The Changing Returns to Crime: Do Criminals Respond to Prices?*

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Abstract

To what extent does crime follow the pattern of potential gains to illegal activity? This paper presents evidence on how criminals respond to this key incentive by reporting crime-price elasticities estimated from a comprehensive crime dataset containing detailed information on stolen items for London between 2002 and 2012. Evidence of significant positive crime-price elasticities are shown, for a panel of 44 consumer goods and for commodity related goods (jewellery, fuel and metal crimes). The reported evidence indicates that potential gains are a major empirical driver of criminal activity and a crucial part of the economic model of crime. The changing structure of goods prices helps to explain over 10-15 per cent of the observed fall in property crime across all goods categories, and the majority of the sharp increases in the commodity related goods observed between 2002 and 2012.

JEL Keywords: Crime; Goods Prices; Metal Crime; Commodity Prices.

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1 Introduction

The extent to which criminals respond to changing economic incentives forms a cornerstone of the economic approach to studying criminality. The impact of economic incentives, as first formally outlined by Becker (1968) and Ehrlich (1973), turns on a prospective criminal weighing up the expected benefits of illegal activity against the benefits of staying within the law. Most of the existing evidence on expected benefits considers how changing labour market incentives in the legal market can affect crime participation decisions of individuals on the margins of crime. Some evidence supports the notion that labour market outcomes that underpin the legal sources of returns, such as low wages or youth unemployment, matter for crime.[1]

Less studied in the research on economic incentives has been the question of how changes in the direct benefits or returns to criminal participation in illegal activity affect observed crime levels. A probable reason why is the practical difficulty in eliciting good information on the actual or potential returns from crime. While there are a series of studies on the structure of criminal incomes (see, for example, Viscusi, 1986; Levitt and Venkatesh, 2000; or Campaniello et al, 2016), there is limited evidence on how changes in the value of alternative criminal opportunities drive these incomes.

In the case of property theft (which makes up approximately two-thirds of total crime in the US and Europe[2]) a key determinant of the benefits derived from crime is the financial value of stolen property, which is important both in terms of the resale potential of the property and as a source of personal consumption utility for the criminal. This means that changes in the market prices of goods and services have scope to affect criminal participation decisions. This paper offers the first comprehensive examination of this link between criminality and the returns to crime. To do so, it examines the direct crime-price elasticity in panel data models for market property stolen and for commodities, and then studies the role that changing prices play in explaining aggregate property crime trends.

[1]The large literature on crime and unemployment is reviewed by Freeman (1999) who argues that, whilst some studies do find a significant association between crime and unemployment, many do not. He concludes that the evidence is 'fragile, at best'. Work since the Freeman review does seem to uncover more robust findings for the crime-unemployment relationship amongst youths (see Fougère, Kramarz, and Pouget, 2009; or Gronqvist, 2013; Buonanno et al, 2014, on international comparisons; and the evidence on crime scarring from entry to unemployment by Bell, Bindler, and Machin, 2018). The smaller body of work on crime and low (unskilled) wages also reports significant associations (see Gould, Weinberg, and Mustard, 2002; Grogger, 1998; and Machin and Meghir, 2004).

[2]See Buonanno et al (2011). They calculate that US and European property crime rates run at between 35-50 crimes per 1000 members of the population in the period since 1990, while total crime is in the 50-70 crimes per 1000 range.

Perhaps surprisingly given that the question is of first order significance in the economics of crime, there are only a few empirical studies of the relationship between prices and crime and what work there is often has a focus only on particular goods. Reilly and Witt (2008) provide empirical evidence of this sort in their time series analysis of burglaries and the changing price of audio-visual goods. Also, in criminology there are a small number of case studies focused on particular goods such as copper cable (Sidebottom et al, 2011; and Sidebottom, Ashby, and Johnson, 2014), metals (Brabanec and Montag, 2017), electrical equipment (Wellsmith and Burrell, 2005) and livestock (Sidebottom, 2013). These studies, following the criminological approach outlined by Clarke (1999, 2000), have stressed a role of a range of price and non-price attributes in determining rates of theft across goods.[3] The approach adopted in this paper examines the majority of market property stolen and establishes that changing prices shift criminals to the goods that yield a higher return, at the same time offering a new explanation for recent crime trends.

After outlining a simple theoretical approach to modelling crime and prices, and discussing other related research, the empirical analysis begins by examining whether the changing prices of a range of consumer goods affects both the level and composition of crime across property types. To do so, it utilises detailed monthly data on burglaries, thefts and robberies in London from the Metropolitan Police Service (MPS) between January 2002 and December 2012. In particular, the unique data feature that is exploited is knowledge of the type of property that was stolen in the reported incidents, since the MPS uses a comprehensive 2-digit coding system as part of its standard crime reporting format. This information on crime by property type is then matched to detailed retail goods price data from the UK Office of National Statistics (ONS) to form a consumer goods panel that is used to study how different price movements across goods may affect crime patterns.

In this analysis, crime-price elasticities are estimated using panel data models that relate changes in the quantities of stolen goods to changes in their prices. These results are also compared with estimates from a rather different source, a victimization survey (the British Crime Survey, BCS) where it is also possible to consider how changes in what is stolen relate to changes in the reported value of the item.

[3]Specifically, Clarke (1999) outlines a taxonomy whereby the theft rate of item is determined by the extent that it is "CRAVED" in terms of the attributes of: Concealability, Removability, Availability, Value, Enjoyability, and Disposability. Some inspiration from this approach is taken by distinguishing between the sources of price and non-price heterogeneity across goods that determine the expected return to theft.

The second main part of the crime and prices analysis focuses on a set of commodity-related stolen goods like jewellery, fuel and metals. These goods have the feature that they are relatively homogenous in their quality and that their prices are strongly determined by price movements in international commodity markets. This allows us to track the response of crime to price changes in a clean setting where prices are set exogenously and the quality of the underlying good is fixed over time.

The analysis uncovers a strong link between changing prices and crime. For the consumer goods panel, there is an average elasticity of 0.35. For metals, the elasticity is estimated to be above unity, revealing a very strong sensitivity of crime to price changes. Furthermore, the empirical framework used addresses a large range of potential confounders that could influence the crime-price relationship. Firstly, the approach for the 44-good panel explicitly addresses the issue of non-price sources of heterogeneity across goods. In particular, the fixed effects model that is used is able to absorb many important dimensions of goods heterogeneity. It is able to net out variation in features such as crime success probabilities (for example, the fixed technological costs of stealing a particular type of good) or resale price depreciation factors (i.e. the markdown between a new good valued at retail prices versus a resold version of the good). These factors will, along with price, determine the expected return from stealing a good and the main strategy taken here is to difference them out. This approach of course leaves us with parameters measuring the effect of changing prices on changes in crime at the within-good level.

Practically, the credibility of this approach then depends on crime adjusting to changes in prices at a faster rate than one might plausibly expect the non-price characteristics to adjust to the same stimulus. The monthly models of the lag structure of the crime-price relationship strongly indicate that this is the case, with the majority of the response of crime to prices occurring within the first three months of a given shock to prices. This rapid response of crime to prices greatly limits the scope for time varying unobservables correlated with prices to play a role in influencing the observed relationship. As an example, any confounders related to factors such as investments in extra security by victims, the stock of goods held by the public, or changes in unobservable product quality would need to operate at a similar rapid frequency (and magnitude) as the measured price changes, which is arguably unrealistic at the monthly level.

In particular, it is unlikely that the supply of specific goods (and therefore their potential availability for being stolen) is able to adjust quickly in line with price movements. Further to this, the simple comparative statics of product adoption suggest that consumer supply responses would impart a downward bias on the estimated price-crime relationship. For example, falls in price should stimulate purchases of a good and therefore increase their availability for theft. Such an effect would offset the crime-reducing effects of the original fall in the price of the good.

The last part of the analysis of the 44-product panel looks at the potential bias from endogenous crime reporting behaviour. The concern here is that rising prices make victims more likely to report theft because they suffer larger losses from theft. This would bias the estimates of the price-crime relationship upwards. To study this, information on victim-reported crime (based on the British Crime Survey (BCS)) is used to check for shifts in reporting patterns that are correlated with changes in value. The BCS data strongly corroborates the main findings and indicates that the influence of endogenous reporting is very limited. Related to this, it should be noted that victim precaution is also likely to rise with prices, which would make items more difficult to steal and attenuate the measured link between crime and prices.

The analysis of commodity-related crimes has two main advantages. Firstly, in the case of metals, availability of direct resale prices in the form of detailed reports from scrap metal dealers circumvents issues of possible measurement error that arise when changes in street resale values are proxied with changes in retail prices. Secondly, the study of commodity-related crimes allows parsing out of the biases related to unobserved demand shocks at the goods-level, namely the increases in demand that would simultaneously increase prices and consumer demand for particular goods. This is a problem insofar that an increase in demand could translate into increases in consumer holdings of the good and make the good easier to steal at the same time that prices are rising. However, the shifts in demand that are observed for the commodity-related goods are very clearly exogenously set by trends in global markets rather than demand in the UK. Furthermore, unlike the developing country conflict literature where commodity price variation has been studied as a major determinant (Bazzi and Blattman 2014), the metal and fuel commodities considered are not a driver of local incomes in the UK. Hence, in the context of this paper, commodity price variations are well-positioned to isolate changes in potential returns across property crime opportunities.

Thus, overall, property crime is found to be responsive to changes in both consumer and scrap metal prices. The notion that increases in the potential takings from crime generate ceteris paribus increases in crime is central to the economic approach to modelling crime. The evidence of significant positive consumer and scrap metal price elasticities of crime strongly supports the notion that criminals react to changing economic incentives by carrying out crimes that yield a higher return. In other words, the results indicate that the supply of crime is elastic both within and across activities, with relatively fast adjustment to changes in potential returns.

The strength of this finding raises the additional question: to what extent do prices matter for determining the aggregate level of property theft? The existing crime literature places a firm emphasis on changes in licit incentives (such as wages and unemployment) but our analysis shows that illicit incentives exert a strong influence on crime. In the data analysed in this paper, aggregate property crime fell by 35 percent between 2002 and 2012. For the estimated crime-price elasticities from the consumer panel, price variation accounts for approximately 10-15 percent of the observed crime drop. One way of thinking about this is that the falling real price of loot meant that crimes that would have occurred in the past did not occur because the returns available from them significantly decreased. An extreme example of this is the very rapid fall in the price of audio players. The real fall here was even sharper than average so that price falls can account for approximately 26 percent of the crime drop for this good. Similarly for the highly price elastic metal crimes, where rapidly rising world commodity prices actually drove crime up, the vast majority of the metal crime can be accounted for by real price increases.

The rest of the paper is structured as follows. Section 2 develops a simple choice theoretic model where crime and prices are connected to one another. This enables derivation of a positive crime-price elasticity that acts to motivate the empirical analysis undertaken later in the paper. Other relevant research that relates to the analysis is also discussed. Section 3 describes the data and offers some descriptive analysis. Section 4 reports the modelling approaches that are used. Section 5 gives the results from the consumer panel, and Section 6 from the analysis of commodity and metal crimes. In Section 7 some interpretation and discussion of the results is offered, together with a decomposition of the importance of price changes in explaining crime trends. Section 8 concludes.

2 Modelling Crime and Goods Prices

The starting point is a standard model of crime and economic incentives which develops, for example, the way in which Freeman (1999) or Machin and Meghir (2004) set up the classic Becker (1968) or Ehrlich (1973) model for use in empirical work. The approach is extended, without loss of generality, to consider choices of theft across consumer goods with different prices. It derives a crime-price elasticity that can be estimated and also clarifies the role of other crime determinants like wages, sanctions, and the probability of detection in relation to the crime-price elasticity.

Consider first a general set up of the model. If P is defined as the gain from successful crime, π the probability of being caught, S the punishment if caught and W the gain from legitimate labour, then the decision-maker will chose to commit crimes when the following inequality, comparing the expected returns from crime to the legal labour market wage, holds:

$$(1 - \pi_{ig})P_g - \pi_{ig}S_g > W_i \tag{1}$$

In (1) the subscript gi on the probability of being caught π reflects heterogeneity in the good to be stolen g and the type of criminal i (e.g. a thief, burglar or robber). The gain P reflects the market value of the good g (i.e. its resale value or personal value). Legislation punishes individuals equally for thefts of a given type of good g, while wages depend on the criminal type i. Different cases that allow for goods g and criminals i to vary in terms of types can be examined.

