. Before constructing a reputation based model, it is important to establish the extent to which trade is repeated.

Galenianos et al. (2012) use the Arrestee Drug Abuse Monitoring dataset (ADAM) to provide strong evidence that repeat purchases are commonplace, showing that frequent users of powder cocaine, crack cocaine and heroin made their most recent purchase from their regular dealer 79%, 62% and 76% of the time respectively. The prevalence of repeated interaction is sufficiently large such that reputation is a plausible explanation for the existence of high purity trade.

[12]Retail transactions are for small quantities and are often conducted in high risk, public locations. Wholesale transactions typically occur in private locations and buyers have stronger incentives to verify purity prior to trade.

3 Theoretical Framework

This section outlines a stylised theoretical framework, the purposes of which are to capture the key trade-offs faced by sellers, to explain the trends in per-gram prices, purity and seizures and to motivate an empirical specification. The analysis focuses first on the case where dilution is observable, and then incorporates moral hazard.

The model is a local monopoly consisting of a seller and a continuum of buyers.[13] Time is discrete and interaction is infinitely repeated. The seller is risk neutral and maximises the stream of expected, discounted profits with discount factor $\delta > 0$. Retail drugs are produced using two main factors of production: narcotics purchased from the wholesale market and less costly adulterant. Purity is strictly increasing in the ratio of wholesale narcotics to adulterant. This implies that the seller faces a trade-off between cost and purity, the size of which is determined by supply disruption affecting the wholesale market.

In this section supply shocks and seizures are amalgamated into a single binary shock denoted $v_t \in \{0, 1\}$, with $\text{Prob}[v_t = 1] = \gamma \in (0, 1)$. The shock determines the cost of wholesale narcotics. The seller has cost function $c(q_t, v_t, x_t)$, where $q_t \geq 0$ is purity and $x_t \geq 0$ is output. The cost function is continuous and twice differentiable with respect to x_t, q_t, and verifies:

$$
\begin{aligned}
& c_x(q_t, v_t, x_t) > 0 && && (1)\\
& c(q_H, 1, x_t) > c(q_H, 0, x_t) > c(q_L, 1, x_t) > c(q_L, 0, x_t) && \forall x_t > 0, q_H > q_L \\
& c(q_H, 1, x_t) - c(q_H, 0, x_t) > c(q_L, 1, x_t) - c(q_L, 0, x_t) && \forall x_t > 0, q_H > q_L
\end{aligned}
$$

The conditions in (1) imply that purity is costly, and that supply shocks increase the cost of high purity to a greater extent than low purity. The subsequent analyses contrain the seller to choose between high and low purity, such that $q_t \in \{q_L, q_H\}$ with $q_H > q_L \geq 0$. This simplifies the exposition whilst preserving the key trade-offs. Following Mailath & Samuelson (2001), the seller offers the same purity to all buyers. Demand is characterised by the continuous, twice differentiable inverse demand function:

[13] Following Mailath & Samuelson (2001), a continuum ensures that each buyer has no market power. The buyers' role is to maximise expected utility through forming accurate purity expectations. Competition between sellers and buyers' location decisions are not modelled.

$$p_t = p(q_t^E, x_t) \tag{2}$$

where $p_t \geq 0$ is the per-gram price and $q_t^E \in [q_L, q_H]$ denotes buyers' purity expectations. The inverse demand function satisfies $p_x(q_t^E, x_t) < 0, p_{q^E}(q_t^E, x_t) > 0, p(q_t^E, 0) > c_x(q_t, v_t, 0)$, and is such that there exists a unique output $x^c(q_t^E)$ such that $p(q_t^E, x^c(q_t^E)) = c_x(q_t, v_t, x^c(q_t^E))$ for all $q_t^E \in [q_L, q_H], q_t \in \{q_L, q_H\}, v_t \in \{0, 1\}$. These restrictions imply that the demand curve is downward sloping in output, that buyers have a taste for purity, and that there is always a unique, strictly positive profit maximizing output. The seller's profit function is:

$$\pi(q_t^E, q_t, v_t, x_t) = x_t p(q_t^E, x_t) - c(q_t, v_t, x_t) \tag{3}$$

In each period, the seller chooses purity and output given buyers' purity expectations and the shock. Denote as $x_t^* = x^*(q_t^E, q_t, v_t) > 0$ the unique period t profit maximizing output verifying:

$$p(q_t^E, x_t^*) + p_x(q_t^E, x_t^*)x_t^* - c_x(q_t, v_t, x_t^*) = 0 \tag{4}$$

and denote as $p_t^* = p(q_t^E, x_t^*)$ the corresponding per-gram price. Buyers observe output and price but do not observe shocks. The subsequent analysis considers the cases where buyers observe purity prior to trade, and where trade is subject to moral hazard.

3.1 Observable Purity

In this setting $q_t^E = q_t$ and the seller faces a static optimization problem in each period. Depending on the primitives, there are four cases to consider:

(a) Purity is always low and does not depend on shocks
$\pi(q_L, q_L, 1, x^*(q_L, q_L, 1)) > \pi(q_H, q_H, 0, x^*(q_H, q_H, 0))$.

(b) Purity is always high and does not depend on shocks
$\pi(q_H, q_H, 1, x^*(q_H, q_H, 1)) > \pi(q_L, q_L, 0, x^*(q_L, q_L, 0))$.

(c) Purity is high in the event of a shock and low otherwise
$\pi(q_H, q_H, 1, x^*(q_H, q_H, 1)) \geq \pi(q_L, q_L, 1, x^*(q_L, q_L, 1))$ and

$\pi(q_L, q_L, 0, x^*(q_L, q_L, 0)) \geq \pi(q_H, q_H, 0, x^*(q_H, q_H, 0))$.

(d) Purity is low in the event of a shock and high otherwise

$\pi(q_H, q_H, 0, x^*(q_H, q_H, 0)) \geq \pi(q_L, q_L, 0, x^*(q_L, q_L, 0))$ and

$\pi(q_L, q_L, 1, x^*(q_L, q_L, 1)) \geq \pi(q_H, q_H, 1, x^*(q_H, q_H, 1))$.

In case (a) the seller always chooses low purity. In case (b) the seller always chooses high purity. In both of these cases, shocks reduce output and increase per-gram prices. Case (c) is infeasible since shocks increase the cost of purity.

The more interesting case is (d). In this case, shocks increase the cost of purity by a sufficiently large amount such that the seller chooses low purity in response to shocks and high purity otherwise. Shocks decrease purity and have an ambiguous effect on output and per-gram prices, depending on the primitives of the cost and inverse demand functions. To see this, use $q_t^E = q_t$ and differentiate (4):

$$\begin{aligned} \frac{dx_t^*}{dq_t} &= -\frac{p_{q^E} + x_t^* p_{xq^E}}{2p_x + x_t^* p_{xx} - c_{xx} - c_{xq}} \\ \frac{dp_t^*}{dq_t} &= \frac{p_{q^E}(p_x - c_{xx} - c_{xq}) + x_t^*(p_{q^E} p_{xx} - p_x p_{xq^E})}{2p_x + x_t^* p_{xx} - c_{xx} - c_{xq}} \end{aligned} \tag{5}$$

which are ambiguously signed. If shocks incentivise low purity there are two competing effects. First, demand falls since buyers have a taste for purity. Second, costs fall since adulterant is less costly than wholesale narcotics. Consequentially, there is an ambiguous effect on output and per-gram prices.

Consider two benchmark models in (6) and (7). In the first, demand is linear in per-gram prices and expected purity. In the second, demand is for pure drugs, such that the expected pure quantity demanded is unchanged if expected purity and per-gram prices change by the same factor.[14] In both models, costs are convex and marginal cost is increasing in purity.

$$p(q_t^E, x_t) = \omega_0 + \omega_1 x_t + \omega_2 q_t^E, \qquad \omega_1 < 0, \omega_2 > 0, \quad c_{xx}(q_t, v_t, x_t) \geq 0, c_{xq}(q_t, v_t, x_t) \geq 0 \tag{6}$$

$$p(q_t^E, x_t) = \omega_0 {q_t^E}^{\frac{\omega_1}{1+\omega_1}} x_t^{-\frac{1}{1+\omega_1}}, \qquad \omega_0 > 0, \omega_1 > 0, \quad c_{xx}(q_t, v_t, x_t) \geq 0, c_{xq}(q_t, v_t, x_t) \geq 0 \tag{7}$$

For both the linear demand model in (6) and the demand for pure drugs model in (7) we have $\frac{dx_t^*}{dq_t} < 0, \frac{dp_t^*}{dq_t} > 0$, such that shocks cause purity and per-gram prices to fall and output to rise.

In sum, shocks may either increase the per-gram price and decrease output, or decrease purity and

[14] If x is the quantity demanded at per-gram price p and expected purity q, then $2x$ is the quantity demanded at per-gram price $0.5p$ and expected purity $0.5q$. In both cases, the quantity of expected pure drugs demanded is qx.

ambiguously effect the per-gram price and output, depending on the primitives. In the benchmark models (6)-(7), shocks may reduce purity and per-gram prices and increase output. This implies that supply disruption may have unanticipated consequences, even in the absence of moral hazard.

3.2 Moral Hazard

The remainder of this section supposes that buyers do not observe purity prior to trade. Instead, purity is observed on consumption and buyers use this to update their purity expectations. In this setting there must be some link between current purity and future profits in order to sustain non-trivial equilibria.[15] The mechanism proposed in this essay is seller reputation.[16] Theories of reputation can generally be classified into models based either on the folk theorem or on seller heterogeneity. The notion of reputation adopted in this essay is that of Mailath & Samuelson (2001), which falls into the latter category.

Seller hetereogeneity gives rise to reputation equilibria in which the seller incurs the cost of high purity so as to convince buyers that his type is 'good' and hence that he is more likely to sell high purity in the future. In addition to hetereogeneity, reputation equilibria also require that the seller's type change from time to time, and that buyers do not observe these changes (Mailath & Samuelson 2001).[17]

In the context of the drugs market, seller heterogeneity with type replacement is natural, and is best thought of in terms of the state of the wholesale market. Variation in enforcement or other external factors such as meteorological events leads to changes in the volatility of supply, such that shocks are less probable in 'good' states than in 'bad' states. In the simplest case there are two types, G and B. The type in period t is $i_t \in \{B, G\}$. The probability of shocks is lower for G, such that $\text{Prob}[v_t = 1 | i_t = i] = \gamma_i$, with $1 > \gamma_B > \gamma_G > 0$. At the end of period t, the type may change according to a Markov process:

$$\begin{aligned} i_t &= i_{t-1} && \text{with prob. } \lambda \in (0,1) \\ &= \psi_t && \text{with prob. } 1-\lambda \end{aligned} \tag{8}$$

[15] Otherwise moral hazard precludes trade in high purity such that the unique equilibrium is one in which purity is low in every period.

[16] Another mechanism which yields qualitatively similar results is rational addiction, as first studied in Becker & Murphy (1988).

