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ABSTRACT

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

In economic models of crime individuals respond to changes in the potential value of criminal opportunities. We analyse this issue by estimating crime-price elasticities from detailed data on criminal incidents in London between 2002 and 2012. The unique data feature we exploit is a detailed classification of what goods were stolen in reported theft, robbery and burglary incidents. We first consider a panel of consumer goods covering the majority of market goods stolen in the crime incidents and find evidence of significant positive price elasticities. We then study a particular group of crimes that have risen sharply recently as world prices for them have risen, namely commodity related goods (jewellery, fuel and metal crimes), finding sizable elasticities when we instrument local UK prices by exogenous shifts in global commodity prices. Finally, we show that changes in the prices of loot from crime have played a role in explaining recent crime trends.

JEL Classification: K42

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 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 evidence that exists on the question of 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 seems to support 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 has been the question of how changes in the direct benefits or returns to criminal participation in illegal activity affect observed crime levels. Probably the explanation why is the practical difficulty in eliciting good information on the actual or potential returns from crime. While there is a series of studies on the structure of criminal incomes (see, for example, Viscusi, 1986, or Levitt and Venkatesh, 2000), 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

[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 et al., 2009, or Gronqvist, 2013, and the evidence on crime scarring from entry unemployment by Bell et al., 2014). The smaller body of work on crime and low (unskilled) wages also reports significant associations (see Gould et al., 2002, 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.

source of personal consumption utility for the criminal. This means that the changing market prices of goods and services may have scope to affect criminal participation decisions.

This question is fundamental to the issue of how the return to types of property crime may change, yet there are few empirical studies of the relationship between prices and crime. An exception is Reilly and Witt's (2008) 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 goods such as copper cable (Sidebottom et al., 2011, 2014), electrical equipment (Wellsmith and Burrell, 2005) and livestock (Sidebottom, 2012). These studies, following the criminological approach outlined by Clarke (1999, 2000), have stressed the role of a range of price and non-price attributes in determining rates of theft across goods.[3]

In economics, studies that 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, 2015); research on the link between crime and stolen goods markets (Miles, 2007, and d'Este, 2014); the influence of smuggling on cigarette demand (Gruber et al., 2003, and Lovenheim, 2008);[4] and experimental work testing how changes in the value of loot affect the incentive for theft (Harbaugh et al., 2013).[5]

On one level, the lack of study of crime and prices might be thought of as surprising. Police forces are often seen to run dedicated enforcement campaigns around the theft of commonly held, high-value property types. As an example, London's Metropolitan Police Service

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[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. We take some inspiration from this approach in our paper by distinguishing between the sources of price and non-price heterogeneity across goods that determine the expected return to theft.

[4] We mention this literature on cigarettes because, while it focuses primarily on health and taxation issues, it also brings into play the modelling of movements in an incentive for illegal activity (that is, how changes in taxes affect the returns to smuggling).

[5] 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.

(MPS) has run high-profile public initiatives in recent years focusing on jewellery and mobile phone theft, such as the prominent "Operation Ringtone" in 2013 which involved around 5000 officers in measures to reduce phone theft.[6] This was conducted alongside a general public awareness campaign around both electronics and jewellery-related crime.[7]

Adding to this, the media has also linked falls in the burglary rate to the falling prices of home electronic goods.[8] Empirically, there is *prima facie* evidence to support such a link. Figure 1, drawn from the database we have constructed for this paper, shows monthly trends in crime shares and price indices for two selected goods - audio players and watches - over the 2002 to 2012 time period. The indexed trends shown in the Figure make it clear that crime shares of the former audio player group fall in tandem with prices, while there is an increase in the crime shares of watches as this category of goods became more valuable over time.