2.1 Deriving the Crime-Price Elasticity

When both agents and goods are homogeneous there is only one crime choice to be made. The decision to commit a crime with return P occurs when the inequality below holds:[4]

$$(1 - \pi)P - \pi S > W \tag{2}$$

The most relevant case for the empirical analysis is of homogeneous agents and heterogeneous goods, as the data available about the type of criminal is limited, but there is a lot of detail

[4]The inequality in this case is, of course, the standard one from the Becker (1968) and Ehrlich (1973) economic model of crime.

identifying the type of stolen good. Specifically, information on type of criminal refers only to modes of crime (i.e. burglary, theft, or robbery). Now the basic inequality becomes:

$$(1 - \pi_1)P_1 - \pi_1 S_1 > (1 - \pi_2)P_2 - \pi_2 S_2 \tag{3}$$

In (3), the individual takes more than one decision about whether to engage in crime or not as a potential criminal compares the net benefit of stealing over alternative goods, g.

Suppose there are two products, indexed by 1 and 2 respectively. If the inequality in (3) holds for both, the thief has the choice between the two goods. Conditional upon doing crime, an individual chooses to steal good 1 rather than good 2 if also the following inequality strictly holds:

$$(1 - \pi_g)P_g - \pi_g S_g > W \tag{4}$$

However, as crime for good 1 increases, the gap between the left and right hand side of (4) declines and an equilibrium occurs when it holds with equality. A natural way to model crime in this setting is to allow the probability of being caught to change. For instance π_1 should increase as crime opportunities for good 1 become scarce in the short run. This means that stealing property of type 1 is less risky in the beginning: however, as more thieves choose to steal the same good, the probability of being caught increases.[5] So π_1 can be written as an increasing function of the stolen quantity of property 1: $\pi_1 = kC_1$ with $k > 0$ and C_1 denoting the quantity of crime in good 1.

Thus the quantity of crime in equilibrium can be derived. For one good only,

$$(1 - kC_1)P_1 - kC_1 S_1 > W \tag{5}$$

which can be rearranged as:

$$C_1 = (P_1 - W)/[k(P_1 + S_1)] \tag{6}$$

Taking the partial derivative of (6) with respect to price and multiplying by (P_1/C_1) gives a

[5]This is essentially what Ehrlich (1996) characterises as the demand side of the market for offenses.

crime-price elasticity:

$$(\partial C_1/\partial P_1)(P_1/C_1) = \{(S_1 + W)/[k(P_1 + S_1)^2]\} \tag{7}$$

In (7) this elasticity is always positive, so that increases in the price of good 1 generate increases in stolen quantity of product 1. However, notice that (7) describes the response of crime to price changes for a single product. The model can be further developed by adding a second good to make the role of relative prices between goods explicit. To introduce the second good, first assume that both wages and sentences are the same for potential criminals choosing between goods. That is, the punishment for stealing product 1 or product 2 is the same ($S1 = S2 = S$) and the certainty equivalent legal wage is W. This makes the decision of whether to steal good 1 as opposed to good 2 solely driven by the relative prices of good 1 and 2.[6] The point about equal punishments across goods is returned to when discussing empirical specifications in the next section below.[7] A crime-price elasticity for good 1 can then be derived as

$$(\partial C_1/\partial P_1)(P_1/C_1) = \{(S_1 + P_2)(1 - kC_2)/[k(P_1 + S)^2]\}(P_1/C_1) \tag{8}$$

In the two-good model, again the crime-price elasticity is always positive. This feature of the model is what is tested with the rich matched data on crime and prices in the rest of the paper.

2.2 Related Literature

As discussed in the introduction to the paper, research that directly discusses the empirical link between crime and prices is very limited. However, there has been a range of related work that has addressed factors that determine the potential return to crime. Studies that

[6]Thus there would be crime switching. To our knowledge, the only paper of relevance to the notion of possible crime switching is the rather differently focused paper by Levitt (1998), which attempts to distinguish between incapacitation and deterrence effects of increased arrest rates. Levitt argues deterrence predicts increasing arrest rates for a particular crime will raise other crimes as criminals substitute away because of a higher perceived probability of being caught, and tests the prediction on US recorded crime and arrests.

[7]The issue needs discussion because, while sanctions like sentences for particular crimes tend to be fixed (e.g. if they are mandated or if sentencing guidelines exist) in some circumstances they vary. Two examples from the economics literature include Kessler and Levitt (1999) who study sentence enhancements to do with the California three strikes laws and Bell, Jaitman and Machin (2014) who study the tougher sentences given to individuals who were convicted for participating in the London riots of August 2011.

have considered issues indirectly related to the question of value and returns include: work on the impact of security technologies (for example, Ayres and Levitt, 1998; and Vollaard and Van Ours, 2011, 2016); research on the link between crime and stolen goods markets (Miles, 2007; and d'Este, 2014); the influence of taxes on cigarette smuggling[8] (Gruber, Sen, and Stabile, 2003; Lovenheim, 2008); the consumption of 'conspicuous goods' in response to changing crime risks (Mejía and Restrepo, 2016); and experimental work testing how changes in the value of loot affect the incentive for theft (Harbaugh, Mocan, and Visser, 2013).[9]

The general issue of potential criminal returns has also underpinned recent work on the nature of criminal decision-making. For example, Mastrobuoni (2015) studies the money versus risk trade-off that bank robbers face when making decisions about the duration of their robberies. Further to this, Mastrobuoni and Rivers (2016) provide quantitative estimates of criminal discount factors in the context of a large-scale Italian prison pardon. Lochner (2007) harnesses US longitudinal data to study the nature of belief updating regarding the perceived probability of arrest among criminals. Recent historically-oriented work has also examined the effects of large, externally induced income shocks on criminal participation (Bignon et al, 2017; Traxler and Burhop, 2010).

Finally, some recent contributions have assessed determinants of crime that fall outside the 'rational criminal' paradigm. These include the field experiments of Blattman et al (2016) and Heller et al (2015) who report strong crime reduction effects due to programmes designed to affect behavioural changes in treated participants. A particular feature of these programmes is that they have been very effective in reducing violent crime, an area of criminal activity where the effect of incentives has been found to be weaker (Freeman, 1999; Machin and Meghir 2004). Hence, while the current study does add major new evidence that incentives matter strongly for determining crime, it is also worth emphasising that the results pertain only to property crime and it is likely that other factors come into play when considering both violent crime as well as sustained participation in crime that is not consistent with personal economic incentives.

[8]This literature on cigarettes is mentioned because, while its principal focus is on health and taxation issues, it also models movements in an incentive to engage in illegal activity (e.g. how changes in taxes affect the return to smuggling).

[9]See Draca and Machin (2015) for a more detailed review of the literatures on criminal earnings, the impact of security technology and other studies that discuss the determinants of the returns to crime.

3 Data and Initial Descriptive Analysis

Our analysis matches data on property crime to prices, with the aim of estimating empirical crime-price elasticities. This is done in two main ways. First, sources of crime data are matched to the prices or values of what was stolen for a number of market goods. Second, a specific group of commodity and metal crimes are studied, in part because they have seen a significant rise in prices over the period that is studied, and also because their plausibly exogenous price variations can be thought of as being driven by prices in international commodity markets. Furthermore, in the case of metals accurate price data is available from scrap metal dealers, which are the actual resale prices on offer to criminals.

3.1 Crime by Property Type

Two data sources are used to study crime by property type. The first is administrative data drawn from the Crime Record Information System (CRIS) of the London Metropolitan Police Service (MPS). The second comes from survey responses on crime victimization from the British Crime Survey (BCS). We have obtained monthly data between 2002 and 2012 for the MPS crime data, and have looked at annual data from the repeated cross-sections of the BCS over the same period.

The CRIS represents the Metropolitan Police's standard reporting format for crimes. As part of this standard format, the MPS uses a coding system to describe the type and count of goods stolen in thefts, burglaries and robberies. The structure of this coding system broadly resembles the analogous systems used for economic data on retail/wholesale goods or on internationally traded goods. Specifically, the property types are coded at two-digit level, with 203 products distributed across 19 one-digit product categories. The latter are listed in Table A1 of the Appendix, together with one-digit crime shares.

The measures of crime are counts of the number of items stolen. For example, if a burglary is reported to the police then the range of items stolen as part of this incident (for example, jewellery, electronic equipment or household tools) will be listed as part of the crime report. The data then represents the *count of a stolen property type across all incidents*, for example, the total number of DVD players stolen in London in a given month pooled over all burglary incidents. This count of the number of stolen items per goods category is therefore the measure of 'crime' that is used throughout the paper.

The British Crime Survey (BCS) is a crime victimization survey which, since 2001 when it was restructured into a larger survey than before, asks around 40,000 individuals in households about their crime experiences in the previous year.[10] It is useful to us as it has information on what was stolen in crimes and thus offers a complementary data source for us to study. Furthermore, the BCS also has questions asking whether a crime was reported to police or not. This is useful for gauging the potential scope for endogenous reporting by victims, that is, increases in recorded crime driven not by an increase in underlying quantity stolen but rather by the fact that the stolen items could have become more or less valuable to victims over time.

3.2 ONS Product Prices

For the majority of the product groups in the CRIS data, crime counts in each month between January 2002 and December 2012 can be matched to product price data from the UK Office of National Statistics (ONS). The product price data is based on the price quotes data that underpins the calculation of the UK Consumer Price Index (CPI). The data contains the original quoted prices that the ONS draws from shops across the UK, that is, the actual price in pounds and pence of goods being sold on store shelves.[11]

3.3 Matching MPS and ONS Product Groups

The MPS product codes were matched to ONS retail price codes by inspecting the label descriptions for the codes across the datasets. This proved to be feasible only for the crimes with market codes in the MPS data. It was not possible to match stolen property classified as non-market (around 46.3 percent in terms of crime counts) such as credit cards or personal documents that cannot be priced as they are not tradable in conventional retail or second hand markets.[12]

For the market goods, however, the high level of detail in the ONS price data makes it

[10] The British Crime Survey began in 1982 and was first a biennial survey and remained a smaller scale survey until being overhauled in 2001 to become the much bigger survey of around 40,000 adults per year. The survey has (more accurately) been renamed the Crime Survey of England and Wales (CSEW) since 2011.

[11] The quotes data gives us the flexibility to aggregate the shop-level information to product level and calculate price indexes from the ground up, setting the base period to January 2002, the first month in the MPS crime data. In cases where the ONS does not make the shop-level price quotes data available their calculated price index information is used, re-setting the base values to January 2002.

[12] A further "rare/unusual" group (around 1.5 percent of crime counts) contains property types such as those related to animals or weapons that also cannot be feasibly matched to prices.

possible to find credible matches for many two-digit goods categories reported in the MPS property type system. For example, separate matches amongst prices for the different types of clothing covered in the MPS data are feasible to be identified (e.g. menswear, ladies wear, children's wear and for different types of electronic, durable and food products).[13] In total, 44 goods categories could be matched for all months between January 2002 and December 2012, comprising approximately 73.5 percent of the market good crime counts. From this a balanced panel of crime counts and retail prices across 132 monthly periods can be studied. The remaining 26.5 percent could not be matched because of either incomplete crime or price data.[14]

3.4 BCS Value of Stolen Property

For the British Crime Survey there is also data on the reported replacement value of what was stolen in victim-reported criminal incidents. An analogous data set to the MPS crime-consumer goods panel can be constructed by looking in each year how many items were stolen and by calculating their average value. This is a direct measure of the value of the item stolen and provides an alternative to the measure based on the retail price index. There is not as much detail as in the MPS data, but it proved possible to put together data in 2002 and 2012 on 21 items, some of which match those in the MPS data, together with their average replacement value.[15] These data are used below to draw a comparison with results from the MPS consumer panel.

3.5 Metal Crimes

The MPS product coding system features a one-digit group of metal crimes.[16] Apart from indirect cases such as gold's close relationship with jewellery products, the price of these metals is not measured as part of the CPI calculations. We have therefore collected direct data on scrap metal prices. These prices are likely to reflect the true resale value obtained by

[13] An example of the label description matching is given in Table A2 in the Appendix.

[14] For example, the Metropolitan Police added new categories after 2002 as they became prominent as distinct goods categories (e.g. MP3 players were included from 2006), and the ONS regularly revises and drops price series in ways that cannot be easily concorded over time (this was most common in the electronics, furnishing and building materials 1-digit categories).

[15] Because of the available sample sizes by stolen product, three adjacent years were used to construct these measures for 2002 (pooling 2001-3) and 2012 (pooling 2011-13). This means in the statistical analysis below one cannot feasibly set up an annual panel and therefore look at long changes between 2002 and 2012.

[16] Specifically, the seven metals are gold, silver, copper, lead, aluminium, brass and a residual group of other metals.

criminals in the case of metal theft. The data comes from *letsrecycle.com*, a trade industry media outlet that services the waste management and recycling sector. They maintain a historical archive of detailed, monthly scrap metal prices across many types of metal. This allows matching of scrap metal prices to the MPS metal crimes. As well as these local, UK-focused scrap metal prices, data on world prices comes from international commodity markets. International metal commodity prices were obtained from the online platform "Index Mundi". All prices are collected at the monthly frequency and are measured in pounds sterling.