[17] If this were not the case, buyers become increasingly convinced of the seller's type over time, such that they eventually assign probability one to his true type. At this point observed purity has no impact on buyers' beliefs such that the seller loses his purity incentive and the equilibrium unravels. Unobserved type replacement prevents this by bounding buyers' beliefs away from the extremes.

where $\psi_t \in \{B, G\}$ and $\text{Prob}[\psi_t = G] = \theta \in (0, 1)$. The remainder of this section makes an additional restriction on the cost function:

Assumption 3.1 (Cost separability) $c(q_t, v_t, x_t) = c_0(x_t) + q_t(F_1 + F_2 v_t)$

where $F_1 > 0, F_2 > 0$ determine the cost of purity in the absence of a shock ($q_t F_1$) and in the event of a shock ($q_t(F_1 + F_2)$). To preserve the ordering of costs in (1), it is further assumed that $q_H > q_L \left(1 + \frac{F_2}{F_1}\right)$. These restrictions maintain the seller's purity incentives, but imply that the profit maximizing output in each period does not depend on purity given buyers' purity expectations. This greatly simplifies the analysis by ruling out cases where prices signal purity.[18]

Buyers form their purity expectations based on the seller's strategy and on their beliefs about his type. At the beginning of period t, buyers attach probability ϕ_t to type G. The prior belief is $\phi_0 = \theta$. Buyers update their beliefs at the end of each period after observing purity, and form purity expectations according to the function $q_t^E = q^E(\phi_t)$, which is determined by the seller's equilibrium strategy. The sequence of events in period t is as follows:

(1) The shock $v_t \in \{0, 1\}$ is realised and observed by the seller. The probability that $v_t = 1$ is $\gamma_{i_t} \in (0, 1)$.

(2) The seller chooses the purity $q_t \in \{q_L, q_H\}$ and output $x_t \geq 0$.

(3) The seller accrues profit $\pi(q_t^E, q_t, v_t, x_t)$.

(4) Buyers observe purity, update ϕ_t and form $q_{t+1}^E = q^E(\phi_{t+1})$.

(5) The seller's type changes with probability λ. In this event, it becomes G with probability θ.

Seller behaviour is restricted to be Markov with state variables i_t, v_t, ϕ_t. The seller's strategy depends only on his type, buyers' beliefs, and the shock. Importantly, it does not depend on the history of play. A Markov strategy for the seller is:

$$\mu(i_t, v_t, \phi_t) = \text{Prob}[q_t = q_H | i_t, v_t, \phi_t] \tag{9}$$

Buyer behaviour is captured by an updating rule and a purity expectation function:

[18] The analysis does not allow for purity signalling based on price. The presence of rip-off transactions in the data suggests that price is not routinely used to signal purity. The restriction in (3.1) implies that the seller need not strategically manipulate the price so as to mask low purity, since the profit maximizing price is identical for high and low purity. The literature on seller reputation in markets for experience goods typically rules out signalling based on price through fixing output such that demand, and hence prices depend solely on buyers' quality expectations. This is the case in Mailath & Samuelson (2001). This assumption is not appropriate here since it rules out a Walrasian response of per-gram prices and consumption to shocks.

$$\phi_t = \varphi(q_{t-1}, \phi_{t-1}) \tag{10}$$
$$q_t^E = q^E(\phi_t)$$

A Markov Perfect Equilibrium (MPE) is an equilibrium in which the seller's strategy maximises the expected, discounted stream of profits, buyers' expectations are accurate and buyers adopt Bayes' rule to update their beliefs. To focus on the impact of supply disruption and to maintain comparability with the analysis under observable purity, the subsequent analysis focuses on characterizing pure strategy equilibria in which the seller's strategy depends solely on the shock v_t, such that $\mu(i_t, v_t, \phi_t) = \mu_0(v_t) \in \{0, 1\}$. Under this restriction, there are two feasible equilibria, which are detailed in proposition 3.2.

Proposition 3.2 (Markov Perfect Equilibria with $\mu(i_t, v_t, \phi_t) = \mu_0(v_t) \in \{0, 1\}$) *Consider the model with moral hazard and seller heterogeneity, and suppose that the seller's strategy is* $\mu_0(v_t) \in \{0, 1\}$.

(a) There is an MPE in which purity is always low ($\mu_0(v_t) = 0$).

(b) There is no MPE in which purity is always high ($\mu_0(v_t) = 1$).

(c) There is no MPE in which purity is high in the event of a shock and low otherwise ($\mu_0(v_t) = v_t$).

(d) There is $\bar{F}_1 > 0$ *and* $0 < \underline{F}_2 < \infty$ *such that for* $0 < F_1 \leq \bar{F}_1, F_2 \geq \underline{F}_2$ *there is an MPE in which purity is low in the event of a shock and high otherwise* ($\mu_0(v_t) = 1 - v_t$).

The equilibrium in proposition 3.2(a) is the unique equilibrium in the stage game. Buyers expect low purity, and given these expectations the seller's best response is to sell low purity. Shocks increase per-gram prices and reduce consumption. Proposition 3.2(b) states that there is no equilibrium in which purity is always high: if there were, buyers would expect high purity with certainty, and given these beliefs the seller has a profitable deviation in low purity. Proposition 3.2(c) rules out the infeasible equilibrium in which shocks increase purity.

The more interesting case is proposition 3.2(d), in which the seller responds to shocks through dilution. The equilibrium is governed by:

$$q_t = v_t q_L + (1 - v_t) q_H \tag{11}$$

$$\phi_t = \begin{cases} \varphi(q_L, \phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}\gamma^G}{\phi_{t-1}\gamma^G + (1-\phi_{t-1})\gamma^B} + \lambda\theta & \text{if } q_{t-1} = q_L \\ \varphi(q_H, \phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}(1-\gamma^G)}{\phi_{t-1}(1-\gamma^G) + (1-\phi_{t-1})(1-\gamma^B)} + \lambda\theta & \text{if } q_{t-1} = q_H \end{cases}$$

$$q_t^E = q^E(\phi_t) = q_H - (q_H - q_L)\gamma_B + \phi_t(q_H - q_L)(\gamma_B - \gamma_G)$$

$$x_t = x^*(q^E(\phi_t), v_t q_L + (1 - v_t) q_H, v_t)$$

$$p_t = p(q^E(\phi_t), x^*(q^E(\phi_t), v_t q_L + (1 - v_t) q_H, v_t))$$

Observed purity reveals shocks such that in period $t+1$ buyers know v_t with certainty and use this to update their beliefs and purity expectations. Output and the per-gram price transmit no new information to buyers since they depend solely on buyers' existing beliefs and not on current purity. The buyers' belief that his type is G may be interpreted as the seller's reputation. Unobserved type replacement bounds $\phi_t \in (\lambda\theta, 1 - \lambda(1-\theta))$ such that buyers can never become so certain of his type that the seller loses incentives for high purity in the absence of shocks. Through selling high purity today the seller strengthens his reputation, convincing buyers that he is more likely to sell high purity tomorrow, and increasing future demand.[19] A good reputation carries a profit premium.

In the absence of a shock, the seller must be willing to incur the cost of high purity in order to enhance his reputation. This requires that the wholesale cost of narcotics be modest compared to expected, discounted future profits ($0 < F_1 \leq \bar{F}_1$). Caulkins & Padman (1993) document substantial mark ups on wholesale drugs, suggesting that small F_1 is reasonable. In the event of a shock, the seller's purity decision depends on the present values of current profits and his reputation. If shocks increase the cost of purity by a sufficiently large amount ($F_2 \geq \underline{F}_2$), the latter outweighs the former. Consequentially, the equilibrium in proposition 3.2(d) exists if supply disruption is sufficiently successful in increasing wholesale costs.

In principal, the complexity of the model implies that there may exist an abundance of other equilibria in which the seller's strategy also depends on his type and on buyers' beliefs. Nevertheless, there can never exist an equilibrium in which buyers expect high purity with certainty in any period, since if this were the case the seller has a profitable deviation in low purity. Consequentially, in any equilibrium there is a nonzero probability of low purity in every period. Moreover, shocks incentivise dilution, such that average purity must always be lower in the event of a shock than otherwise.

[19] There is no active reputational behaviour in this equilibrium since both types of seller pursue the same strategy. In this sense, reputation is purely statistical. Nevertheless, for the purposes of this essay, such an equilibrium is sufficient.

3.3 Empirical Predictions

This section makes empirical predictions for the responses of per-gram prices and purity to seizures under the assumption that the seller's strategy takes the form $\mu(i_t, v_t, \phi_t) = \mu_0(v_t) \in \{0, 1\}$.[20] In this case, there are two equilibria, characterised in proposition 3.2(a) and 3.2(d). In the equilibrium in proposition 3.2(a), a period t shock has no effect on purity and increases the period t per-gram price.

The more interesting case is proposition 3.2(d). In equilibrium, shocks have no effect on current per-gram prices, decrease current purity, and ambiguously affect future per-gram prices, depending on the primitives of the inverse demand and cost functions. There are two cases to consider, depending on the response of per-gram prices to changes in buyers' purity expectations.[21] Differentiating (4) with respect to q_t^E:

$$\frac{dp_t^*}{dq_t^E} = \frac{p_{q^E}(p_x - c_{xx}) + x_t^*(p_{q^E}p_{xx} - p_x p_{xq^E})}{2p_x + x_t^* p_{xx} - c_{xx}} \tag{12}$$

which is ambiguously signed. Figure 6 illustrates the case where $\frac{dp_t^*}{dq_t^E} > 0$, as is the case for the benchmark models (6)-(7). A shock in period t causes period t purity to be low, whilst the period t per-gram price is determined by buyers' purity expectations, which depend solely on past purity. On observing low purity, buyers revise downwards their belief that the seller's type is G, dampening future purity expectations. A shock in period t reduces the per-gram price in period $t+1$ and all subsequent periods.

These dynamics imply that a shock in period t causes the per-pure-gram price to increase in period t and decrease in subsequent periods. The predictions are consistent with the trends documented in figures 2 and 3. Moreover, the model suggests that purity and per-gram prices may have fallen as a direct consequence of rising disruption.