Study of the more general empirical connection between crime and prices forms the subject matter of our paper. We do this in various ways. After outlining a simple theoretical approach to modelling crime and prices, we first begin our empirical analysis 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, we utilise 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 we exploit is that we know 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

[6] See Home Office (2014) and BBC News (2013) "Arrests after Met Police Crackdown on Mobile Phone Thefts" for details on Operation Ringtone.
[7] See Metropolitan Police Service (2013). This initiative was a radio and poster campaign that highlighted in particular the street robbery risks of prominently displaying jewellery and encouraged members of the public to exercise extra caution when wearing or carrying these items.
[8] See for example, the Economist (2013) and Morris (2014).

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 we use to study how different price movements across goods may affect crime patterns. In this analysis, we estimate crime-price elasticities 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 we can also consider how changes in what is stolen relate to changes in the reported value of the item.

The second main part of our crime and prices analysis then focuses on a set of commodity-related goods – 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.

Our analysis uncovers a strong link between changing prices and crime. For the consumer goods panel we estimate an average elasticity of 0.35. For metals we estimate an elasticity of above unity, revealing a very strong sensitivity of crime to price changes. Furthermore, the empirical framework we adopt addresses a large range of potential confounders that could influence the crime-price relationship. Firstly, the approach we outline for the 44-good panel explicitly addresses the issue of non-price sources of heterogeneity across goods. In particular, the fixed effects model that we adopt is able to absorb many important dimensions of goods heterogeneity. By this we mean 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 our main strategy 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 we could plausibly expect the non-price characteristics to adjust to the same stimulus. Our 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.

The last part of our analysis of the 44-product panel looks at the potential bias from endogenous crime reporting behaviour. As prices rise and goods become more valuable, owners are more likely to report that an item has been stolen and, since our MPS data is indeed based on crimes officially reported to the police, this could account for some of the observed positive relationship between prices and crime. We therefore construct a further goods-level panel using the annual British Crime Survey (BCS), which, as a victimization survey, distinguishes between reported and non-reported crime. We find that the crime-price relationship is robust using this broader definition of crime and that the potential biases from endogenous reporting are minimal.

We then move on to study metal and other commodity-related crimes (namely fuel and jewellery). Recently, there has been a huge upsurge in metal-related crimes in particular, with many reports of infrastructure-related thefts from targets such as public buildings and railway lines.[9] The prices of metals have risen very sharply through the 2000s as rapidly growing countries (especially China) have increased their demands for these metals. A very good example is the case of copper where prices have been driven up very sharply by demand from China. Thus exogenous increases in world prices have caused thieves to concentrate their activities into stealing metal, a crime where the monetary returns are much higher now than in the past. In a similar fashion, goods like jewellery and fuel are also exposed to changes in prices (specifically the prices of gold and oil respectively) that are primarily determined in international markets.

Our analysis of commodity-related crimes has two main advantages. Firstly, in the case of metals we are able to obtain direct resale prices in the form of detailed reports from scrap metal dealers. This allows us to overcome the problem of measurement error that comes up when we proxy street resale values with retail prices, as we do in the previous consumer goods panel. Secondly, this study of commodity-related crimes allows us to parse out the biases related to unobserved demand shocks at the goods-level. By this we mean increases in the 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 we observe for the commodity-related goods are very clearly exogenously set by trends in global markets rather than demand in the UK.

[9] See for example, the review by Bennett (2008) which provides UK examples such as "240,000 passenger minutes lost in 2006" due to delays caused by copper cable theft. Kooi (2010) provides a guide to US metal theft trends and Berinato (2007) provides an evocative account of the US copper theft epidemic as a "red gold rush".

Thus, overall, we find property crime 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. Our 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, our results indicate that the supply of crime is elastic both within and across activities, with relatively fast adjustment to changes in potential returns.

The finding of significant and positive crime-price elasticities shows that prices matter for crime, and so we conclude the analysis of this paper by considering the quantitative importance of changing prices in explaining crime trends in the period we study. In our data, aggregate property crime fell by 35 percent between 2002 and 2012. For our estimated crime-price elasticities from the consumer panel, we find that price variation accounts for somewhere around 20 percent of the 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 so that price falls accounted for almost 40 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, we find that the vast majority of the metal crime can be accounted for by real price increases.