3.6 Initial Descriptive Analysis

Figure 1 shows trends in the total number of crimes and metal crimes in the MPS data. It shows a sharp fall in crime across all groups, with the aggregate of burglaries, thefts and robberies (the left axis) falling from just under 50,000 in January 2002 to just over 30,000 by December 2012, or a 35 percent fall. The metal crimes (right axis) fluctuate quite a lot but more than double over the 2002-12 time period.

Table 1 reports some descriptive statistics on the changing composition of thefts by property type as observed in the balanced panel of 44 goods categories. Changes in the shares of total thefts per two-digit product were calculated and the Table reports figures for the top 10 and bottom products over the 2002-2012 period. This is useful to indicate movements that are consistent with changing prices driving crime trends. The fastest growing categories are dominated by either high-tech, high-value electronic goods (i.e. mobile phones, power tools) or jewellery-related goods. The products with declining shares are goods where there has been strong downward pressure on prices, like Audio Players.

Figure 2 shows a scatterplot of average 12-month changes in the log of the crime count and the log of the price index for the 44 product panel and for the 21 stolen items from BCS. The averaged changes are clearly related as the positively sloped (and statistically significant) regression line fit through the points in both charts shows. The charts very clearly reveal that products with bigger price increases – like the jewellery categories (Rings, Necklace and Watch) and goods such as Bicycles – saw relative crime increases. On the other hand those experiencing price falls – most notably the big price decreases for Audio Players – saw crime fall the most. The other point of note is the strong similarity between the two charts. They are based on different data on crime and prices/values, yet both show a strong correlation between changes in crime and changes in the potential values of goods. Study of the two charts reveals that, for the most part, the same goods line up closely.[17]

4 Empirical Models of Crime and Prices

The descriptive analysis uncovered an empirical connection between changes in crime and prices. This section sets out a modelling approach which enables this initial finding to be subjected to a more stringent statistical evaluation, including discussion of a number of threats that may be posed to the identification of a crime-price elasticity.

4.1 Baseline Empirical Models – Consumer Goods Panel

A monthly panel data log-log specification to estimate crime-price elasticities for goods category g in month-year period t ($t = my$, where m is month and y is year) is:

$$Log(C_{gt}) = \alpha_g + \beta Log(P_{gt}) + \tau_m + \tau_y + \epsilon_{gt} \tag{9}$$

where C is the number of crimes (the count of items stolen) and P is the price index for each good. In (9), α_g is a product-specific fixed effect and, to control for common seasonal and annual effects, month and year dummies denoted by τ_m and τ_y respectively are included, and ϵ_{gt} is an error term. Inclusion of the product, month and year fixed effects ensures that the estimated elasticity β is a within-product elasticity identified from changes in crime and prices.

The within-groups specification can be used for the long T panel of 132 observations (12 months by 11 years) for 44 matched crime-price groups. More stringent empirical models can also be estimated so as to generalise the baseline approach. Firstly, use of monthly data over multiple years permits inclusion of a full set of time effects as month-by-year dummies, τ_t (or τ_{my}). Month effects can also be allowed to vary by good g to make the pattern of seasonality

[17] Closer inspection reveals one difference that is pertinent, given the differences in data sources, namely that the Mobile Phones category is close to the regression line in the BCS chart, but is somewhat to the left in the MPS 44 product plot. This probably reflects that higher price mobiles are more likely to be stolen. This is not picked up in the overall average retail price index, but is likely to be better reflected when crime victims report replacement costs associated with thefts of more valuable mobile phones in the BCS data.

fully flexible at goods level. Incorporating these amends the specification as follows:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \tau_t + \epsilon_{gt} \tag{10}$$

where α_{gm} denotes fixed effects for each product-month cell. This seasonally adjusted, within-groups model is the preferred specification as it incorporates a full set of time effects and conditions out good-specific seasonality.

4.2 Issues

These estimating equations capture the salient features of the crime-price relationship as described in the model of Section 2 and, at the same time, the initial descriptive findings to face a more rigorous evaluation. In doing this, some issues require some discussion.

Firstly, in terms of the model an issue is that, since wages (W) and sanctions (S) do not vary across goods, they are absorbed into the time effects.[18] In the case of sanctions, there is a limited sentencing gradient according to the value of thefts in the UK.[19] Second, any constant differences in the specific success probability associated with stealing each good – $(1 - \pi_g)$ in the model – are absorbed into the good-specific fixed effect αg. It is realistic to expect this success probability – which can also be viewed as a general difficulty to steal – to vary across goods according to factors like: the typical pattern of security or protection afforded to each good; the location or placement of the good; the available stock of the good held by consumers; and physical characteristics such as weight and size bear on the practicality of stealing the good.

The product fixed effects αg also play a role when considering measurement issues to do with the price data. Resale value, the amount of money a criminal can obtain for a stolen good, is not observed and needs to be proxied with the ONS retail prices. The fraction of analogous retail value a criminal can recoup will depend on a range of factors, such as

[18] It is worth noting that, in the basic Becker-Ehrlich model of crime, changes in apprehension probabilities (including the effect of police resources to the extent they are constant across different stolen goods) are also netted out in the general time effects.

[19] The UK's Sentencing Guidelines for theft provide scope for sentences to vary with the value of thefts (Sentencing Council, 2014). The guidelines set out a sentencing grid based on the two dimensions of "harm" and "culpability", with the value of thefts helping to determine the level of harm. The grid lists three harm categories based on value bands of: £125-£250; £250-£1000; and over £1000. The bands and associated sentences are changed infrequently and can be treated as fixed for the purposes of the monthly analysis that is presented. Changes in the value of goods over time may push the expected sanction into a higher sentencing band, but this is unlikely to be a common enough experience to affect the estimated elasticities. Hence sanctions are treated as fixed and homogenous across goods.

traceability, the size of potential resale markets, and product durability. However, one can think of the relationship between retail prices and resale value in terms of a simple linear markdown function, $Resale_{gt} = (1 - \lambda)Retail_{gt}$, the resale price is a constant fraction $1 - \lambda$ of the retail price. To the extent that $1 - \lambda$ is stable over time, it will be netted out by the product fixed effects in the above specifications. Thus, within groups estimates using retail prices will capture the underlying changes in resale value that drive the crime participation decision.

4.3 Dynamic Specifications – Consumer Goods Panel

The assumption of constant, or slowly changing, non-price heterogeneity has implications for the interpretation of the estimated β parameter. If non-price factors like the success probability $(1 - \pi_g)$ or the resale depreciation factor λ vary at the same frequency as price effects, this could be a source of omitted variable bias. Thus, measured price changes could pick up correlated effects related to unmeasured changes in success probabilities or the state of the resale market.

To establishing the time profile of the estimated price effects the empirical model can be extended to incorporate dynamics. Firstly, a lagged dependent variable can be included to account for persistence and to proxy for additional omitted factors:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \delta Log(C_{g(t-1)}) + \tau_t + \epsilon_{gt} \tag{11}$$

In (11), the long-run crime-price elasticity is $(\beta)/[1 - \delta]$.[20] Additional price dynamics can also be introduced through the inclusion of extra price lags to allow for possible adjustment of crime to price shocks over prior time periods:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \Sigma_{k=1}^{K} \gamma_k Log(P_{g,(t-k)}) + \tau_t + \epsilon_{gt} \tag{12}$$

where k denotes the order of the lag in prices (from a one month lag to a maximum lag of K).

The specification in (12) can prove helpful in validating the argument presented above re-

[20]The inclusion of a lagged dependent variable is typically subject to caveats regarding Nickell (1981) bias but in our case this is mitigated by the reasonably long T structure of the panel.

garding the potential influence of changing patterns of non-price heterogeneity across goods. That is, the observed pattern of price effects imposes a required structure for the potential non-price factors discussed above. Specifically, for such non-price factors to play a role as omitted variables they need to operate at the same frequency or speed as the price effects. In practice, this means that the faster is the observed adjustment of crime to price shocks, the narrower is the channel for the non-price effects to play a confounding role. Discussion of possible confounders is returned to in the results section, where other sources of time-varying confounders, in particular the biases that could result from endogenous reporting behavior (namely the hypothesis that victims are more likely to report their more valuable stolen property) are also considered.

4.4 Instrumental Variable (IV) Approach

While the above framework for the consumer goods panel can deal with a large range of possible omitted confounders, the research design can also be extended to deal with the potential influence of good-specific demand shocks over time. The issue of possible concern is unmeasured demand shocks that could increase both the price and the public holdings of a good at the same time, with the converse case (lower prices and reduced holdings) also applying.

As an example, consider recently popular goods such as smart phones or bicycles. Prices for these goods have increased but so have public holdings, with widespread adoption of new smart phones and greater usage of bicycles. The increased stock of a good in the population will increase the opportunities for theft and this could bias the measured effects of prices upwards. In principle, this demand shocks problem is still subject to the argument about dynamics above, namely that the rapid adjustment of crime to prices will impose a tight structure on any series of confounding shocks. That is, while the price of bicycles or mobile phones changes on a month-to-month basis it is hard to envisage perfectly matching shifts in the local availability of bikes or phones. As a case in point, the within-good variation for mobile phones and bicycles is very strong with correlations between prices and crime of 0.62 and 0.45 respectively. A plot of the 12-month differences for these goods is shown in Appendix Figure A2 and the period-to-period tracking is very apparent. However, concern about unspecified sources of bias may still apply, so to address this it is possible to consider a group of commodity-related goods where the source of the demand shocks shifting around prices is external to local holdings of the good and can be clearly pinned down.

Specifically, the empirical strategy is to instrument the local prices for jewellery, fuel and metals with their related prices in world commodity markets. In the case of jewellery the related world price is gold and for fuel is the oil price. Metals are mapped directly to their associated world commodity prices. In addition, for metals availability of directly measured local UK scrap metal prices ameliorates concerns of using retail price indexes for new goods as a measure of the resale value that could be recouped by the criminal.[21]

This approach can be viewed as a quasi-experiment where prices change exogenously due to demand shocks in international markets (consider the very clear example of rapidly rising copper prices related to recent economic growth in China) while local stocks of these goods are fixed in the short-run. In addition, these commodity-related goods are effectively homogenous and constant in the quality over time. Indeed, this is part of their appeal to criminals – metals in particular can be melted down so that they are untraceable and more easily traded. In terms of the quasi-experiment, this homogeneity shuts down the type of unobservable changes in product quality that are a potential source of confounding shocks when considering electronics or other relatively sophisticated types of consumer goods.

The empirical specifications used are analogous to those for the consumer goods panel but a focus on specific time series models observing crime and prices. In the single good time series models the seasonality of crime issue discussed above in the context of the goods panel is dealt with by estimating 12-month differenced models (denoting the differencing by the 12-month difference operator, Δ12). Thus denoting the world commodity price by WP, the two reduced forms in seasonal differences with time effects modelled by a time trend are:

$$\Delta_{12}Log(C_t) = \delta_1 + \theta_1 \Delta_{12}Log(WP_t) + \psi_1 t + \omega_{1t}$$

$$\Delta_{12}Log(P_t) = \delta_2 + \theta_2 \Delta_{12}Log(WP_t) + \psi_2 t + \omega_{2t} \tag{13}$$

The structural form is:

$$\Delta_{12}Log(C_t) = \delta_3 + \theta_3 \Delta_{12}Log(P_t) + \psi_3 t + \omega_{3t} \tag{14}$$

For the system of equations in (13) and (14), the instrumental variable (IV) estimate of the crime-price elasticity is then the ratio of the reduced form coefficients in (13), so that

[21] So in the context of the resale price markdown function introduced earlier as $Resale_{gt} = (1 - \lambda)Retail_{gt}$ the markdown λ can be thought of as close to zero since criminals do get the spot price by selling to scrap metal dealers.

$\theta_3 = \theta_1/\theta_2$.

5 Results – Consumer Goods Panel

5.1 Baseline Models – Consumer Goods Panel

Columns (1) to (3) of Table 2 report estimates of crime-price elasticities from the balanced panel of 44 consumer goods. The three specifications produce a robust, statistically significant elasticity of crime with respect to prices. The estimate does not vary much across the three specifications, which differ in the way they model the common time effects, and is estimated to be about 0.35. This suggests a 10 percent increase in the (relative) price of a good is associated with a 3.5 percent increase in crime. From these baseline models, crime seems to be sensitive to prices in the way the economic incentives model of crime predicts.

The remainder of the Table takes the column (3) seasonally adjusted estimates and generalises them in different directions. Firstly, the model is estimated for different crime types – respectively theft and (burglary + robbery) – in the specifications reported in columns (4) and (5) of Table 2.[22] The elasticity is a little higher for thefts, at 0.419 compared to 0.259 for (burglary + robbery), but both are significant and positive showing important price sensitivities, and it is not possible to formally reject the null hypothesis that they are equal to one another.[23] For the remainder of the analysis therefore consider all crimes are studied.