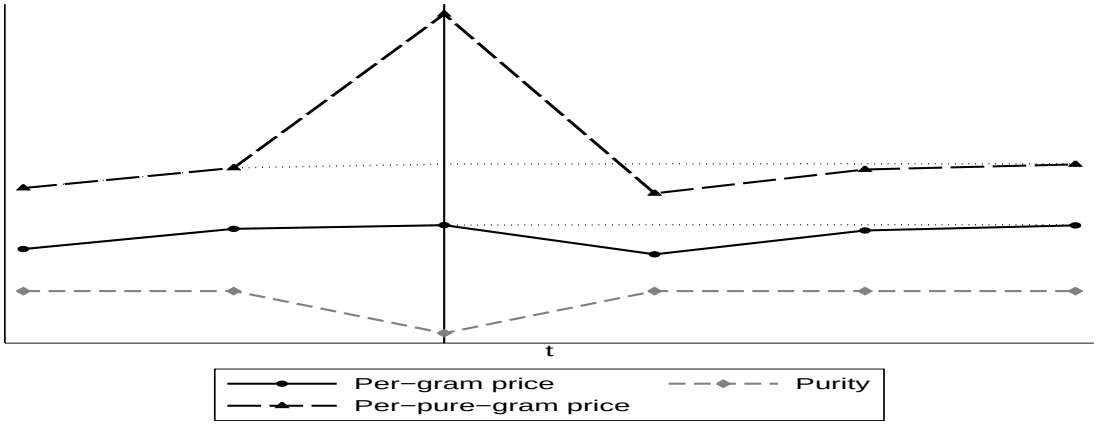
Figure 7 illustrates the case where $\frac{dp_t^*}{dq_t^E} < 0$. The purity effect is identical to the previous case, as is the timing of the impact on per-gram prices. However, in this case the decline in buyers' purity expectations has the opposite effect, causing per-gram prices to rise. The dynamics in per-gram prices and purity cause the per-pure-gram price to rise in period t and all future periods.

In sum, the equilibria in proposition 3.2 predict either that shocks have no effect on purity and increase per-gram prices, or that shocks decrease purity and have an ambiguous effect on future per-

[20] A lack of reliable output data imply that only predictions pertaining to per-gram prices and purity can be empirically evaluated.

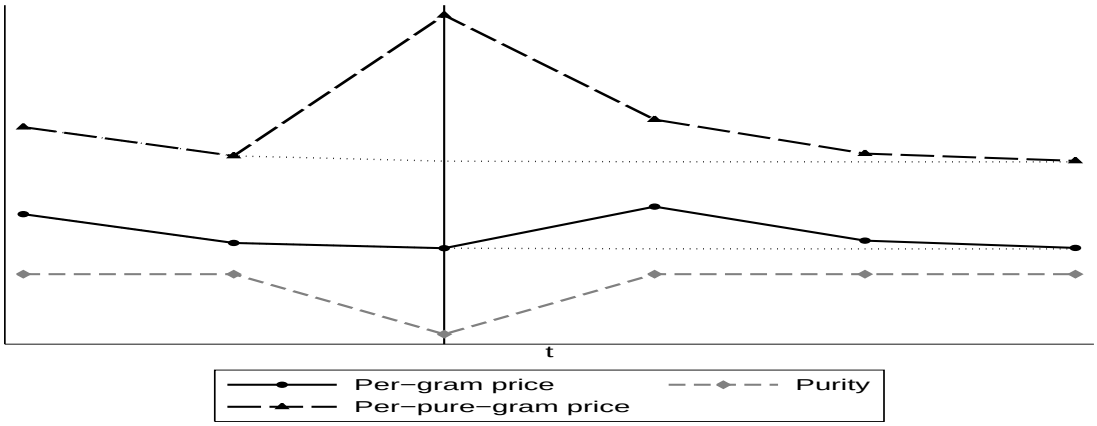
[21] It is of course feasible that shocks have different impacts on the per-gram price at different points in time, though this is not the case for the benchmark model (6).

Fig. 6 Predicted effect of supply shocks if per-gram prices are increasing in purity expectations



Notes: This figure illustrates the impact of a period t supply shock on purity, per-gram prices and per-pure-gram prices for the equilibrium in proposition 3.2(d), in which the seller offers low purity in response to shocks and high purity otherwise. This is the case where per-gram prices are positively related to purity expectations $\left(\frac{dp_t^*}{dq_t^E} > 0\right)$.

Fig. 7 Predicted effect of supply shocks if per-gram prices are decreasing in purity expectations



Notes: This figure illustrates the impact of a period t supply shock on purity, per-gram prices and per-pure-gram prices for the equilibrium in proposition 3.2(d), in which the seller offers low purity in response to shocks and high purity otherwise. This is the case where per-gram prices are negatively related to purity expectations $\left(\frac{dp_t^*}{dq_t^E} < 0\right)$.

gram prices. Section 4 seeks to recover the causal effect of seizures on current purity and current and future per-gram prices.

4 Empirical Analysis

To conduct empirical analysis the theoretical model must be temporally and spatially matched to the data. The market for crack cocaine in Washington DC is selected due to data constraints: the number of crack cocaine observations is considerably larger than for any other city or any other drug. This

owes to the fact that both the DEA and the DC Metropolitan Police (MPDC) submit samples to STRIDE, whereas in other cities only the DEA makes a significant contribution. The lowest feasible empirical frequency is monthly. For this reason, this section interprets a period in the theoretical model as one month.

Matching seizures to retail markets is hindered by the unobserved destination of seized narcotics. However, if shipments follow the path of least resistance they are unlikely to traverse an urban environment other than their destination retail market. For this reason, the analysis focuses on the local impact of cocaine seizures conducted in Washington DC. Another issue is that the model is of a representative local monopoly, whilst there are likely to be multiple sellers in a city. If one thinks of a city as a collection of local monopolies, the basic predictions of the model persist for the mean per-gram price and purity at the city level. This is consistent with there being a few large sellers in a city, each of which controls a different neighbourhood.

The STRIDE data are used to derive monthly measures of real per-gram retail prices, purity and seizures in Washington DC for 300 months spanning January 1987 to December 2011. The variables p_t and q_t are the log mean real per-gram price and purity of retail crack cocaine purchases in month t. These are constructed from 9,379 undercover purchases according to the method in the appendix. Seizures are measured both by number and mass. The variables s_t^{no} and s_t^{kg} correspond to the log total number and log total mass of cocaine seizures in month t respectively. These measures are constructed from 27,776 seizures of total mass 1,341 kilograms.

This empirical analysis distinguishes between Washington DC seizures, denoted s_t, and unobserved supply shocks, denoted u_t, which form the shock in the theoretical framework. Examples of unobserved supply shocks may be meteorological events which influence production, enforcement at the production phase or seizures which occur prior to Washington DC. Seizures mirror supply, and are hence correlated with unobserved supply shocks. Seizures and supply shocks are persistent due to dependence on the state of the wholesale market governed by (8).

Under the assumption that the seller's equilibrium strategy takes the form $\mu(i_t, v_t, \phi_t) = \mu_0(v_t) \in \{0, 1\}$, the theoretical framework predicts the following empirical relationships:

$$\begin{aligned} q_t &= Q(u_t, s_t, \epsilon_t^q) \\ p_t &= P\left(q_t^E, s_t, u_t, \epsilon_t^p\right) \end{aligned} \tag{13}$$

Purity is determined by seizures, supply shocks and other unmodelled factors ϵ_t^q. The per-gram

price is a function of expected purity, seizures and unmodelled factors ϵ_t^p. Only p_t, q_t and s_t are observed in the data. Owing to its stylised nature, a structural estimation of the theoretical model is not undertaken. Instead, equation (13) is linearised:

$$q_t = \alpha_0 + \alpha_1 s_t + \alpha_2 u_t + \epsilon_t^q \tag{14}$$

$$p_t = \beta_0 + \beta_1 q_t^E + \beta_2 s_t + \beta_3 u_t + \epsilon_t^p \tag{15}$$

Buyers' purity expectations are unobserved, however, the model predicts that expectations are adjusted each month according to $q_t^E = Q^E(q_{t-1}^E, q_{t-1})$. To keep the empirical model as simple as possible the baseline specification for expectations is:

$$q_t^E = q_{t-1}^E + (q_{t-1} - \gamma_0) + \epsilon_{t-1}^{q^E} \tag{16}$$

where $\epsilon_{t-1}^{q^E}$ is the disturbance. This specification captures the important dynamics whilst yielding a model which is straightforward to identify. Purity expectations increase if purity exceeds a fixed threshold, and decrease otherwise. Using (16) in (15):

$$q_t = \alpha_0 + \alpha_1 s_t + \xi_t^q \tag{17}$$

$$p_t = \delta_0 + \delta_1 q_{t-1} + \delta_2 s_t + \xi_t^p \tag{18}$$

where $\delta_0 = -\delta_1\gamma_0$, $\delta_1 = \beta_1$, $\delta_2 = \beta_2$, $\xi_t^q = \alpha_2 u_t + \epsilon_t^q$ and $\xi_t^p = \beta_1(q_{t-1}^E + \epsilon_{t-1}^{q^E}) + \beta_3 u_t + \epsilon_t^p$.

Seizures are endogenous in the purity and per-gram price equations since they are correlated with unobserved supply shocks contained in the disturbances. Lagged purity is endogenous in the price equation since the disturbance contains lagged purity expectations, which are accurate in equilibrium.

The equilibrium in proposition 3.2(a) predicts $\alpha_1 = 0, \delta_1 = 0, \delta_2 > 0$. The equilibrium in proposition 3.2(d) predicts $\alpha_1 < 0, \delta_2 = 0$, whilst the sign of δ_1 is theoretically ambiguous, depending on the average response of per-gram prices to purity expectations. For the benchmark models (6)-(7), proposition 3.2(d) predicts $\delta_1 > 0$.

Identification hinges on the persistence of the disturbances in equations (17) and (18), which are assumed to follow autoregressive processes:

$$\xi_t^q = \sum_{i=1}^{a^q} \rho_i^q \xi_{t-i}^q + \upsilon_t^q \tag{19}$$
$$\xi_t^p = \sum_{i=1}^{a^p} \rho_i^p \xi_{t-i}^p + \upsilon_t^p$$

where the innovations verify $\mathbb{E}[\upsilon_t^i] = 0$, $\mathbb{E}[\upsilon_t^i \upsilon_s^i] = 0 \quad \forall\, i \in \{p, q\}, t, s \neq t$. Applying the autoregressive transformation to (17) and (18) yields a model with non-serially correlated errors:

$$q_t - \sum_{r=1}^{a^q} \rho_r^q q_{t-r} = \alpha_0 \left(1 - \sum_{r=1}^{a^q} \rho_r^q\right) + \alpha_1 \left(s_t - \sum_{r=1}^{a^q} \rho_r^q s_{t-r}\right) + \upsilon_t^q \tag{20}$$
$$p_t - \sum_{r=1}^{a^p} \rho_r^p p_{t-r} = \delta_0 \left(1 - \sum_{r=1}^{a^p} \rho_r^p\right) + \delta_1 \left(q_{t-1} - \sum_{r=1}^{a^p} \rho_r^p q_{t-1-r}\right) + \delta_2 \left(s_t - \sum_{r=1}^{a^p} \rho_r^p s_{t-r}\right) + \upsilon_t^p \tag{21}$$

Persistence in per-gram prices, purity and seizures permits the use of exogenous lags as instruments for the endogenous regressors. The theoretical framework details persistence in per-gram prices owing to seller reputation and persistence in purity, seizures and shocks owing to persistence in the volatility of wholesale supply. The empirical counterparts of the series also demonstrate substantial persistence. Figure A1 in the appendix shows that per-gram prices, purity and seizures exhibit strong autocorrelation: lagged values up to 2 years are good predictors of current levels.

Equation (20) is identified by the moment conditions $\mathbb{E}[\upsilon_t^q] = 0$, $\mathbb{E}[\upsilon_t^q s_{t-i}] = 0$, $\mathbb{E}[\upsilon_t^q q_{t-j}] = 0$ for $i, j = (1, 2, ...)$. Similarly, equation (21) is identified by the moment conditions $\mathbb{E}[\upsilon_t^p] = 0$, $\mathbb{E}[\upsilon_t^p q_{t-i}] = 0$, $\mathbb{E}[\upsilon_t^p s_{t-j}] = 0$, $\mathbb{E}[\upsilon_t^p p_{t-k}] = 0$ for $i, j, k = (2, 3, ...)$.[22] Given the large number of instruments, the model is potentially overidentified.

Parameters are estimated by one-step GMM with Huber White standard errors.[23] Equations (17) and (18) are estimated by OLS for comparison. GMM estimation of (20) and (21) is conducted for each order of the autoregressive process $a \in \{0, ..., 3\}$. The value of a in the baseline specification is chosen using the method in Borowczyk-Martins et al. (2013). Beginning with $a = 0$, the baseline value of a is increased up until $a + 1$ ceases to be statistically significant at the 5% level.

The moment conditions above yield a large number of potential instruments, however, it is good practice to avoid using too many (Roodman 2009).[24] Conversely, overidentification is useful so as

[22] The innovations υ_t^p depend on $q_{t-1}^E, \epsilon_{t-1}^{q^E}$, implying that per-gram prices, seizures and purity in period $t-1$ are not exogenous.

[23] The optimal two-step estimator is not employed since it may perform poorly in small samples. In particular, estimated standard errors are likely to be downwards biased (Windmeijer 2005).

[24] Specifying too many instruments overfits endogenous variables and weakens the Hansen test.

to permit tests of overidentifying restrictions. For equation (20), the moment conditions above are used with $i = (1, 2)$ and $j = (1, ..., a^q)$. For equation (21) the moment conditions above are used with $i = (2, ..., 5)$, $j = (2, ..., 5)$ and $k = (2, ..., a^p + 5)$. These values imply that the estimated purity equation is overidentified of order one and the estimated per-gram price equation is overidentified of order ten. The number of moment conditions is greater in the per-gram price equation since valid instruments are lagged further and the number of endogenous regressors is greater than in the purity equation.[25] Overidentifying restrictions are tested by means of a Hansen test, which is computed by two-step GMM.[26]

Augmented Dickey-Fuller tests do not reject the unit root hypothesis for p_t, q_t, s_t^{no} and s_t^{kg} at the 0.05 significance level. Augmented Engle-Granger tests for cointegration do not reject the null that the series are not cointegrated for the purity equation (17) regardless of the measure of seizures. For the per-gram-price equation (18), the null is rejected at the 0.05 level for seizures measured by number and at the 0.1 level for seizures measured by mass.

Non-stationarity may be a cause for concern due to the potential for spurious relationships between the series. However, as argued in Borowczyk-Martins et al. (2013), the results of Hsiao (1997) imply that these concerns do not apply to GMM estimation of (20) and (21). In short, the empirical analysis in this essay seeks to recover the structural relationships between the series as opposed to cointegrating vectors. Hsiao (1997) demonstrates that GMM estimation of (20) and (21) is consistent in this setting.

4.1 Results

Table 2 reports baseline results. Results for all autoregressive specifications are in tables A2 and A3 in the appendix. All variables are in natural logs, hence parameters may be interpreted as elasticities.

Beginning with the purity equation, and looking at models (1) and (3) of table 2, OLS estimates of the seizures elasticity of purity are positive and statistically significant for both measures of seizures. A 10% increase in the number (mass) of seizures is associated with a 2.3% (0.7%) increase in purity. In contrast, the baseline GMM estimates in models (2) and (4) are negative and statistically significant, suggesting that a 10% increase in the total number (mass) of seizures decreases purity by 4.7% (0.2%). Table A2 shows that all GMM estimates are negative and do not vary substantially between specifications. The exception is the AR(0) specifications, in which case results are similar to OLS. These findings are consistent with upwards bias generated by seizures mirroring supply.

[25] Standard errors are large and parameter estimates vary substantially across autoregressive specifications if the number of moment conditions is too small.

[26] The Hansen statistic is valid only if the weight matrix is the inverse of the covariance matrix of the moment conditions, which is not the case with the one-step GMM estimator.

Table 2 Baseline estimates of the response of purity & per-gram prices to seizures

	Purity (q_t)				Per-gram price (p_t)			
	(1)	(2)	(3)	(4)	(5)	(6)		
Estimator	OLS	GMM	OLS	GMM	OLS	GMM	OLS	GMM
AR		2		2		2		2
Seizures (s_t^{no})	.233***	-.473**			.297***	.154		
	(.0341)	(.221)			(.0460)	(.117)		
Seizures (s_t^{kg})			.0666***	-.0240**			.0788***	-.00652
			(.0146)	(.0105)			(.0191)	(.0240)
Purity (q_{t-1})					.0217	.493*	.287***	.920**
					(0.0139)	(0.292)	(.110)	(.452)
T	300	298	300	298	299	293	299	293
OverID		1		1		10		10
Hansen		.58		.56		.62		.32

Notes: q_t and p_t are the natural logs of the month t mean purity and real per-gram price of retail (0.1g-1g) crack cocaine in Washington DC respectively. s_t^{no} and s_t^{kg} are the natural log of the month t total number and mass of cocaine seizures of mass greater than 1 gram in Washington DC respectively. Huber White standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. The 'T' row reports the number of observations. The 'OverID' row reports the degree of overidentification. The 'Hansen' row reports the p-value for the J statistic. OLS estimates are for (17) and (18). GMM estimates are for (20) and (21). The 'AR' row reports the autoregressive order of the disturbance. The constant and parameter estimates for the autoregressive components are in table A2 and table A3 in the appendix.

Moving on to the per-gram price equation, and looking at models (5) and (7) of table 2, the OLS estimates of the purity elasticity of per-gram prices are positive. If seizures are measured by number, the OLS estimate is small in magnitude and statistically insignificant. If seizures are measured by number, the OLS estimate is an order of magnitude larger and is statistically significant. A 10% increase in month t purity is associated with a 0.2% increase in month $t+1$ per-gram prices for seizures measured by number, and a 2.9% increase for seizures measured by mass. OLS estimates of the seizures elasticity of per-gram prices are positive and statistically significant. A 10% increase in the number (mass) of month t seizures is associated with a 3.0% (0.7%) increase in month t per-gram prices.

Looking at models (6) and (8), baseline GMM estimates of the purity elasticity of per-gram prices are positive and statistically significant. A 10% increase in month t purity leads the month $t+1$ per-gram price to rise by 4.9% if seizures are measured by number, and 9.2% if seizures are measured by mass. Baseline GMM estimates of the seizures elasticity of per-gram prices are small in magnitude and statistically insignificant. The estimated elasticity is positive for seizures measured by number and negative for seizures measured by mass. Table A2 shows that GMM estimates do not vary substantially between specifications once the disturbance is permitted to follow an autoregressive process. This is consistent with endogeneity of seizures and lagged purity in the per-gram price equation.

GMM estimates account for endogeneity and are consistent with the predictions of the equilibrium in proposition 3.2(d): month t seizures have no direct effect on the per-gram price, and reduce the

month $t+1$ per-gram price through incentivizing dilution in month t. Results also suggest that per-gram prices respond positively to heightened purity expectations such that $\frac{dp_t^*}{dq_t^E}$ is positive on average. This is consistent with the benchmark models in (6)-(7). Taken together, baseline GMM estimates of the purity and per-gram price equations imply that the total effect of a 10% rise in the number (mass) of month t seizures is a 2.3% (0.2%) reduction in the month $t+1$ per-gram price.

Baseline GMM estimates suggest that purity and per-gram prices are more responsive to the total number of seizures than to the total amount seized. This difference is not due to scaling since the mean log number of seizures per month (4.42) is substantially larger than that for total kilograms seized (0.83). There are two potential explanations. The first stems from the fact that the total mass seized is dominated by a few large seizures. A total of 28,318 seizures were conducted during the sample period, of which the largest 3 account for more than 10% of the combined mass of 1,341kg. If the likelihood that a shipment is destined for the DC market is decreasing in its size, then large seizures may have had no impact on the local retail market, which could lead estimates to be small in magnitude for seizures measured by mass. The second explanation is that seizures measured by mass exhibit much lower persistence than those measured by number (see figure A1 in the appendix) so that specifications based on mass are likely to be weakly identified in comparison to those based on number. It is well known that weak identification biases IV towards OLS (Stock et al. 2002), which could account for the difference.

Baseline GMM specifications perform well in the Hansen test, as do most GMM specifications of sufficiently high autoregressive order. Performance is poor for low order autoregressive models. This provides evidence in favour of endogeneity generated through persistent supply shocks.

4.2 Discussion

The existing empirical literature has documented no impact on the per-pure-gram price, whilst empirical results in this essay suggest an initial rise followed by a subsequent decline. This can be reconciled with DiNardo (1993) and Caulkins & Yuan (1998) through the supposition that time aggregation of data is likely to mask the short run impact as the initial rise and subsequent decline cancel each other out. It is also possible that the effects are lost through spatial aggregation. Caulkins & Yuan (1998) use monthly data at the national level, whilst DiNardo (1993) uses annual data at the state level. Through using monthly data at the city level, this essay's results are less suseceptible to aggregation effects. Moreover, neither DiNardo (1993), nor Caulkins & Yuan (1998) account for endogeneity, making a direct comparison misleading.

Reconciling results with Dobkin & Nicosia (2009) is less straightforward. The response of purity

to disruption is found to be negative in each case, however this essay finds no evidence of the positive per-gram price response documented in Dobkin & Nicosia (2009). This disparity could arise as a consequence of differences in market characteristics or differences in the interventions. The markets for crack cocaine and methamphetamine may contrast in the degree to which trade is subject to moral hazard: for example, in the extent to which it is possible to ascertain purity by visual inspection. Moreover, the interventions may operate through different channels. Results in Dobkin & Nicosia (2009) could be explained by the Walrasian model, in which the precursor restrictions constrain production in terms of output and purity. This could lead per-gram prices to rise, so long as the output effect dominates the purity effect.

5 Policy Implications & Conclusion

This essay provides a theoretical and empirical evaluation of the impact of supply disruption on the retail market for illicit drugs. Seizures incentivise low purity, reducing future demand. This is consistent with the observed declines in per-gram prices and purity amid rising supply disruption. The empirical analysis supports the predictions of the theoretical framework, showing that increases in month t seizures serve to reduce month t purity and the month $t+1$ per-gram price.