It is well known that crime is highly persistent and so a lagged dependent variable is included in specification (6) reported in Table 2. The estimates do indeed reveal this persistence, as the coefficient on the lag is strongly significant even in the presence of the seasonal differencing within goods. However, the short run crime-price elasticity remains significant and positive at 0.106, and translates into a long run elasticity of 0.34 (= 0.106 / [1-0.691]). Thus the estimates are robust to crime dynamics.

[22]Burglary and robbery are aggregated since the number of robberies is relatively small, representing 6 percent of total items stolen, while thefts represent 59 percent of them.

[23]The most likely explanation for the slightly lower burglary elasticity is one based on the composition of goods. For example, the type of goods that dominate burglary incidents (jewellery, home electronics) may have lower elasticities due either to intrinsic factors or more measurement error in their prices. It is also plausible that the 'fixed costs' of burglary (e.g. breaking and entering) mean that criminals are less likely to discriminate sharply on price for the marginal items in a burglary.

5.2 Price Dynamics – Consumer Goods Panel

Given the structure of the models that have been estimated, concern about bias in the elasticities would need to arise from time-varying unobservables that drive both crime and prices over and above the seasonal adjustment that has been incorporated. As discussed earlier, one way to assess this is to examine the lag structure of the price effects as a means of gauging the time window for which time-varying observables may play a role. Briefly put, the speed of the short-run adjustment between crime and prices determines the structure that any time-varying unobservables would need to follow to impart a systematic bias. This is where the monthly data delivers important information. In principle, a lower frequency of observations on prices and crime (for example, annual data) is compatible with a wide set of gradual adjustment responses by potential victims, producers of goods or police. However, it is much more demanding to expect these confounding adjustment processes to be operating strongly at the monthly frequency.

Table 3 shows estimates of the lag structure of prices in the seasonally adjusted within-groups model. The specifications gradually build up, first entering the price variable dated t only, then t and $(t-1)$, up to a model including all price terms dated t to $(t-3)$. Looking at columns (1)-(4) for all crimes, the picture that emerges is of some price dynamics, but around half of the effect is contemporaneous, and that adjustment is rapid. Moreover, the long run elasticity in the model remains at 0.35 and strongly significant.

The overall implication of this observed lag structure is that any confounding time-varying unobservable would need to follow a sharp, short-run pattern to account for the price effect measured in the main specifications. Furthermore, to follow prices so closely these unobserved effects would need to have at least some mechanical link to prices. The obvious channel here would be through some reaction function related to investments in security and the protection of goods from theft. But note that an increase in the value of a good is actually an incentive for individual goods owners to invest in security – any such investments would attenuate the effect of price and impart a downward bias to the estimates. The same argument applies for police campaigns related to the thefts of particular goods (for example, mobile phones or jewellery). These campaigns are designed to reduce crime and would also attenuate price effects on crime. In addition to the measurement error that arises from using retail rather than direct resale prices, this suggests that estimates of the crime-price elasticity are most likely biased downwards.

However, one plausible source of an upward bias is endogenous reporting behaviour by victims – as prices rise and goods become more valuable then victims of crime may be more likely to report the incident. Since the MPS data is based on reported crime this source of bias is potentially relevant. A counterpoint that can be used is British Crime Survey data on reported and non-reported thefts so as to determine some bounds for the potential influence of endogenous reporting.

5.3 British Crime Survey

Data on the number of stolen items and their value for 2002 and 2012 were obtained from BCS microdata on reported victimizations. In terms of reporting behaviour, aggregate statistics between 2002 and 2012 for the numbers of police recorded crime and victim reports based on the aggregate BCS indicate that the two measures of crime tend to move in parallel.[24] There is no evidence to indicate that they have diverged, which would be the case if there was a shift in reporting behaviour based on average good value. However, this could conceal compositional shifts in reporting patterns by type of stolen item – goods that have become more expensive could have increased in their reporting rates while goods whose value has fallen may have experienced reduced reporting.

Panel A of Table 4 shows results from studying the relationship between reporting rates and the average value for the two period panel (2002 and 2012) of 21 goods. Column (1) reports a modest relationship between reporting rates and value in levels with a 10 per cent higher value being associated with a 1.2 per cent higher reporting rate. However, the within-groups estimates in column (2) show the relationship to be weaker in changes, so that victim reporting is less sensitive to shifts in value over time. Thus, in terms of within-group evolutions through time, there has been little change in the reporting probability as a function of changing prices.

Estimates of crime-price elasticities from a within-groups specification for BCS data are given in the final two columns of Table 4. They show a remarkably consistent pattern with the baseline results from the consumer goods panel. Two specifications are reported, column (3) shows results from victimizations reported to the police and column (4) from all reported victimizations. The former are consistent with the MPS data and comprise about half of all

[24]This is shown in Appendix Figure A1.

BCS victimizations. Those not reported are mostly much less significant, minor crimes. The estimated crime-price elasticity is significant and positive in both cases, and is estimated to be 0.42 in column (3) and 0.52 in column (4). These (especially the 0.42 from the reported crimes) are close in magnitude to the 0.35 from the consumer panel and this can be viewed as strong corroboration of the core findings.

6 Results – Commodity and Metal Crimes

6.1 Instrumental Variable (IV) Estimates

The results presented in the analysis of the consumer goods panel give us confidence that a robust and strong relationship exists between goods prices and crime. Furthermore, the relationship is close enough in the short run that it is hard to reconcile the observed correlation with potential confounding effects associated with such factors as investments in security, movements in the resale/retail mark-up or endogenous reporting behaviour by theft victims. However, as has already been noted, a remaining issue is the potential influence of demand shocks pushing prices and local public holdings of goods up (or down) at the same time.[25]

To rule this kind of behaviour out, a quasi-experimental design can be set up where price movements in international commodity markets shift the corresponding domestic UK prices of a subset of related goods. Hence the changes in price identified through this approach are not related to changes in local factors such as availability that could be simultaneously affecting the expected benefit of stealing a good. Also, these goods are homogenous in their quality over time thereby shutting down this particular source of confounding demand shocks.

The descriptive statistics for commodity and metal goods are shown in Table 5. The upper panel of the Table shows numbers for jewellery and fuel, also comparing their changes over time with the overall crime and price growth from the consumer goods panel. The lower panel shows numbers on all metal crimes and on copper crimes. The jewellery category is the count of thefts pooled across the 2-digit jewellery categories that appear in the 44-good consumer goods panel which typically feature a high level of gold content.[26] Since fuel is only

[25]Sophisticated consumer goods such as electronics (a major component of overall goods stolen) are particularly susceptible to this problem since they are subject to sometimes rapid changes in quality that are correlated with changing consumer demand patterns.

[26]These 2-digit categories (with MPS property type codes in parentheses – see the Appendix) are: Necklace/Pendant

reported as a separate crime category by the MPS from 2005 onwards means are reported across 96 months rather than the 132 months observed for all other goods. The numbers in the Table show that the number of jewellery crimes was fairly constant over time changing by -0.6 percent per year, but that this is a relatively muted decline compared to the -3.9 percent annual fall in all crimes. At the same time, the jewellery price and the world gold price grew significantly. Fuel crimes were static in net terms over the period considered but, as we show later, the intra-period correlation between fuel crimes and prices is high.

Turning to the metal crimes in the lower panel of the Table, there are significant increases over time in both crime and prices. All metal crimes rose by 10.1 percent a year between 2002 and 2012. Copper crimes grew by an extraordinary 26.7 percent per year, while both the scrap metal price and the world prices rose sharply. For all metals, the average scrap metal price from the letsrecycle.com data rose by 10.9 percent a year and the copper scrap price by 14.0 percent a year. The world prices (a composite for all metals from Index Mundi and the world copper price) showed similarly strong rises.[27] A further feature of note of this research design is the tight relationship between local and global prices. The correlation between local jewellery prices and international gold prices is 0.42 in 12-month differences and 0.77 for fuel and international oil prices.

For the metals commodities (shown in Figure 4), there is direct information on the levels of scrap metal and world prices. Statistically, the price transmission between world and local scrap metal prices is very rapid, with adjustment occurring either contemporaneously or within the first few lagged periods. Formal evidence on this is reported in Appendix Table A3, which models scrap prices in terms of contemporaneous and 1-period lagged effects, indicating that the majority of pass-through occurs in the current period. Institutionally, this tight relationship between scrap and world prices is due to the structure of the scrap metal industry. The Home Office records 3,600 permitted scrap metal dealers in the UK (circa 2011) and describes a pyramid structure for the industry whereby scrap is moved between dealers until it becomes concentrated among a small sub-group of dealers who are better equipped to process and refine the scrap (Home Office, 2012). At this point a large amount of processed material is actually exported, accounting for the tight integration of

(JA), Ring (JB), Bracelet/Bangle (JD) and Earrings (JE).

[27] The general commodity boom of the mid-2000s has been reckoned as the biggest in 50 years (see Abbot, 2009, Bennett, 2008, and The Economist, 2009). In term of metals commodities, the specialist historical evidence indicates there is a high spread of common versus commodity-specific sources of variance across different industrial and precious metals (see Bidarkota and Crucini, 2000; or Chen, 2010).

local scrap and international metal prices.[28]

Given this background of strong local and world price correlations, the statistical relationship between crime and prices for the commodity-related goods can next be studied. Figure 3 shows the plot of 12-month differences for jewellery and fuel price indices against their analogous crime series, with correlations of 0.27 and 0.53 respectively. Figure 4 shows plots of crime against the associated change in scrap metal price. For all metals and for copper, the price and crime series track each other well, with some jumps in places, and are highly correlated at 0.54 for all metals and 0.73 for copper.

Statistical estimates of crime-price elasticities for jewellery and fuel are presented in Table 6. The Tables shows two sets of estimates of four seasonally-differenced specifications, namely the OLS estimates, the crime and price reduced forms where the instrument is the world price, and the IV estimates. The two sets differ in that columns (1)-(4) are the basic seasonally differenced estimates and columns (5)-(8) additionally include a linear trend to capture macro effects.

Considering the Panel A results for jewellery first, it is clear that there is a significant and positive crime-price elasticity of 0.50 in column (1). Further to this, there is strong reduced form relationship between jewellery crimes and world gold prices (column (2)). The first stage is also reasonably strong with an F-statistic of 16.8 and the IV resulting elasticity estimate is 1.53 (0.65). These basic results are sensitive to the inclusion of deterministic trends in columns (5)-(8). As we will see from estimates for other commodities, the distinguishing feature in the case of jewellery is the less powerful first stage relationship.

Crime-price elasticities for fuel are then reported in Panel B of Table 6. In this case, the OLS estimates are much the same irrespective of the inclusion of the trend at 0.70 in column (1) and 0.71 in column (5). As with jewellery, the two reduced forms also uncover significant positive crime-world price and UK price-world price relationships, and again the F-statistics indicate a strong first stage. The IV estimates are slightly lower than the OLS estimates, and are between 0.65 and 0.70, thus showing there to be a sizable fuel crime-price elasticity.[29]

[28] The Home Office reported that 430,000 tonnes of copper was exported to China from the UK in July 2011. See https://www.justice.gov.uk/downloads/legislation/bills-acts/legal-aid-sentencing/laspo-metal-theft-ia.pdf.

[29] An interesting feature of fuel thefts is that a large fraction are thefts from petrol stations where consumers drive away without paying. MPS figures on the breakdown of fuel thefts by type (available only from 2010) indicate that 56% of all fuel thefts fit the description of drive away thefts. Hence a significant fraction of these fuel crimes involve direct benefits in terms of personal consumption by the criminal.

Table 7 shows the statistical estimates of the crime-price elasticities for all metals and for copper. The OLS estimates show metal crime to be highly elastic to price, with point estimates of 1.35-1.43 for all metals and 1.66-1.70 for copper being comparable to the upper range of estimates for the goods studied in the consumer goods panel. Consistent with the rapid and high level of price transmission that has already been noted, the first stages shown in columns (3) and (7) are extremely strong with very high F-statistics. In the specifications including the trend (column (8)) the IV crime-price elasticity is estimated at 1.49 for all metal crimes and even higher at 1.81 for copper.[30] Thus metal crimes are very highly price sensitive.

As discussed, the commodity-related sub-group of goods, especially the metals, provides a striking setting for studying the response of crime to a series of exogenous price shocks with the quality of goods relatively fixed over time. This offers the cleanest evidence available on the responsiveness of criminals to changes in price with minimal changes in other factors that could determine the expected benefit of theft.

6.2 'Red Gold Rush' Effects?