Together, the theoretical and empirical analyses suggest that per-gram prices and purity may have fallen as a direct consequence of heightened supply disruption. However, the efficacy of supply disruption as a policy to decrease consumption is unclear. If the aim is to decrease total consumption of pure narcotics, supply disruption is unambiguously successful. However, the theoretical framework suggests that the impact of disruption on consumption is ambiguous, whilst the absence of reliable consumption data precludes empirical evaluation. If the equilibrium is that of proposition 3.2(d), the marginal effect of supply disruption on output is:

$$\frac{dx^*_{t+1}}{ds_t} = -\left(\frac{p_{q^E} + x^*_t p_{xq^E}}{2p_x + x^*_t p_{xx} - c_{xx}}\right)\frac{dq^E_{t+1}}{ds_t} \tag{22}$$

By construction $p_{q^E} > 0$ and $p_x < 0$, whilst empirical results suggest that supply disruption dampens purity expectations such that $\frac{dq^E_{t+1}}{ds_t} < 0$. However, for the general case the signs of p_{xq^E}, p_{xx}, c_{xx} are unknown. Consequentially, the theoretical and empirical evidence documented in this essay is insufficient to sign the effect of supply disruption on consumption. An important implication of this is that falling per-gram prices do not indicate policy failure: the observed trends in per-gram prices, purity and seizures can be consistent with any trend in consumption. Moreover, figure 4 shows that

the number of past month users is positively associated with mean purity, such that increases in supply disruption may decrease consumption through the purity channel. In order to make more precise statements, it is imperative that reliable consumption data be collected.

Estimation results are consistent with the benchmark models in (6)-(7). In these cases, the equilibrium in proposition 3.2(d) predicts an output response to supply disruption given by:

$$\frac{dx^*_{t+1}}{ds_t} = -\left(\frac{p_{q^E}}{2p_x - c_{xx}}\right)\frac{dq^E_{t+1}}{ds_t} > 0 \tag{23}$$

This implies that supply disruption increases consumption, which may be in direct conflict with the policy objective.

Declines in per-gram prices and purity may also have a direct impact on user outcomes. Darke et al. (1999) find that mean purity is positively associated with the number of overdoses, suggesting that supply disruption may improve health outcomes. Conversely, Chang et al. (2010) show that harmful adulterants are increasingly used in cocaine, implying that supply disruption may worsen outcomes. Finally, Hyatt & Rhodes (1995) document that emergency room visits, deaths and positive drug tests among arrestees are negatively associated with the per-pure gram price of cocaine, though it is not clear whether these findings are driven by purity or the per-gram price.

The potential for supply disruption to have unintended effects stems from the impact on sellers' purity incentives. By increasing the cost of wholesale narcotics, disruptive interventions incentivise dilution, leading to reductions in both demand and costs. This may cause per-gram prices to fall and consumption to rise. It is therefore likely that policies aimed at increasing costs uniformly over purity may be more effective. The theoretical framework predicts that these policies increase per-gram prices and decrease consumption. For example, an increase in the arrest rate of sellers raises costs independently of purity, and may lead to higher per-gram prices and lower consumption. Kuziemko & Levitt (2004) show that this hypothesis is consistent with the data.

The analysis is limited by an absence of competition between sellers, market imperfections such as search frictions and substitution between different drugs. The absence of substitution effects may be an important omission, since disrupting the supply of a particular drug may increase consumption of other, potentially more harmful drugs. To capture these effects, future work may seek to augment the theoretical and empirical models to include additional drugs.

The empirical analysis is constrained by spatio-temporal matching of supply disruption to local retail markets resulting from the unobserved destination of seized narcotics. This constrains the

analysis to focus on the impact of local supply disruption on the local market in Washington DC. Future work may seek to evaluate the extent to which enforcement at each phase of the supply chain impacts upon different local retail markets. This could offer insights into the relative efficacy of small scale local interventions and large scale distant interventions, such as those conducted in producer nations.

References

Akerlof, G. A. (1970), 'The market for 'lemons': Quality uncertainty and the market mechanism', *Quarterly Journal of Economics* pp. 488–500.

Arkes, J., Pacula, R. L., Paddock, S., Caulkins, J. & Reuter, P. (2008), Why the dea stride data are still useful for understanding drug markets, NBER Working Papers 14224, National Bureau of Economic Research, Inc.

Becker, G. & Murphy, K. (1988), 'A theory of rational addiction', *Journal of Political Economy* **96**(4), 675–700.

Borowczyk-Martins, D., Jolivet, G. & Postel-Vinay, F. (2013), 'Accounting for endogeneity in matching function estimation', *Review of Economic Dynamics* **16**(3), 440–451.

Caulkins, J., Pacula, R., Arkes, J., Reuter, P., Paddock, S., Iguchi, M. & Riley, J. (2004), The price and purity of illicit drugs: 1981 through the second quarter of 2003, Technical report, Washington, DC: Office of National Drug Control Policy.

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

Caulkins, J. & Yuan, Y. (1998), 'The effect of variation in high-level domestic drug enforcement on variation in drug prices', *Socio-Economic Planning Sciences* **32**(4), 265–276.

Chang, M., Osterloh, J. & Thomas, J. (2010), 'Levamisole: A dangerous new cocaine adulterant', *Clinical Pharmacology & Therapeutics* **88**, 408–411.

Darke, S., Hall, W., Weatherburn, D. & Lind, B. (1999), 'Fluctuations in heroin purity and the incidence of fatal heroin overdose', *Drug and Alcohol Dependence* **54**(2), 155–161.

DiNardo, J. (1993), 'Law enforcement, the price of cocaine and cocaine use', *Mathematical Computer Modelling* **17**(2), 53–64.

Dobkin, C. & Nicosia, N. (2009), 'The war on drugs: Methamphetamine, public health, and crime', *American Economic Review* **99**(1), 324–49.

Dobkin, C., Nicosia, N. & Weinberg, M. (2014), 'Are supply-side drug control efforts effective? evaluating otc regulations targeting methamphetamine precursors', *Journal of Public Economics* **120**, 48–61.

Galenianos, M., Pacula, R. L. & Persico, N. (2012), 'A search-theoretic model of the retail market for illicit drugs', *Review of Economic Studies* **79**, 1239–1269.

Holmström, B. (1999), 'Managerial incentive problems: A dynamic perspective', *Review of Economic Studies* **66**(1), 169–182.

Hörner, J. (2002), 'Reputation and competition', *American Economic Review* **92**(3), 644–663.

Horowitz, J. (2001), 'Should the dea's stride data be used for economic analyses of markets for illegal drugs', *Journal of the American Statistical Association* **96**(456), 1254–1262.

Hsiao, C. (1997), 'Statistical properties of the two-stage least squares estimator under cointegration', *Review of Economic Studies* **64**(3), 385–398.

Hyatt, R. & Rhodes, W. (1995), 'The price and purity of cocaine: The relationship to emergency room visits and death, and to drug use among arrestees', *Statistics in Medicine* **14**, 655–668.

Kelly, E. & Rasul, I. (2014), 'Policing cannabis and drug related hospital admissions: Evidence from administrative records', *Journal of Public Economics* **112**, 89–114.

Kuziemko, I. & Levitt, S. D. (2004), 'An empirical analysis of imprisoning drug offenders', *Journal of Public Economics* **88**(9), 2043–2066.

Liu, Q. (2011), 'Information acquisition and reputation dynamics', *Review of Economic Studies* **78**(4), 1400–1425.

Mailath, G. & Samuelson, L. (2001), 'Who wants a good reputation?', *Review of Economic Studies* **68**(2), 415–41.

Manski, C. F., Pepper, J. V. & Petrie, C. V. (2001), *Informing America's policy on illegal drugs: What we don't know keeps hurting us*, The National Academies Press.

Miron, J. (2003), 'The effect of drug prohibition on drug drices: Evidence from the markets for cocaine and heroin', *Review of Economics and Statistics* **85**(3), 522–530.

Reuter, P. & Caulkins, J. (2004), 'Illegal lemons: Price dispersion in the cocaine and heroin markets', *U.N Bulletin on Narcotics* .

Reuter, P. & Kleiman, M. (1986), Risks and prices: An economic analysis of drug eenforcement, *in* M. Tonry & N. Morris, eds, 'Crime & Justice: A Review of Research', Chicago, IL: University of Chicago Press.

Roodman, D. (2009), 'A note on the theme of too many instruments', *Oxford Bulletin of Economics and Statistics* **71**(1), 135–158.

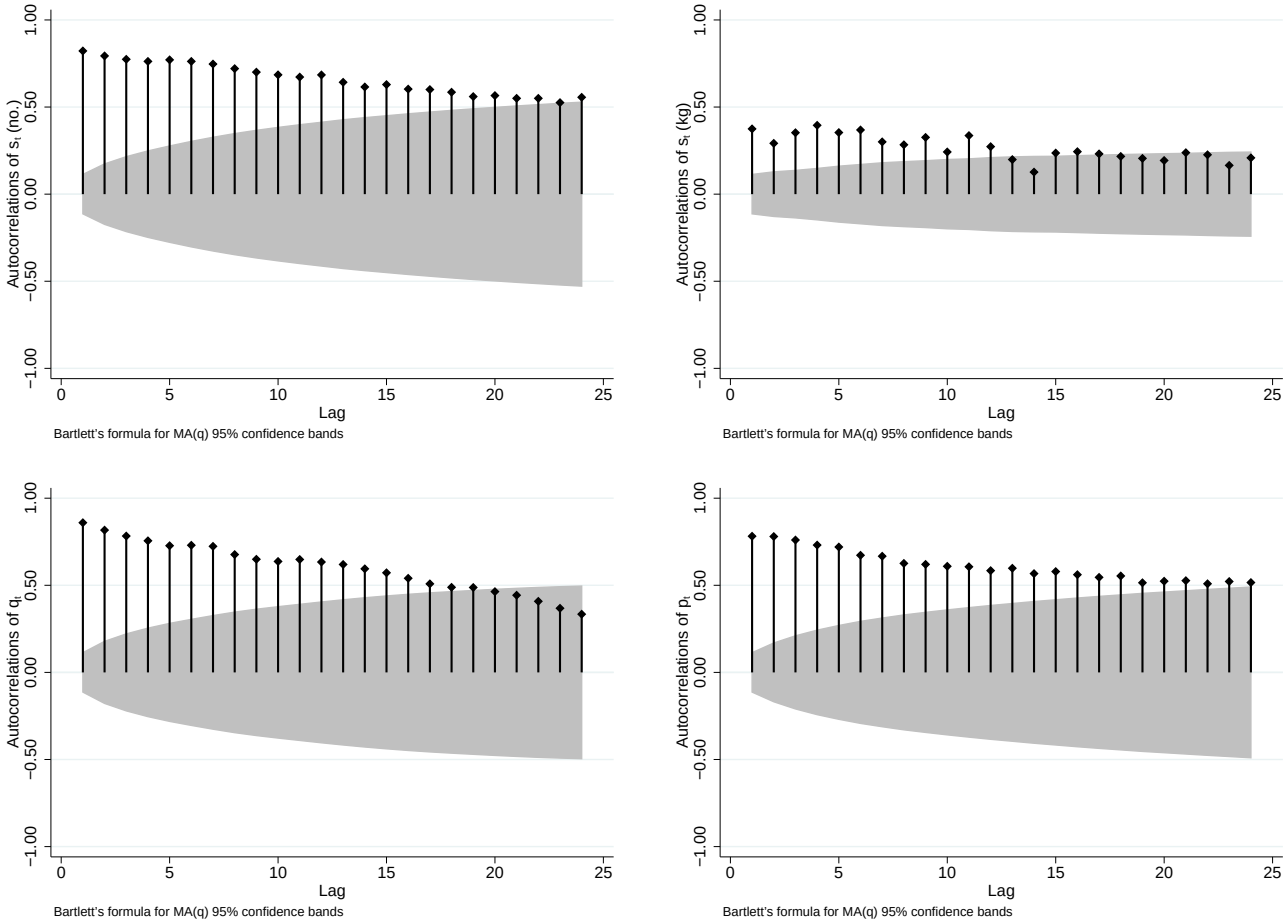
Stock, J. H., Wright, J. H. & Yogo, M. (2002), 'A survey of weak instruments and weak identification in generalized method of moments', *Journal of Business & Economic Statistics* **20**(4).

Windmeijer, F. (2005), 'A finite sample correction for the variance of linear efficient two-step gmm estimators', *Journal of Econometrics* **126**(1), 25–51.

Appendix

Figures

Fig. A1 Autocorrelations of log seizures, per-gram prices & purity



Tables

Table A1 Summary statistics for STRIDE: US 1987-2011

Powder cocaine							
Purchases							
	Units	**Obs.**	**Mean**	**Median**	**S.D.**	**Min.**	**Max.**
Price	2011 dollars	47128	3285.53	1472.42	9987.80	8.29	709504.10
Per-gram price	2011 dollars	47128	78.74	54.91	106.16	11.59	5623.43
Per-pure-gram price	2011 dollars	46565	162.20	96.65	661.97	13.17	84798.96
Purity	Percent	50063	61.97	67.00	24.54	0.00	100.00
Mass	Grams	50073	92.95	27.60	545.85	0.00	74420.00
Seizures							
Purity	Percent	122869	65.57	78.00	29.17	0.00	100.00
Mass	Kilograms	122891	14.29	0.21	167.09	0.00	21470.40
Crack cocaine							
Purchases							
Price	2011 dollars	75638	1010.81	510.02	1724.08	0.03	83927.31
Per-gram price	2011 dollars	75638	116.28	79.38	104.59	14.13	2621.05
Per-pure-gram price	2011 dollars	72452	191.15	129.70	942.69	17.38	168990.20
Purity	Percent	79671	61.98	65.00	23.16	0.00	100.00
Mass	Grams	79676	21.46	5.9	81.92	0.00	10747.00
Seizures							
Purity	Percent	101225	59.20	67	29.74	0.00	100.00
Mass	Kilograms	101232	0.18	0.002	14.34	0.00	3498
Heroin							
Purchases							
Price	2011 dollars	499	8009.03	781.15	27460.99	10.96	328875.1
Per-gram price	2011 dollars	499	330.42	279.72	231.82	22.54	1283.13
Per-pure-gram price	2011 dollars	449	4438.16	1336.51	30292.28	62.90	624391.9
Purity	Percent	596	24.74	18.00	22.78	0.00	99.60
Mass	Grams	596	33.05	1.95	119.98	0.00	1058.10
Seizures							
Purity	Percent	1282	26.62	20.50	26.46	0.00	96.00
Mass	Kilograms	1283	0.495	0.02	1.73	0.00	25.84

Notes: The data are cleaned following the method described in the appendix. The per-gram price is the real price divided by mass in grams. The per-pure-gram price is the real price divided by mass in pure grams.

Table A2 GMM estimates for the purity equation

	Purity (q_t)			
AR	0	1	2	3
No. of seizures (s_t^{no})	0.293***	-0.199***	-0.473**	-0.499**
	(0.0216)	(0.0559)	(0.221)	(0.253)
Constant	2.914***	5.069***	6.236***	6.293***
	(0.0999)	(0.268)	(0.999)	(1.155)
ρ_1^q		0.923***	0.638***	0.577***
		(0.0232)	(0.0619)	(0.0776)
ρ_2^q			0.314***	0.197**
			(0.0628)	(0.0838)
ρ_3^q				0.191*
				(0.113)
T	298	298	298	297
OverID	1	1	1	1
Hansen	0.70	0.01	0.58	0.93
Mass of seizures (s_t^{kg})	0.205***	-0.0238***	-0.0240**	-0.0246**
	(0.0366)	(0.00752)	(0.0105)	(0.0117)
Constant	4.037***	4.220***	4.204***	4.192***
	(0.0355)	(0.0496)	(0.0826)	(0.104)
ρ_1^q		0.885***	0.595***	0.553***
		(0.0300)	(0.0600)	(0.0695)
ρ_2^q			0.335***	0.254***
			(0.0651)	(0.0696)
ρ_3^q				0.135*
				(0.0720)
T	298	298	298	297
OverID	1	1	1	1
Hansen	0.32	0.29	0.56	0.66

Notes: The dependent variable q_t is the natural log of the month t mean purity of retail (0.1g-1g) crack cocaine in Washington DC. s_t^{no} and s_t^{kg} are the natural log of the month t total number and mass of cocaine seizures of mass greater than 1g in Washington DC respectively. The ρ parameters correspond to the AR process of the disturbance. Huber White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. The 'T', 'OverID' and 'Hansen' rows report the number of observations, the degree of overidentification and the p-value for the J statistic respectively.

Table A3 GMM estimates for the per-gram price equation

	Per-gram price (p_t)			
AR	0	1	2	3
Purity (q_{t-1})	-0.330***	0.0788	0.493*	0.545**
	(0.112)	(0.231)	(0.292)	(0.275)
No. of seizures (s_t^{no})	0.499***	-0.0947	0.154	0.166
	(0.0391)	(0.172)	(0.117)	(0.104)
Constant	4.322***	5.064***	2.366*	2.091*
	(0.366)	(1.248)	(1.384)	(1.259)
ρ_1^p		0.980***	0.676***	0.567***
		(0.0382)	(0.112)	(0.141)
ρ_2^p			0.200**	0.213***
			(0.0874)	(0.0819)
ρ_3^p				0.0799
				(0.0806)
T	295	294	293	292
OverID	10	10	10	10
Hansen	0.00	0.78	0.62	0.59
Purity (q_{t-1})	-0.437*	0.109	0.920**	0.960**
	(0.230)	(0.284)	(0.452)	(0.447)
Mass of seizures (s_t^{kg})	0.335***	-0.0512	-0.00652	-0.000497
	(0.0524)	(0.0412)	(0.0240)	(0.0244)
Constant	6.707***	4.628***	1.258	1.080
	(0.930)	(1.225)	(1.920)	(1.891)
ρ_1^p		0.971***	0.632***	0.533***
		(0.0410)	(0.0991)	(0.116)
ρ_2^p			0.241***	0.232***
			(0.0905)	(0.0856)
ρ_3^p				0.108
				(0.0779)
T	295	294	293	292
OverID	10	10	10	10
Hansen	0.00	0.65	0.32	0.29

Notes: The dependent variable p_t is the natural log of the month t mean per-gram price of retail (0.1g-1g) crack cocaine in Washington DC. q_t is the natural log of the month t mean purity of retail (0.1g-1g) crack cocaine in Washington DC. s_t^{no} and s_t^{kg} are the natural log of the month t total number and mass of cocaine seizures of mass greater than 1g in Washington DC respectively. The ρ parameters correspond to the AR process of the disturbance. Huber White standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. The 'T', 'OverID' and 'Hansen' rows report the number of observations, the degree of overidentification and the p-value for the J statistic respectively.

Metrics for purity, price & seizures

Retail per-gram prices and purity are derived using undercover purchases in STRIDE. Retail purchases are defined as those weighing more than 0.1g and less than or equal to 1g for crack cocaine and heroin, and more than 0.1g and less than or equal to 2g for powder cocaine. Wholesale purchases are defined as those weighing more than 1g and less than or equal to 15g for crack cocaine, more than 1g and less than or equal to 10g for heroin and more than 2g and less than or equal to 10g for powder cocaine. These values are taken from Caulkins et al. (2004). The sample is restricted to purchases made in the US between 1987 and 2011. This is because there are few observations for crack cocaine prior to 1987. Only purchases measured in grams are used, though these account for more than 95% of the data.[27].

Real prices are obtained by deflating nominal prices using the Non Seasonally Adjusted Consumer Price Index for all urban consumers, obtained from the Bureau of Labor Statistics. Prices are normalized to June 2011 US dollars. Price outliers are common in STRIDE (Arkes et al. 2008). For this reason, the top and bottom 2% of the annual distribution of per gram prices are recoded as missing for powder cocaine and heroin, and the top and bottom 1% are recoded as missing for crack cocaine.[28] Purity outliers are also present. Purity is recoded as missing for all entries with purity outside the interval $[0, 100]$.

The derivation of per-gram prices is complicated by the joint distribution of price and mass. Quantity discounts lead the association to be positive and concave in mass price space (Caulkins & Padman 1993). However, defining a narrow mass range for the retail market permits the adoption of a linear approximation. Figure A2 depicts fitted values from OLS estimation of the retail market price mass relationship for linear and fifth order polynomial specifications.[29] It shows that the linear approximation is reasonable, hence per-gram prices are derived by dividing price by mass in grams.