One concern could be that the estimated metal elasticities are dominated by variation associated with the large jumps in prices that occurred in the first half of the sample, particularly in 2005-2007 when the prices of all metals and copper increased by their largest amounts. Consider the case of copper, where the upward price movements were especially pronounced. It is plausible that such a sharp increase in returns could have induced a rush into so-called 'red gold rush' (i.e. copper) as criminals sought to pick off low hanging fruit in terms of the least secure metal goods. On the other side of the market, the sharp increase in the value of metal may have boosted the reporting rate of metal crimes. The available evidence on metal crime indicates that there is a limited margin of effect for reporting to change in this context. Since most metal crime is focused on infrastructure and commercial businesses, reporting propensities are very high to the point of being automatic. For example, 45-60 percent

[30] Crime-price elasticities were also estimated for lead and aluminium crimes. For lead (for example, as in the case of "lifted from the roof of a Holy Named church"), the analysis had to be confined to the second half of the sample period (i.e. from July 2007 onwards) as separate numbers were not well recorded prior to that. Aluminium crimes only comprise a relatively small share and so the time series is quite noisy at the monthly time series frequency. Nonetheless, similarly high magnitude IV elasticities were obtained for both lead and aluminium (using world lead and aluminium prices to instrument scrap prices). The IV elasticity estimate from a trends seasonally differenced specification comparable to column (8) of Table 7 for lead was 2.2 and for aluminium was 1.6. Full estimates are shown in Appendix Table A4, together with associated plots comparable to Figures 3 and 4 in Appendix Figure A3.

of metal crimes are infrastructure-related in the sample[31] with the remainder comprised of commercial businesses, where reporting rates are typically high.[32]

However, as a robustness check against the 'gold rush' effects an exercise was undertaken based on recursive, period-by-period estimation of elasticities for all metal crimes and copper. This is designed to pick up the extent to which responses to the price booms of 2005-2007 may have pushed up the average elasticity. The approach first estimates the IV model for metal crimes and scrap metal prices (i.e. the specification used in column (8) of Table 7) on the last fifty periods of the sample (October 2008 to December 2012). This reflects the sub-period by which the initial set of major prices rises have settled in, giving elasticities that are based on variations around a stable mean and consolidated levels of security amongst owners of metal assets. Then the sample can be iteratively extended one month at a time, incorporating observations before 2008 until the 120 observation (seasonally differenced) full sample is reached by going back to January 2003. This shows the influence on the crime-price elasticity of incorporating the potential 'gold rush' observations between 2005 and 2007. The coefficient and confidence interval plots shown in Figure 5 do not reveal any explosive sensitivity to the inclusion of each sub-period – in all cases there are precisely estimated elasticities for each sample period considered. In the case of copper it is evident that the inclusion of the earlier period boosts the measured elasticity a little as more observations in the 2005-2007 period are included, but the most conservative estimate is still high at approximately 1.4.[33]

In summary, in both cases (all metals and copper) there is no evidence to suggest that the estimates are affected by either explosive 'gold rush' effects biasing the elasticities upwards or by strong adaptation effects as potential victims change their behaviour.[34] Note also here

[31] The MPS only began explicitly coding up metal crimes as infrastructure or non-infrastructure related in April 2012. Over this period, the share of infrastructure related crimes for metals fluctuates between 45-60 percent. In terms of general statistics, the ONS (2014) reports that 48.7 percent of all metal theft in England and Wales for 2012-13 was infrastructure related, defined as the removal of metals that have an impact of the functioning of live services such as railways and utilities. The remaining 51.3 percent of non-infrastructure related thefts still contains a large quantity of public sector and business targets (for example, factories, metal gates, and memorial plaques) that have similar characteristics to infrastructure but do not necessarily have their basic functions threatened by the metal theft.

[32] For example, the UK *Commercial Victimization Survey* (CVS) (a survey that measures crimes against business establishments) indicates that reporting rates to police are over 80 percent for burglary and major categories of theft.

[33] The recursive elasticities in Figure 5 are from estimates using the IV metal crime / scrap price specification from column (8) of Table 7.

[34] An exercise re-estimating the IV models dropping the years 2006 and 2010, when the largest price spikes occurred, yielded elasticity estimates (with associated standard error) of 1.649 (0.263) for all metals and 1.532 (0.196) for copper (N = 96). The comparable baseline regressions that include all years yield estimates of 1.493 (0.143) and 1.812 (0.154) respectively.

that strong adaptation effects (that is investments in security by victims that would make metal harder to steal) would be a force that would make crime less sensitive to prices and in practice this would drive down the measured elasticities. Together with there being minimal product quality changes in the case of the metals commodities, this reinforces the relevance of these estimates as the cleanest example of the response of criminals to changes in the returns to criminal opportunities.[35]

7 Discussion

The finding of significant crime-price elasticities fits well with the basic tenets of the economic model of crime where the decisions of individuals contemplating engaging in criminal activity are shaped by different incentives. This section discusses the implications of the finding that 'returns matter' firstly in terms of determining aggregate crime levels (defined here as the total volume of items stolen) and then secondly in comparison to other incentives that have been established as significant determinants of crime.

7.1 The Contribution of Changing Prices

The evidence of price responsiveness sheds light on one route whereby the returns to crime emphasised in the standard Becker/Ehrlich model may work. A question that follows is whether changing prices are a factor in explaining crime trends. The issue of falling crime rates across countries since the early 1990s has become a frequent topic of discussion (e.g. Blumstein and Wallman, 2005; or Levitt, 2004, for the US crime drop and Buonanno et al., 2011, for Europe's property crime fall). Various hypotheses have been proposed, and many ruled out. Prices, and the change in the composition of crime that price changes generate, have to our knowledge not yet been systematically considered in these discussions.

The finding that the positive crime-price elasticity holds across a range of goods implies that part of any crime drop could be explained by a falling real value of goods that were traditionally stolen by criminals. This is an especially compelling empirical question, since the structure of consumer prices is highly correlated across countries, making price a plausible

[35] Finally, one pertinent question that does emerge from these sizable elasticities is whether the earlier 44 product group results are driven by metals/jewellery. The answer is no, first because the metals were not included there and second because the jewellery categories are not pivotal to the regression results. Running a robustness check of the baseline regression in Table 3 and dropping all the jewellery categories produces an estimated elasticity of 0.294 (with an associated standard error of 0.144).

common factor that could help to explain falls in property crime rates internationally. In contrast, other more frequently mentioned determinants of crime, such as labour market conditions, sanctions and policing, fluctuate differentially across countries and as such are less plausible candidates to explain the observed cross-country crime trends.

An empirical counterfactual exercise can be undertaken to look at the contribution of changing prices to aggregate crime levels for the main samples. Note here that in this discussion 'aggregate crime' is specifically defined as the total volume of items stolen, since this is the focus of the data used in this paper. Violent crime is evidently subject to other important non-economic determinants. Over the period of study, total crime falls by 3.9 percent per year between 2002 and 2012 (see Figure 1 and Table 5 above). Given the evidence on the price-crime relationship, the counterfactual exercise adopted is to ask what the crime fall would have been had the relative structure of prices stayed the same in real terms. This is done in practice by considering price growth for the goods in the consumer panel as a proxy for shifting returns to criminal activity.

Our price index for stolen items in the 44-good panel indicates a fall of -1.4 percent per year on average between 2002 and 2012. One can ask how this fall in real terms could map into reduced crime rates by noting that the real price decline when multiplied by the elasticity of 0.35 predicts a 0.49 percent a year fall in crime, or 12.6 percent of the overall crime drop. Note that these effects only consider the shifts directly attributable to the falling value of stolen goods. At the same time that the prices of stolen goods were falling legal market returns were increasing. The London 10th percentile weekly wage – proxy for legal market returns for individuals on the margins of crime – increased by 3.6 percent per year over this period. Adjusting for the general increase in consumer prices (which grew by 2.1 percent on average over the period) this indicates that real legal market returns grew by 1.5 percent per year. In net terms, this increase in legal market returns would therefore plausibly have the effect of amplifying the crime-reducing effects of falling prices for stolen goods. Our exercise in the next sub-section evaluates these effects of changing legal and illegal market returns at the aggregate level for London.

The analysis so far has considered the magnitudes of crime responses on average. For some goods, however, the observed price falls have been very sizable. An example highlighted earlier in the paper was the very rapidly falling real price of audio-visual goods. Between 2002 and 2012 their nominal price fell by a huge 7.8 percent per year on average compared to the -1.4 percent fall across the 44-good panel on a weighted basis and 2.1 percent per year increase for the economy-wide CPI. The magnitude calculation for audio-visual goods based on these basic numbers therefore indicates that prices drive annual falls in crime of 2 percent per year, which accounts for approximately 26.3 percent of the total drop in crime for this set of goods.[36]

As a last calculation consider metals, where there were very rapid price increases that coincided with sharp upsurges in metal crime and where a high sensitivity of crime to price changes was estimated. Taking the case of copper, crime grew at a rate of 26.7 percent on an annualized basis with price growth of 14 percent (Table 5). Multiplied by the by the estimated IV elasticity of 1.756 (Table 7) this predicts an increase in copper thefts of 24.5 percent per year, accounting for the majority of the observed growth. This validates that the very big price increases that occurred in this market are in fact the dominant force behind the rise in metal crimes between 2002 and 2012.

7.2 Changing Prices and Other Factors

What about other factors? As a further exercise to benchmark the effects of prices on crime it is possible to study price effects in an aggregate London time series model of property theft for the 44-good series alongside the kind of labour market measures that have featured prominently in existing research on crime and economic incentives. For the aggregate prices series a 'stolen goods price index' was constructed. This weights each of the 44-goods by their crime share in 2002, the beginning year of the sample. The notion here is that the changing value of this basket is a good representation of how the value of the typical 'haul' from property crime is changing. This measure of illegal market returns is then compared to the labour market measures that can be measured for London, namely a legal market return in the form of the 10th percentile hourly wage, as well as the male unemployment rate.

The results from seasonally differenced time series regressions for London are reported in Table 8. In columns (1)-(3) estimates of price, wage and unemployment elasticities are presented from models that include the relevant variable plus a time trend. In column (4), all three variables are entered simultaneously. For the individually entered variables reported in the first three columns, the estimates show there to be significant elasticities of crime with

[36] This comes from multiplying the 7.8 percent real price drop by the good-specific elasticity of 0.253, which predicts a crime fall of 2 percent a year (or 26.3 percent of the total crime fall of 7.6 percent a year).

respect to prices and the labour market variables that reflect the expected signs (respectively positive for prices and unemployment, and negative for wages). When all three variables are entered simultaneously, as shown in column (4) there are still significant price and wage elasticities and the price elasticity is bigger (in absolute magnitude) than the wage elasticity. The former is close to 0.4, as were the earlier panel estimates, whilst the latter is numerically (in absolute terms) about half of that at just under -0.2. Thus there is evidence that both licit and illicit incentives matter for crime, as the Becker/Ehrlich model of crime suggests there should be. Moreover, the positive crime-price elasticity remains important even when controlling for changes in the rewards from legal work.

Returning back to the model of Section 2, the key prediction was that when the price of a particular good increases crime for this good rises too. Strong empirical evidence in line with this has been presented, for both the intensive margin within-product analysis and the extensive margin aggregate property crime analysis. However, it is worth noting for future research that, even though the partial effect of a price increase generates a boost in crime for a particular good, ascertaining the effect on total crime remains uncertain. One empirical reason for this in the context of this study is that the focus of study is only on property crimes. Extrapolating to make a link from changes in the price of loot to engagement in violent crimes is not straightforward. A second is that, within the property crime focus, there could be spillover effects where the increase in the price of a good could also generate additional effects on other crimes (as a substitution effect) or alter legal working hours (as an income effect). This extension lies beyond the scope of this study, but it would be a natural research direction to pursue in future research on crime and economic incentives.

Finally, there is the question of whether policing could implement preventive approaches by examining price changes of goods as a means of anticipating shifts in property crime that may occur as expected returns to crime change. At the moment, criminals can stay a step ahead as they respond to prices and target more valuable goods which give a better return. In response, police attempts to reduce crime for these goods can occur but by the time they do, relative prices may change again, thus generating a vicious circle.[37] Study of these types of crime and policing dynamics is also a fertile area for future research, as is how

[37] A good example of such crime dynamics relates to the dynamics of motor vehicle theft and technology introduced to prevent it. The introduction of engine immobilizer technologies (like Lojack as studied in Ayres and Levitt, 1998, and EU legislative changes studies by Vollaard and Van Ours, 2016) first reduced vehicle theft. However, as criminals figured out the new technologies they also found ways to circumvent them, so that vehicle theft was no longer deterred. See the New Scientist (2010) piece entitled "Criminals find the key to car immobilisers".

the crime-price link could more generally be affected by law enforcement.[38]

8 Conclusions

This paper reports results from a study of how changes in the prices of goods that criminals may steal affect criminal behaviour. It offers a direct test of whether shifts in economic incentives, working through movements in returns to crime driven by price changes, impact on crime. While the notion that the returns to legal market activities (as measured by wages or unemployment) matter for crime has been discussed in research over a long period, there has been limited evidence on the impact of changing illegal market returns. The empirical analysis suggests that the returns to illegal activity are an important input into criminal decision-making.