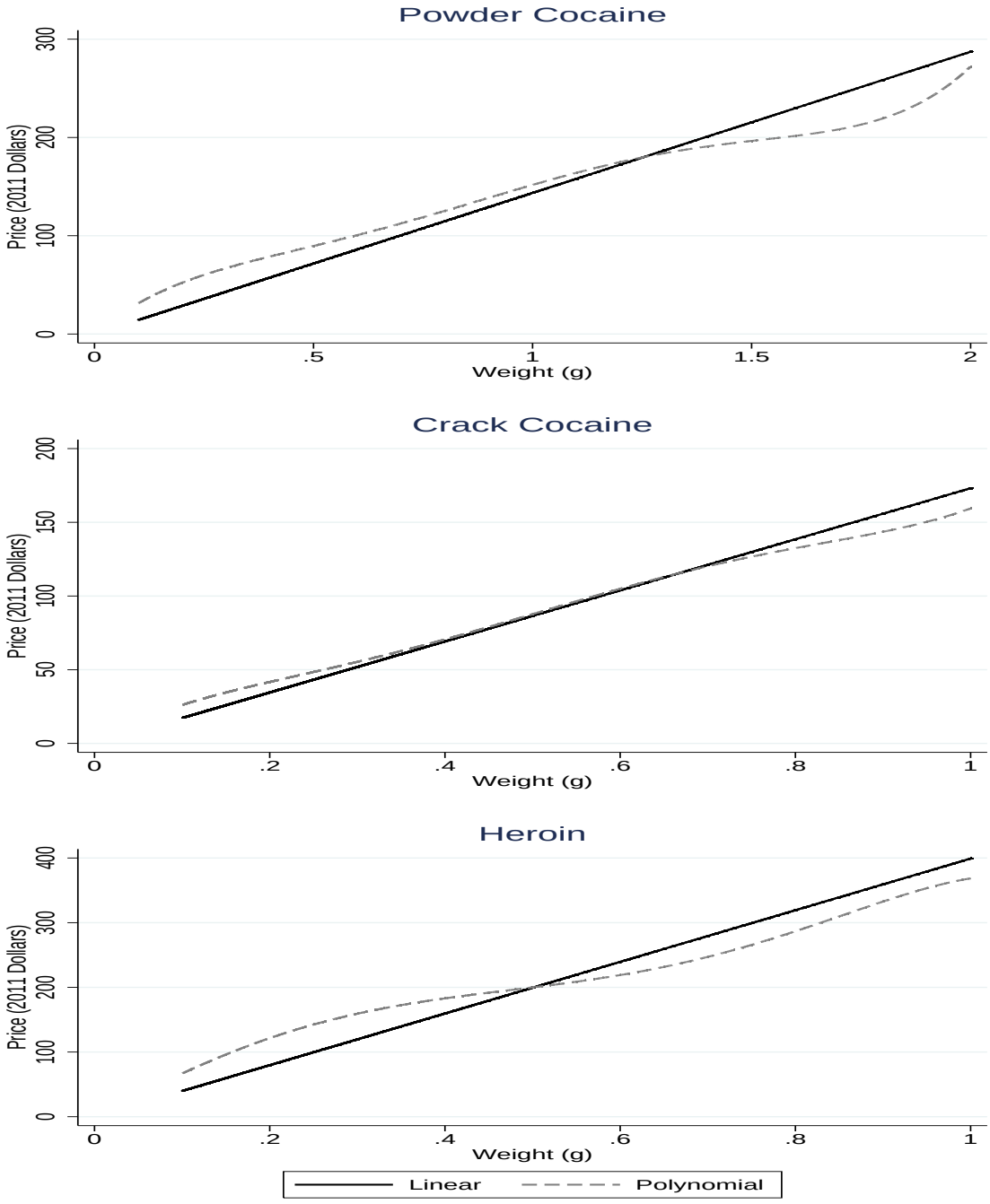
Figure A3 depicts fitted values from estimation of the retail market purity mass relationship by OLS with a linear and fifth order polynomial specification. The near horizontal slopes indicate a limited relationship. Based on this, purity is not standardized by mass.

Measures of seizures are derived from STRIDE. A seizure is defined as a specimen collected by seizure, lab seizure or by flashing money.[30] Seizures for all types of cocaine are included since crack cocaine is synthesized from other forms, particularly cocaine hydrochloride. The same is true for heroin. The data do not differentiate between seizures from suppliers and those from users. For this reason, seizures of mass less than the upper bound of the retail market are excluded.

[27] Some entries are measured in terms of capsules or leaves, making it impossible to quantify their mass accurately.
[28] The frequency of implausible purchases in STRIDE is lower for crack cocaine than powder cocaine or heroin.
[29] The constant is restricted to be zero.
[30] This practice involves the undercover agent posing as a potential buyer by flashing money at the seller.

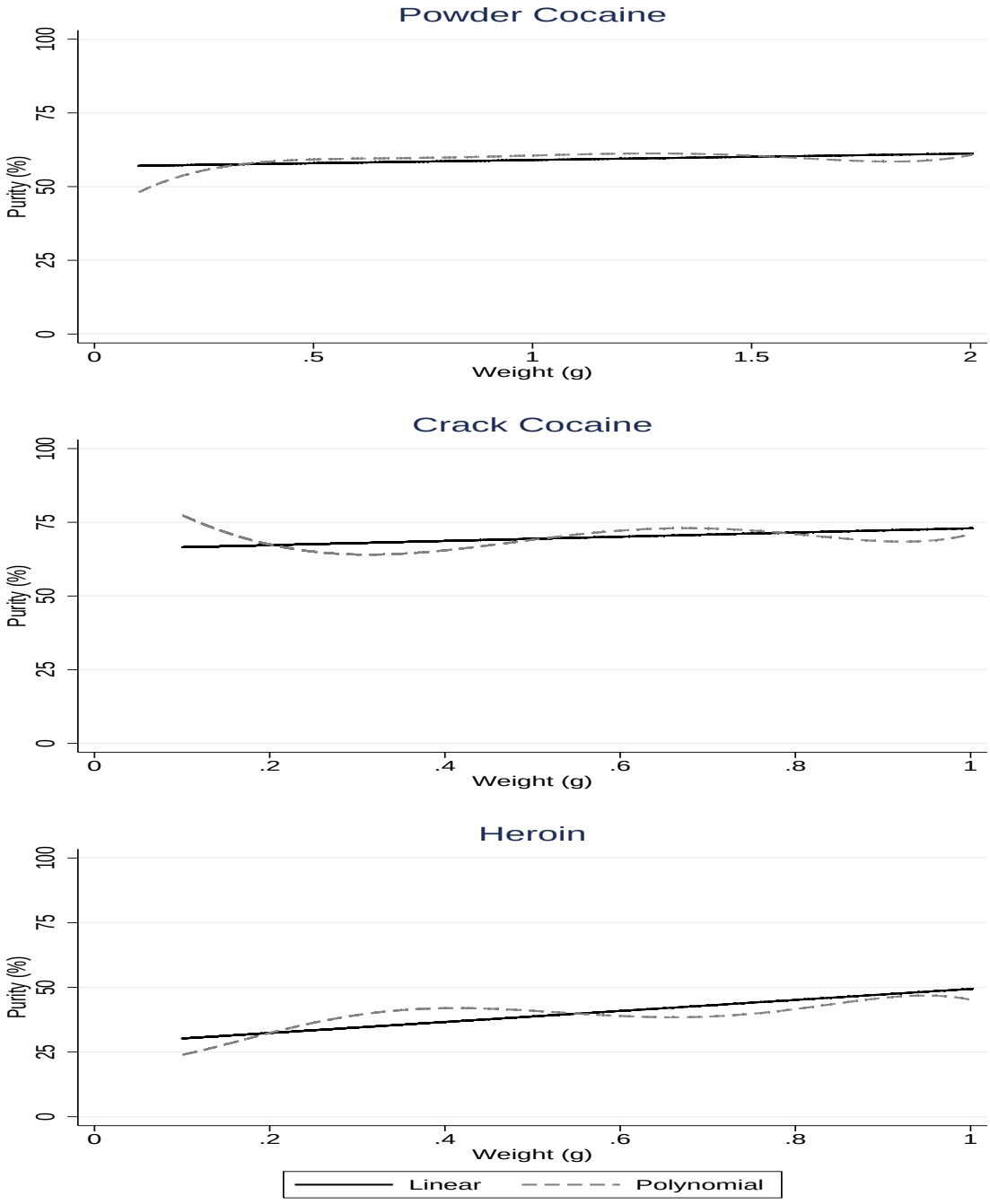
The monthly measures for Washington DC are derived from the subset of retail crack cocaine purchases made in Washington DC between January 1987 and December 2011. The measure of per-gram prices, p_t, is defined as the natural logarithm of the mean per-gram price of purchases in Washington DC in month t. The measure of purity, q_t, is defined as the natural logarithm of the mean purity in month t. These are constructed from 9,547 undercover purchases. Seizures are measured in terms of frequency and mass. The empirical analysis is conducted for each of these measures. The variable s_t is defined as the natural logarithm of the total number or mass in kilograms of seizures conducted in Washington DC in month t. These are constructed from 28,318 seizures of total mass 1,334kg.

Fig. A2 Price & mass of retail narcotics: US 1987-2011



Notes: Plots are of fitted values for linear and polynomial (order 5) regressions of real price on mass for retail market drugs. The intercept is restricted to zero.

Fig. A3 Purity & mass of retail narcotics: US 1987-2011



Notes: Plots are of fitted values for linear and polynomial (order 5) regressions of purity on mass for retail market drugs.

Proofs

Proof of proposition 3.2(a) Suppose that buyers believe that purity is low in all states such that $q^E(\phi) = q_L \quad \forall \phi$. The seller faces a static optimization problem in each period, and maximizes period t profits with $\{q_t, x_t, p_t\} = \{q_L, x^*(q_L, q_L, v_t), p(q_L, x^*(q_L, q_L, v_t))\}$. Buyers' beliefs are accurate, so $\mu_0(v_t) = 0$ constitutes an equilibrium strategy. □

Proof of proposition 3.2(b) Suppose that buyers believe that purity is high in all states such that $q^E(\phi) = q_H \quad \forall \phi$. The seller faces a static optimization problem in each period, and maximizes period t profits with $\{q_t, x_t, p_t\} = \{q_L, x^*(q_H, q_L, v_t), p^*(q_H, x^*(q_H, q_L, v_t))\}$. Buyers' purity expectations are inaccurate, so $\mu_0(v_t) = 1$ does not constitute an equilibrium strategy. □

Proof of proposition 3.2(c) Suppose that the seller chooses low purity in the absence of a shock and high purity otherwise. Then the equilibrium is governed by:

$$
\begin{aligned}
&q_t = v_t q_H + (1 - v_t) q_L \qquad \text{(A1)}\\
&\phi_t = \begin{cases} \varphi(q_L, \phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}(1-\gamma^G)}{\phi_{t-1}(1-\gamma^G)+(1-\phi_{t-1})(1-\gamma^B)} + \lambda\theta & \text{if } q_{t-1} = q_L \\ \varphi(q_H, \phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}\gamma^G}{\phi_{t-1}\gamma^G+(1-\phi_{t-1})\gamma^B} + \lambda\theta & \text{if } q_{t-1} = q_H \end{cases}\\
&q^E(\phi_t) = q_H - (q_H - q_L)\gamma_G - \phi_t(q_H - q_L)(\gamma_B - \gamma_G)\\
&x_t = x^*(q^E(\phi_t), (1 - v_t)q_L + v_t q_H, v_t)\\
&p_t = p(q^E(\phi_t), x^*(q^E(\phi_t), (1 - v_t)q_L + v_t q_H, v_t))
\end{aligned}
$$

Fix $\phi \in (\lambda\theta, 1 - \lambda(1 - \theta))$, $i \in \{B, G\}$ and $v \in \{0, 1\}$. Let $\phi_H = \varphi(q_H, \phi), \phi_L = \varphi(q_L, \phi)$. Then $\phi_H < \phi < \phi_L$.

Next, note that the restriction in (3.1) implies that $x^*(q^E(\phi), vq_H + (1 - v)q_L, v) = x_1(q^E(\phi))$ and

$$p(q^E(\phi), x^*(q^E(\phi), vq_H + (1 - v)q_L, v)) = p_1(q^E(\phi))$$

for $v \in \{0, 1\}$ such that $\pi(q^E(\phi), q, v, x^*(q^E(\phi), v, v)) = \pi_1(\phi) - (q - q_L)(F_1 + F_2 v)$ for $v \in \{0, 1\}$, where $\pi_1()$ is continuous and strictly decreasing.

The equilibrium value function of the seller is:

$$
\begin{aligned}
V(i,\phi,v) = {} & \pi_1(\phi) - v(F_1+F_2)q_H - (1-v)F_1 q_L \\
& + \delta\omega_i \\
& \left(v\left[\gamma_i V(i,\phi_H,1) + (1-\gamma_i)V(i,\phi_H,0)\right] + (1-v)\left[\gamma_i V(i,\phi_L,1) + (1-\gamma_i)V(i,\phi_L,0)\right]\right) \\
& + \delta(1-\omega_i) \\
& \left(v\left[\gamma_j V(j,\phi_H,1) + (1-\gamma_j)V(j,\phi_H,0)\right] + (1-v)\left[\gamma_j V(j,\phi_L,1) + (1-\gamma_j)V(j,\phi_L,0)\right]\right)
\end{aligned} \tag{A2}
$$

where $j = \{B,G\}\backslash i$, $\omega_B = 1-\lambda\theta$ and $\omega_G = 1-\lambda(1-\theta)$.

The payoff from high purity when $v=0$ and thereafter reverting to the equilibrium strategy is:

$$
\begin{aligned}
V(i,\phi,0;H) = {} & \pi_1(\phi) - F_1 q_H \\
& + \delta\omega_i\left(\gamma_i V(i,\phi_H,1) + (1-\gamma_i)V(i,\phi_H,0)\right) \\
& + \delta(1-\omega_i)\left(\gamma_j V(j,\phi_H,1) + (1-\gamma_j)V(j,\phi_H,0)\right)
\end{aligned} \tag{A3}
$$

The equilibrium requires $V(i,\phi,0) - V(i,\phi,0;H) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ or:

$$
\begin{aligned}
F_1 \geq {} & \\
& + \frac{\delta\omega_i}{q_H - q_L}\left(\gamma_i\left[V(i,\phi_H,1) - V(i,\phi_L,1)\right] + (1-\gamma_i)\left[V(i,\phi_H,0) - V(i,\phi_L,0)\right]\right) \\
& + \frac{\delta(1-\omega_i)}{q_H - q_L}\left(\gamma_j\left[V(j,\phi_H,1) - V(j,\phi_L,1)\right] + (1-\gamma_j)\left[V(j,\phi_H,0) - V(j,\phi_L,0)\right]\right) \\
& \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))
\end{aligned} \tag{A4}
$$

The payoff from low purity when $v=1$ and thereafter reverting to the equilibrium strategy is:

$$
\begin{aligned}
V(i,\phi,1;L) = {} & \pi_1(\phi) - (F_1+F_2)q_L \\
& + \delta\omega_i\left(\gamma_i V(i,\phi_L,1) + (1-\gamma_i)V(i,\phi_L,0)\right) \\
& + \delta(1-\omega_i)\left(\gamma_j V(j,\phi_L,1) + (1-\gamma_j)V(j,\phi_L,0)\right)
\end{aligned} \tag{A5}
$$

The equilibrium requires $V(i,\phi,1) - V(i,\phi,1;L) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ or:

$$
\begin{aligned}
&F_2 \leq -F_1 \qquad \text{(A6)}\\
&+\frac{\delta\omega_i}{q_H-q_L}\left(\gamma_i\left[V(i,\phi_H,1)-V(i,\phi_L,1)\right]+(1-\gamma_i)\left[V(i,\phi_H,0)-V(i,\phi_L,0)\right]\right)\\
&+\frac{\delta(1-\omega_i)}{q_H-q_L}\left(\gamma_j\left[V(j,\phi_H,1)-V(j,\phi_L,1)\right]+(1-\gamma_j)\left[V(j,\phi_H,0)-[V(j,\phi_L,0)\right]\right)\\
&\forall i\{B,G\},\phi\in(\lambda\theta,1-\lambda(1-\theta))
\end{aligned}
$$

From (A4), the right hand side is negative, such that there do not exist $F_1 > 0, F_2 > 0$ such that $V(i,\phi,0) - V(i,\phi,0;H) \geq 0, \quad V(i,\phi,1) - V(i,\phi,1;L) \geq 0 \quad \forall i\{B,G\},\phi \in (\lambda\theta, 1-\lambda(1-\theta))$. So $\mu_0(v_t) = v_t$ does not constitute an equilibrium strategy. □

Proof of proposition 3.2(d) Suppose that the seller chooses high purity in the absence of a shock and low purity otherwise. Then the equilibrium is governed by:

$$
\begin{aligned}
&q_t = v_t q_L + (1-v_t)q_H \qquad \text{(A7)}\\
&\phi_t = \begin{cases} \varphi(q_L,\phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}\gamma^G}{\phi_{t-1}\gamma^G+(1-\phi_{t-1})\gamma^B}+\lambda\theta & \text{if } q_{t-1}=q_L \\ \varphi(q_H,\phi_{t-1}) = (1-\lambda)\frac{\phi_{t-1}(1-\gamma^G)}{\phi_{t-1}(1-\gamma^G)+(1-\phi_{t-1})(1-\gamma^B)}+\lambda\theta & \text{if } q_{t-1}=q_H \end{cases}\\
&q^E(\phi_t) = q_H-(q_H-q_L)\gamma_B+\phi_t(q_H-q_L)(\gamma_B-\gamma_G)\\
&x_t = x^*(q^E(\phi_t), v_tq_L+(1-v_t)q_H, v_t)\\
&p_t = p(q^E(\phi_t), x^*(q^E(\phi_t), v_tq_L+(1-v_t)q_H, v_t))
\end{aligned}
$$

Fix $\phi \in (\lambda\theta, 1-\lambda(1-\theta))$, $i \in \{B,G\}$ and $v \in \{0,1\}$. Let $\phi_H = \varphi(q_H,\phi), \phi_L = \varphi(q_L,\phi)$. Then $\phi_H > \phi > \phi_L$.

Next, note that the restriction in (3.1) implies that $x^*(q^E(\phi), vq_L+(1-v)q_H, v) = x_0(q^E(\phi))$ and $p(q^E(\phi), x^*(q^E(\phi), vq_L+(1-v)q_H, v)) = p_0(q^E(\phi))$ for $v \in \{0,1\}$, such that

$$
\pi(q^E(\phi), q, v, x^*(q^E(\phi), vq_L+(1-v)q_H, v)) = \pi_0(\phi) - (q-q_L)(F_1+F_2v)
$$

for $v \in \{0,1\}$, where $\pi_0()$ is continuous and strictly increasing.

The equilibrium value function of the seller is:

$$
\begin{aligned}
V(i,\phi,v) = {} & \pi_0(\phi) - vF_1q_L - (1-v)F_1q_H \\
& + \delta\omega_i \\
& (v\left[\gamma_i V(i,\phi_L,1) + (1-\gamma_i)V(i,\phi_L,0)\right] + (1-v)\left[\gamma_i V(i,\phi_H,1) + (1-\gamma_i)V(i,\phi_H,0)\right]) \\
& + \delta(1-\omega_i) \\
& (v\left[\gamma_j V(j,\phi_L,1) + (1-\gamma_j)V(j,\phi_L,0)\right] + (1-v)\left[\gamma_j V(j,\phi_H,1) + (1-\gamma_j)V(j,\phi_H,0)\right])
\end{aligned} \tag{A8}
$$

where $j = \{B,G\}\backslash i$, $\omega_B = 1-\lambda\theta$ and $\omega_G = 1-\lambda(1-\theta)$.

The payoff from low purity when $v=0$ and thereafter reverting to the equilibrium strategy is:

$$
\begin{aligned}
V(i,\phi,0;L) = {} & \pi_0(\phi) - F_1q_L \\
& + \delta\omega_i\left(\gamma_i V(i,\phi_L,1) + (1-\gamma_i)V(i,\phi_L,0)\right) \\
& + \delta(1-\omega_i)\left(\gamma_j V(j,\phi_L,1) + (1-\gamma_j)V(j,\phi_L,0)\right)
\end{aligned} \tag{A9}
$$

The equilibrium requires $V(i,\phi,0) - V(i,\phi,0;L) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ or:

$$
\begin{aligned}
F_1 \leq {} & \frac{\delta\omega_i}{q_H - q_L}\left(\gamma_i\left[V(i,\phi_H,1) - V(i,\phi_L,1)\right] + (1-\gamma_i)\left[V(i,\phi_H,0) - V(i,\phi_L,0)\right]\right) \\
& + \frac{\delta(1-\omega_i)}{q_H - q_L}\left(\gamma_j\left[V(j,\phi_H,1) - V(j,\phi_L,1)\right] + (1-\gamma_j)\left[V(j,\phi_H,0) - V(j,\phi_L,0)\right]\right) \\
& \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))
\end{aligned} \tag{A10}
$$

Since $V(i,\phi,v)$ is monotonically increasing in $\phi \in (\lambda\theta, 1-\lambda(1-\theta))$, the right hand side is strictly positive, such that there exists $\bar{F}_1 > 0$ such that $V(i,\phi,0) - V(i,\phi,0;L) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ if $0 < F_1 \leq \bar{F}_1$.

The payoff from high purity when $v=1$ and thereafter reverting to the equilibrium strategy is:

$$
\begin{aligned}
V(i,\phi,1;H) = {} & \pi_0(\phi) - (F_1+F_2)q_H \\
& + \delta\omega_i\left(\gamma_i V(i,\phi_H,1) + (1-\gamma_i)V(i,\phi_H,0)\right) \\
& + \delta(1-\omega_i)\left(\gamma_j V(j,\phi_H,1) + (1-\gamma_j)V(j,\phi_H,0)\right)
\end{aligned} \tag{A11}
$$

The equilibrium requires $V(i,\phi,1) - V(i,\phi,1;H) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ or:

$$
\begin{aligned}
F_2 \geq & -F_1 \\
& + \frac{\delta\omega_i}{q_H - q_L}\left(\gamma_i\left[V(i,\phi_H,1) - V(i,\phi_L,1)\right] + (1-\gamma_i)\left[V(i,\phi_H,0) - V(i,\phi_L,0)\right]\right) \\
& + \frac{\delta(1-\omega_i)}{q_H - q_L}\left(\gamma_j\left[V(j,\phi_H,1) - V(j,\phi_L,1)\right] + (1-\gamma_j)\left[V(j,\phi_H,0) - V(j,\phi_L,0)\right]\right) \\
& \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))
\end{aligned}
\tag{A12}
$$

From (A10), the right hand side is positive yet finite, such that there exists $0 < \underline{F}_2 < \infty$ such that $V(i,\phi,1) - V(i,\phi,1;H) \geq 0 \quad \forall i\{B,G\}, \phi \in (\lambda\theta, 1-\lambda(1-\theta))$ if $F_2 \geq \underline{F}_2$. So $\mu_0(v_t) = 1 - v_t$ constitutes an equilibrium strategy for $0 < F_1 < \bar{F}_1, F_2 \geq \underline{F}_2$. $\square$