This conclusion emerges from the documentation of significant crime-price elasticities from rich administrative data on what was stolen in burglaries, thefts and robberies that took place in London between January 2002 and December 2012. Price elasticities are obtained for two sets of goods, the former a consumer panel of 44 stolen goods categories that are matched to price data over time, the latter for metal and commodity related goods where scrap metal prices are available and where such prices can be considered as being set by world commodity markets. The average estimated elasticity in the consumer panel is 0.35, suggesting a 10 percent increase in prices raises crime by just over a third. This is likely to be a lower bound, for a number of reasons discussed in the main body of the paper. Further to this, our magnitude calculation based on trends in the prices of stolen goods indicates that changes in prices can account for at least 10-15 percent of the fall in crime for the consumer goods we consider.

For the second group of goods, metal and commodity crimes are seen to be highly price elastic and their evolution through time is very sensitive to prices. For these crimes, which increased sharply as their prices rose much faster than general price inflation, there are sizable crime-price elasticities. For metals the elasticities are in excess of unity, and rising world commodity prices over the time period studied play a big role in explaining the rise of these crimes. Of course, these types of crime form a small share of total crime, but their

[38] For example, this could involve a comparison with the crime-sanctions elasticities and implied criminal discount rates estimated, for example, by Drago et al (2009) or Mastrobuoni and Rivers (2016).

evolution over the period that is studied shows that big changes in prices can induce big changes in crime.

Therefore to conclude, the analysis finds crime to be responsive to goods price changes. The evidence of price responsiveness implied by the significant crime-price elasticities that are uncovered is very much in line with the role that changing returns to crime play as a driver of crime in the standard Becker/Ehrlich model. Importantly, the effect of illegal gains on property crime persists when it is contrasted with the impact of legal economic incentives, working through wages and unemployment. More generally, the findings offer strong evidence that changing economic incentives matter for criminality from a rather different perspective than that offered in the economics and criminology literatures to date.

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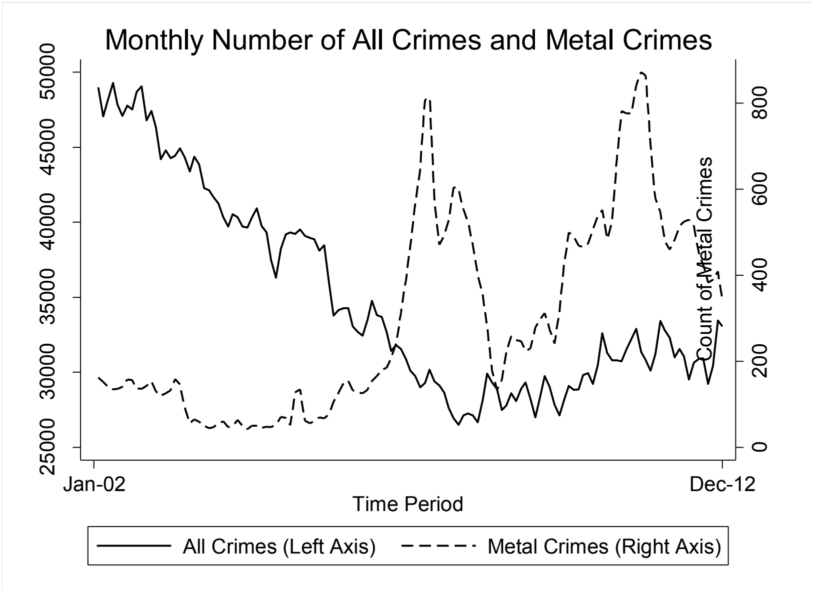
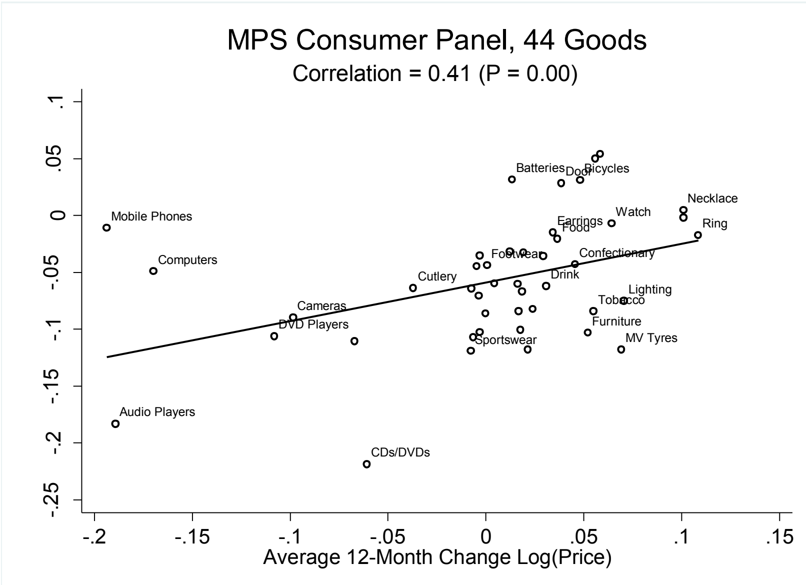
Figure 1: Trends in the Numbers of All Crimes and Metal Crimes

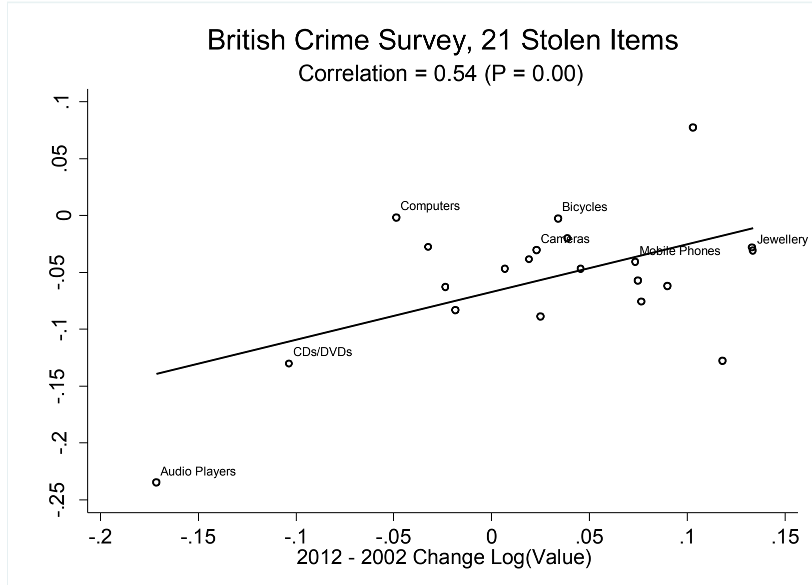


Notes: Levels of crime for the balanced, 44-good consumer goods product panel and the 7-good group of metals (copper, lead, aluminium, gold, silver, brass and other metal). The left vertical axis measures the total number of monthly items stolen for the consumer goods product panel, while the right axis records the total number for the metals group.

Figure 2: Average 12-Month Changes in Log(Crime) and Log(Prices) For Matched MPS Panel - Changes in Log(Crime) and Log(Value) For British Crime Survey, 2002-2012



Notes: Average 12-month change over ten years in Log(crimes) and Log(price) per good across all 44 consumer goods panel. Some labels (mostly on relatively small crime categories) have been omitted for space reasons.



Notes: Change in Log(number of stolen items) and Log(value) for the 21 consistently reported item groups available across the two BCS cross-sections for 2002-2012. Some labels (mostly on relatively small crime categories) have been omitted for space reasons.

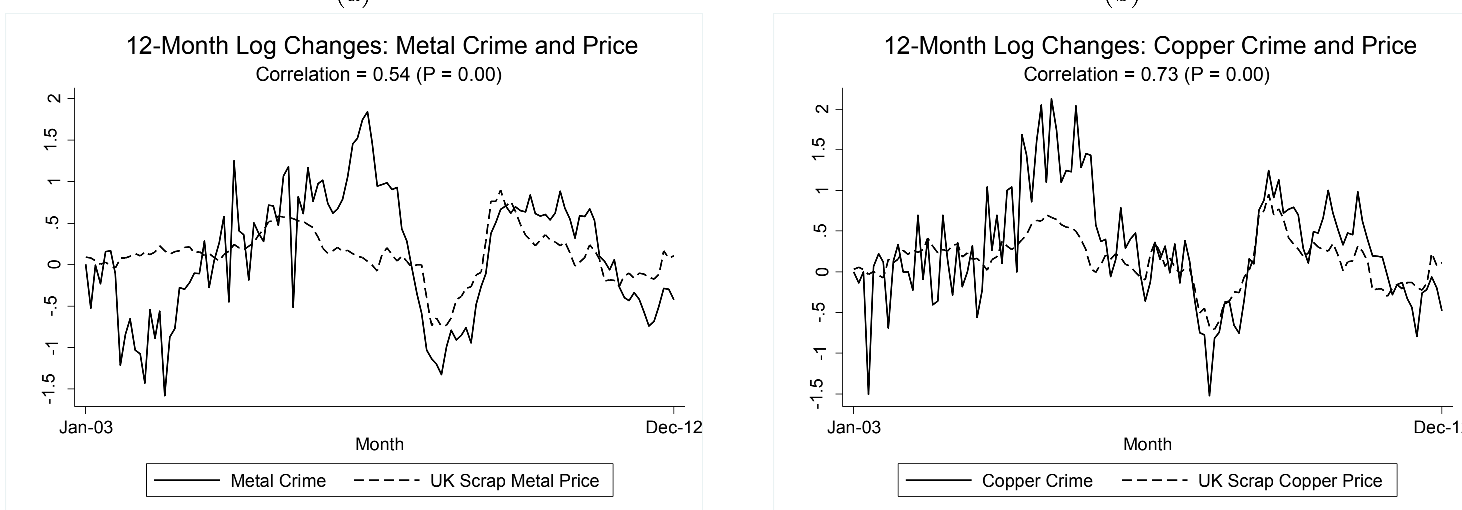
Figure 3: 12-Month Changes in Log(Crime) and Log(Prices), Jewellery and Fuel, 2002-2012

(a) (b)

Notes: 12-month changes in Log(Crime) and Log(Price) for jewellery and fuel.

Figure 4: 12-Month Changes in Log(Metal Crime) and Log(Scrap Metal Prices), 2002-2012

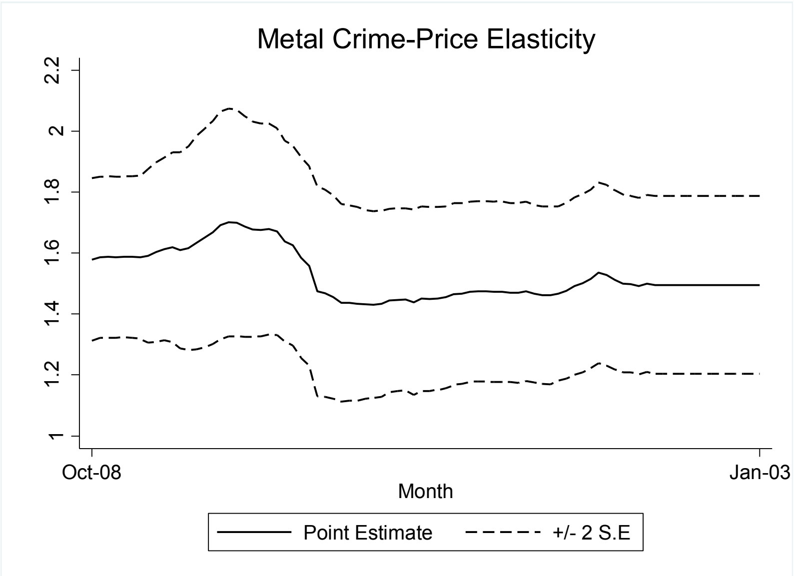
(a) (b)



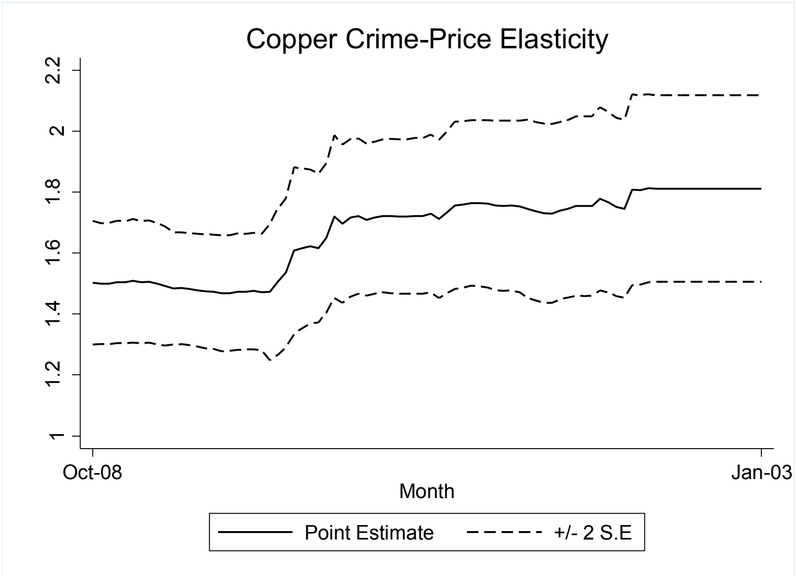
Notes: 12-month changes in Log(Crime) and Log(Scrap Metal Price) for all metals and copper.

Figure 5: Recursive Estimates of Metal Goods Elasticities, Log(Metal Crime) and Log(Scrap Metal Prices), 2002-2012

(a)



(b)



Notes: Metal and copper crime-price elasticities estimated recursively, starting with the last 50 observations (October 2008 – December 2012) and then adding an extra month and iteratively re-estimating the model until all observations are used (i.e.: until January 2003 with T = 120 observations). The Table 7 IV model (column (8)) with 12-month differences, scrap metal prices, time trend and robust standard errors is used.

Table 1: Changes in Property Crime Shares,
Top and Bottom 10 Out of 44 Matched Goods, 2002-2012

PROPERTY TYPE CODE	PROPERTY TYPE DESCRIPTION	10-YEAR CHANGE IN SHARE (%)	FINAL SHARE IN 2012 (%)
ET	Mobile Phones	8.8	31.6
LA	Bicycles and Accessories	4.6	8.8
JA	Necklace / Pendant	2.0	5.2
JC	Watch	1.3	4.2
JB	Ring	1.0	4.3
JD	Bracelets	1.0	2.9
JE	Earrings	0.5	1.9
TA	Hand Tool – Power	0.5	5.9
GA	Foodstuff	0.3	1.7
ER	Battery / Charger	0.2	0.4

PROPERTY TYPE CODE	PROPERTY TYPE DESCRIPTION	10-YEAR CHANGE IN SHARE (%)	FINAL SHARE IN 2012 (%)
EA	Audio/Radio/Hi-Fi/CD	-8.5	2.8
HA	Records/CDs/Tapes/DVDs	-3.0	0.6
EB	TV/Video/DVD/Projectors	-2.0	2.3
SB	Optical Equipment	-1.1	1.8
TB	Hand Tool – Mechanical	-0.8	1.0
AA	Ladies wear	-0.6	2.6
GD	Drink – Alcoholic	-0.6	2.2
DA	Cosmetics / Drugs	-0.6	3.3
AB	Menswear	-0.6	3.4
AD	Toiletries	-0.6	0.5

Notes: This Table reports property type codes and names in the matched, balanced panel (2002-2012) of MPS data that have experienced the ten highest and ten lowest increases in their share of total crime (the sum of burglaries, robberies and thefts).

Table 2: Baseline Estimates of Crime-Price Elasticities -
Metropolitan Police Service Monthly Data, 44 Matched Goods, 2002 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)
		Log(Crime)		Log(Theft)	Log(Burglary + Robbery)	Log(Crime)
Log(Price)	0.350 (0.130)	0.350 (0.132)	0.348 (0.138)	0.419 (0.157)	0.259 (0.123)	0.106 (0.047)
Lagged Dependent Variable						0.691 (0.061)
Long-Run Elasticity						0.344 (0.141)
Goods Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	No	No	No	No	No
Year Fixed Effects	Yes	No	No	No	No	No
Month*Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Month*Goods Fixed Effects	No	No	Yes	Yes	Yes	Yes
Number of Products	44	44	44	44	44	44
Number of Observations	5,808	5,808	5,808	5,808	5,808	5,764

Notes: The sample is a panel of 44 matched products with matched crime and price data. The dependent variable Log(Crime) is the log of the total count of stolen items for each product across the major crime types of thefts, burglary and robbery. The variable Log(Price) is the log of the consumer price index defined for each product. Standard errors clustered by product code in parentheses.

Table 3: Estimates of Crime-Price Elasticities Allowing For Price Dynamics

	(1)	(2)	(3)	(4)
	Log(Crime)			
Log(Price)	0.348	0.197	0.169	0.169
	(0.138)	(0.092)	(0.086)	(0.084)
Log(Price)$_{(t-1)}$		0.154	0.085	0.084
		(0.101)	(0.077)	(0.077)
Log(Price)$_{(t-2)}$			0.098	0.095
			(0.079)	(0.045)
Log(Price)$_{(t-3)}$				0.004
				(0.091)
Long-Run Elasticity	0.346	0.351	0.352	0.352
	(0.138)	(0.140)	(0.140)	(0.142)
Goods Fixed Effects	Yes	Yes	Yes	Yes
Month * Year Fixed Effects	Yes	Yes	Yes	Yes
Month * Goods Fixed Effects	Yes	Yes	Yes	Yes
Number of Products	44	44	44	44
Number of Observations	5,676	5,676	5,676	5,676

Notes: As for Table 2.

Table 4: Estimates of Reporting Rate Sensitivity and Crime-Value Elasticities, British Crime Survey, Annual Data, 2002 and 2012

	(1)	(2)	(3)	(4)
	Share of Reported Crimes		Log(Crime)	
	Levels	(1) + Product Fixed Effects	Reported Incidents	All Incidents
Log(Value)	0.118 (0.026)	0.018 (0.023)	0.421 (0.216)	0.518 (0.278)
Product Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Number of Products	21	21	21	21
Number of Observations	42	42	42	42

Notes: The sample is a two year panel (2002 and 2012) of 21 stolen items reported in the British Crime Survey (BCS). To ensure there is a sufficient sample size the 2002 sample covers stolen items reported from crime victimizations reported in 2001, 2002 and 2003 BCS and 2012 covers those from the 2011, 2012 and 2013 BCS. The dependent variable in columns (1) and (2) is the share of reported items stolen and in columns (3) and (4) is Log(Crime), the log total count of stolen items for the 21 items. Log(Value) is the log of mean reported replacement value of that item. Standard errors clustered by stolen item category in parentheses.

Table 5: Descriptive Statistics, Commodity-Related Goods, 2002-2012

	(1)	(2)	(3)
	Annualised Change in Crime (%)	Annualised Change in UK Prices (%)	Annualised Change in World Prices (%)
A. Consumer Prices Panel			
All Crimes (44-good Panel)	-3.9	-1.4	-
Jewellery	-0.6	8.7	14.8
Fuel	-0.3	7.4	7.0
B. Metal Crimes			
All Metals	10.1	10.9	11.4
Copper	26.7	14.0	14.3

Notes: Annualised percent changes in crime, UK prices and (where relevant) world prices. The jewellery category includes the following MPS property groups (and code): Necklace/Pendant (JA), Ring (JB), Bracelet/Bangle (JD) and Earrings (JE). The All Metals group comprises Copper, Lead, Aluminium, Gold, Silver, Brass and Other Metals. The domestic UK prices for the 44-good panel are calculated as a price index weighted by goods-level shares in crime in 2002. Similarly, the domestic UK jewellery prices are also from an index based on 2002 shares. The world price attached to jewellery is the gold price and the world price attached to fuel is the oil price.

Table 6: Estimates of Jewellery and Fuel Crime-Price Elasticities, Metropolitan Police Service Monthly Data, 2002 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS Reduced Form	First Stage	IV Structural Form	OLS	OLS Reduced Form	First Stage	IV Structural Form
	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Price)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Price)	Δ_{12}Log(Crime)
A. Jewellery								
Δ_{12}Log(Price)	0.496 (0.225)			1.528 (0.651)	-0.666 (0.377)			2.352 (2.080)
Δ_{12}Log(World Price)		0.305 (0.111)	0.199 (0.049)			0.191 (0.131)	0.081 (0.030)	
F-Statistic			16.8				7.3	
Time Trend	No	No	No	No	Yes	Yes	Yes	Yes
Number of Observations	120	120	120	120	120	120	120	120
B. Fuel								
Δ_{12}Log(Price)	0.699 (0.114)			0.626 (0.125)	0.708 (0.116)			0.657 (0.121)
Δ_{12}Log(World Price)		0.229 (0.060)	0.365 (0.061)			0.240 (0.065)	0.366 (0.062)	
F-Statistic			120.3				118.8	
Time Trend	No	No	No	No	Yes	Yes	Yes	Yes
Number of Observations	84	84	84	84	84	84	84	84

Notes: OLS and instrumental variable (IV) estimates of the models relating 12-month changes in jewellery and fuel crimes to 12-month changes in prices for each, where the world commodity price (gold price for jewellery, oil price for fuel) is used as the instrument. Newey-West standard errors in parentheses.

Table 7: Estimates of Metal Crime-Price Elasticities,
Metropolitan Police Service Monthly Data, 2002 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS Reduced Form	First Stage	IV Structural Form	OLS	OLS Reduced Form	First Stage	IV Structural Form
	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Scrap Price)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Scrap Price)	Δ_{12}Log(Crime)
A. All Metals								
Δ_{12}Log(Scrap Price)	1.349 (0.135)			1.320 (0.180)	1.427 (0.164)			1.493 (0.182)
Δ_{12}Log(World Price)		1.333 (0.192)	1.010 (0.066)			1.587 (0.184)	1.063 (0.066)	
F-Statistic			234.2				259.4	
Time Trend	No	No	No	No	Yes	Yes	Yes	Yes
Number of Observations	120	120	120	120	120	120	120	120
B. Copper								
Δ_{12}Log(Scrap Price)	1.657 (0.150)			1.756 (0.172)	1.700 (0.160)			1.812 (0.181)
Δ_{12}Log(World Price)		1.752 (0.151)	0.998 (0.047)			1.811 (0.149)	0.999 (0.050)	
F-Statistic			449.4				399.2	
Time Trend	No	No	No	No	Yes	Yes	Yes	Yes
Number of Observations	120	120	120	120	120	120	120	120

Notes: OLS and instrumental variable (IV) estimates of the models relating 12-month changes in metal and copper crimes to 12-month changes in scrap metal prices for each, where the corresponding world metal commodity price is used as the instrument. Newey-West standard errors in parentheses.

Table 8: Crime, Prices and Labour Market Variables - London Monthly Data, 2002-2012

	(1)	(2)	(3)	(4)
	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)
Δ_{12}Log(Aggregate Price)	0.600 (0.131)			0.411 (0.133)
Δ_{12}Log(10^{th} Percentile Wage)		-0.248 (0.058)		
Δ_{12}Log(Male Unemployment Rate)			0.189 (0.046)	-0.176 (0.059)
Time Trend	Yes	Yes	Yes	0.044
Number of Observations	120	120	120	(0.050)

Notes: Newey-West standard errors in parentheses. The aggregate prices series is a 'stolen goods price index' which was constructed by weighting each of the 44 goods in the crime panel by their crime share in 2002. The 10^{th} Percentile Wage is calculated as a six month moving average of the reported UK Labour Force Survey (LFS) hourly wage rate.

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Appendix

Table A1: Crime Recording Information System (CRIS), 2002-2012

(1)	(2)	(3)	(4)	(5)	(6)	(7)
One Digit Code	Description	Number of Two Digit Products	Share of Total Crime (Full Period)	Share of Total Crime (2002)	Share of Total Crime (2012)	Share Matched (Within One Digit)
A	Clothing	10	0.037	0.041	0.036	0.877
B	Publications	4	0.003	0.004	0.002	0.802
C	Currency and Official Documents	13	0.274	0.299	0.219	na
D	Cosmetics and Drugs	4	0.017	0.018	0.015	0.972
E	Electronic and Electrical	21	0.204	0.198	0.242	0.804
F	Weapons	5	0.001	0.001	0.000	na
G	Food and Drink (inc Alcohol)	7	0.025	0.025	0.027	0.862
H	Furnishing & Household Accessories	22	0.019	0.027	0.012	0.665
J	Jewellery	10	0.063	0.057	0.086	0.887
K	Personal Bags and Cases	8	0.106	0.111	0.089	na
L	Leisure Equipment / Vehicle Accessories	19	0.059	0.039	0.075	0.505
M	Metal Commodities	7	0.003	0.001	0.006	0.791
N	Personal and Vehicle Documents	12	0.046	0.053	0.040	na
P	Office and Art Materials	8	0.004	0.006	0.003	na
R	Building Materials	16	0.002	0.001	0.002	0.525
S	Photographic and Scientific Equipment	5	0.031	0.030	0.025	0.309
T	Building Tools	10	0.032	0.038	0.038	0.816
V	Pets and Animals	7	0.000	0.000	0.000	na
W	Public Property, Fuel and Miscellaneous	15	0.075	0.052	0.082	0.011
	Overall Statistics					
	(1) Share Matched (balanced panel)		0.373			
	(2) Share Commodity (balanced panel)		0.013			
	(3) Share Non-Matched (unbalanced)		0.136			
	(4) Share Non-Market		0.463			
	(5) Share Rare / Unusual		0.015			

Source: London Metropolitan Police Service (MPS). This Table reports the one-digit categories used by the MPS as part of their Crime Record Information System (CRIS). The shares in columns (4)-(6) are calculated with respect to the total count of thefts across all types of property stolen. Column (7) the share of property stolen in each 1-digit category that has been matched into the balanced panels used for the main analysis. These property shares are weighted according the total amount of crime per 2-digit code (i.e. this represents the share of property crime that has been matched). The lower panel breaks down all property stolen on a crime-weighted basis across four groups. These groups are: (1) Share Matched (balanced panel), the share of goods matched to price data for the Consumer Goods panel; (2) Share Commodity (balanced), share of goods matched to price data for the commodities panel (3) Share Non-Matched (unbalanced), the share of goods with incomplete data on either crime or prices; (4) Share Non-Market, goods such as credit cards and personal documents (e.g. licenses, passports) that cannot be classified as tradable products on either the retail or the second-hand markets; and (5) Share Rare / Unusual, goods such as animals, objects of art and weapons that cannot be feasibly matched to a price series. The letters “na” mean “not applicable” to convey that the goods in the corresponding 1-digit group are either Non-Market or Rare / Unusual.

Table A2: Example of Matching Metropolitan Police Service (MPS) Goods Categories to Office of National Statistics (ONS) Item Codes

(1)		(2)	
MPS Goods Category for Clothing		ONS Match for Two Digit Code AC Children's Wear	
MPS Goods Code (2-digit)	MPS Category Label Description	ONS Product Item ID	ONS Item ID Label Description
AA	Ladies wear	510324	Trousers (suitable for school)
AB	Menswear	510328	Boy's Jeans (5-15 years)
AC	Children's Wear	510330	Babygro or Sleep Suit
AD	Sportswear	510336	Girl's Skirt (5-15 years)
AE	Protective Clothing	510340	Girl's Fashion Top (12-15 years)
AF	Fur	510341	Child's Trousers (18 months – 4 years)
AG	Footwear	510342	Girl's Summer Jacket
AH	Clothing Fabric	510343	Girl's Winter Jacket
AJ	Uniform	510344	Girl's Trouser (not denim)
		510345	Boy's Branded Sports Top
		510346	Childs Jumper

Notes: This Table shows an example of the matching of MPS goods categories codes to the ONS retail price index item id codes. Column (1) shows the level of 2-digit detail available within the overall 1-digit Clothing category within the MPS data. Column (2) then shows an example of the 6-digit item ids that have been matched to the MPS "Children's wear" category. Hence the matching by label description process is facilitated by the level of detail available in the ONS data, which allows us to make fine distinctions for appropriate item matches against the MPS data.

Table A3: "Price Pass-Through", World Commodity and Domestic UK Prices, 2002-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Domestic UK Price Index)				Log (Scrap Metal Prices)			
	Jewellery		Fuel		All Metals		Copper	
Log (World Prices)	0.465 (0.037)	-0.139 (0.161)	0.340 (0.065)	0.070 (0.136)	0.870 (0.050)	1.220 (0.252)	0.961 (0.047)	0.830 (0.127)
Log (World Prices)$_{(t-1)}$		0.625 (0.159)		0.290 (0.119)		-0.361 (0.230)		0.137 (0.117)
Number of Observations	131	131	83	83	131	131	131	131

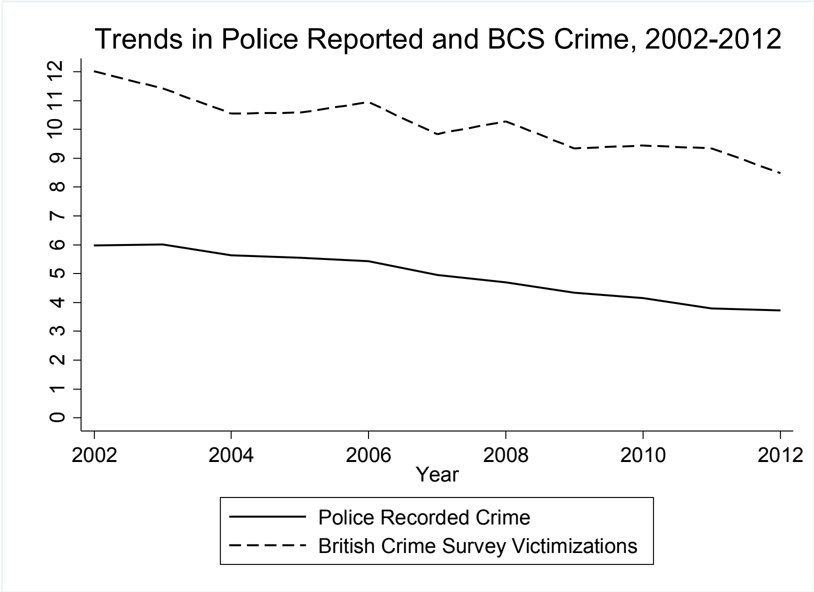
Notes: Ordinary least squares regression results between local goods prices (the ONS price index in the case of jewellery/fuel and scrap metal dealer prices for all metals and copper) and the corresponding world commodity prices. For each good the first column shows the contemporaneous period effect, while the second column includes also a one-period lagged variable for world metal prices. All equations include a time trend. Robust standard errors in parentheses.

Table A4: Metal Crime-Price Elasticities, Lead and Aluminium, 2002-2012

	(1)	(2)	(3)	(4)
	OLS	OLS Reduced Form	First Stage	IV Structural Form
	Δ_{12}Log(Crime)	Δ_{12}Log(Crime)	Δ_{12}Log(Scrap Price)	Δ_{12}Log(Crime)
A. Lead				
Δ_{12}Log(Scrap Price)	1.875 (0.280)			2.151 (0.281)
Δ_{12}Log(World Price)		2.265 (0.250)	1.053 (0.053)	
F-Statistic			394.8	
Time Trend	Yes	Yes	Yes	Yes
Number of Observations	67	67	67	67
B. Aluminium				
Δ_{12}Log(Scrap Price)	1.333 (0.245)			1.560 (0.293)
Δ_{12}Log(World Price)		1.936 (0.403)	1.241 (0.105)	
F-Statistic			139.7	
Time Trend	Yes	Yes	Yes	Yes
Number of Observations	118	118	118	118

Notes: OLS and instrumental variable (IV) estimates of the models relating 12-month changes in lead and aluminium crimes to 12-month changes in scrap metal prices for each, where the corresponding world metal commodity price is used as the instrument. All models include a time trend and are therefore directly comparable to columns (5)-(8) of Table 7. We drop two observations due to zero values for crime in the case of aluminium. Newey-West errors in parentheses.

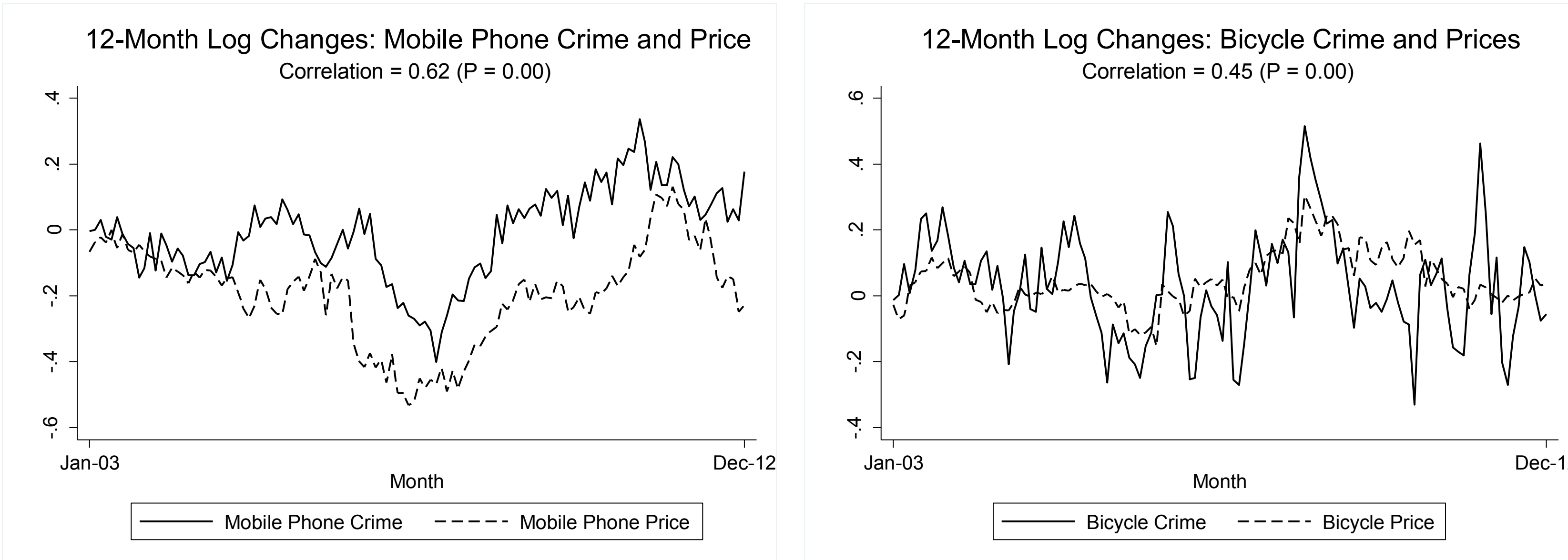
Figure A1: Police Recorded Crime and British Crime Survey Victimizations, 2002-2012



Notes: The number of criminal incidents reported to the police (solid line) compared to survey-based victim-reports from the British Crime Survey (dashed line).

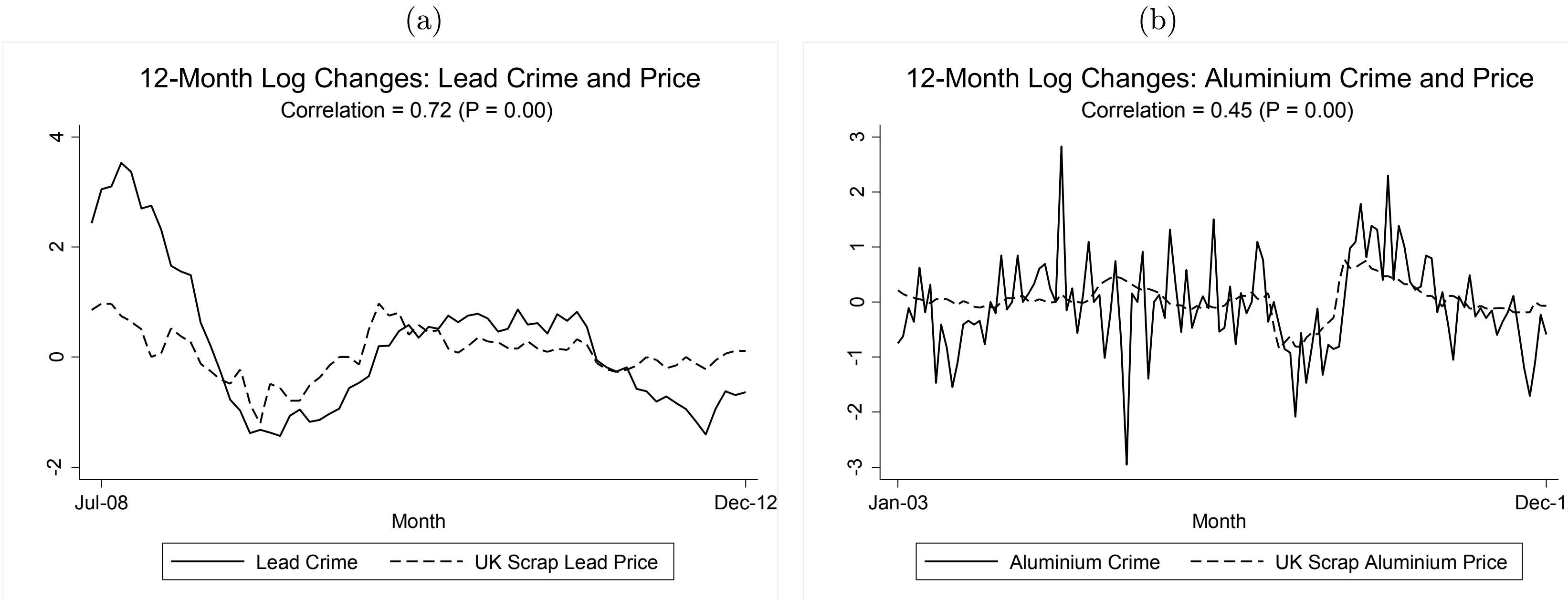
Figure A2: 12-Month Changes in Log(Crime) and Log(Prices), Mobile Phones and Bicycles, 2002-2012

(a) (b)



Notes: 12-month changes in Log(Crime) and Log(Price) for mobile phones and bicycles.

Figure A3: 12-Month Changes in Log(Metal Crime) and Log(Scrap Metal Prices), 2002-2012



Notes: 12-month changes in Log(Crime) and Log(Scrap Metal Price) for lead and aluminium.