The rest of the paper is structured as follows. In Section 2 so as to motivate our empirical analysis we develop a simple choice theoretic model where crime and prices are connected to one another and from which we derive the prediction of a positive crime-price elasticity. In Section 3 we describe the data and offer some descriptive analysis. Section 4 reports the modelling approaches we implement. Section 5 gives the results from the consumer panel, and Section 6 from the analysis of commodity and metal crimes. In Section 7 we offer some interpretation and discussion of our results, together with a decomposition of the importance of price changes for explaining crime trends. Section 8 offers some concluding remarks.

2. Modelling Crime and Goods Prices

The starting point is a standard model of crime and economic incentives following, for example, the way Freeman (1999) or Machin and Meghir (2004) set up the classic Becker (1968) or Ehrlich (1973) model for use and implementation in empirical work. We extend this, without loss of generality, to consider choices of theft across different consumer goods which sell at different prices. In the first step, we reiterate the usual homogenous agent-homogenous good case and then go on to outline a simple homogenous agent-heterogeneous good model that can be applied to our empirical setting. In particular, the model shows how a straightforward price elasticity can be derived and also helps to clarify the role of factors such as wages, the level of sanctions, and the probability of detection or capture in relation to the crime-price elasticity that we are interested in.

A general set-up of the model is as follows. If P is 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, which compares the expected returns from crime to the legal labour market wage, holds:

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

In (1) the subscript gi on the probability of being caught π reflects heterogeneity in both the good to be stolen g and the type of individual thief i (e.g. a burglar or robber). The gain P reflects the market value of the good g to the thief (i.e. its resale value or personal value to the thief). Legislation punishes all individuals equally for thefts of a given type of good *g*, while wages depend also on the type *i* of the individual thief. We now examine different cases that allow for the goods *g* and criminals *i* to vary in terms of types, starting by shutting down both sources of heterogeneity.

Homogeneous Agent - Homogeneous Good

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:

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

Notice that equation (2) is the same as (1), except the subscripts *g* and *i* are dropped, as all goods and all individuals are identical. The inequality in this case is, of course, the standard one from the Becker (1968) and Ehrlich (1973) economic model of crime.

Homogeneous Agent - Heterogeneous Goods

This is the most relevant case for our empirical exercise, since in the data we have information about the type of the thieves is limited but we can in detail identify the type of stolen good. Specifically, we can only characterise the type of criminal from modes of crime (i.e. burglary, theft, or robbery) rather than observing individual criminals specialising in the theft of particular goods. Hence, in this case the basic inequality becomes:

$$(1-\pi_g)\,P_g-\pi_g\,S_g>W \tag{3}$$

which means that the individual takes more than just one decision about whether to engage in crime or not. Instead, they compare the net benefit of stealing over alternative goods, denoted by *g*. So if there are two products, indexed by *1* and *2* respectively, and if inequality (3) holds for both of them, the thief still has the choice between the two goods. Conditional upon doing crime, an individual would therefore choose to steal good *1* rather than good *2* if also the inequality below holds strictly:

$$(1 - \pi_1)\, P_1 - \pi_1\, S_1 > (1 - \pi_2)\, P_2 - \pi_2\, S_2 \tag{4}$$

However, as crime for good *1* increases in the society, the gap between the left and right hand side of the expression above declines. An equilibrium with crime in both products occurs when the expression holds with equality. The natural way to model this 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. Intuitively, this means that stealing property of type *1* is less risky in the beginning (as in what might be thought of as a low-hanging fruit explanation): however, as more thieves choose to steal the same good, the probability of being caught increases.[10] That is why we can express π_1 as an increasing function of the quantity theft of property *1* so that $\pi_1 = k\, C_1$ with k being positive.

By treating expressions (3) and (4) as equalities we can derive the quantity of crime in equilibrium. For one good only, we have

$$(1 - k\, C_1)\, P_1 - k\, C_1\, S_1 = W \tag{5}$$

which can be rearranged as:

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

Equation (6) shows that a wage increase results in a fall in stolen quantities. The intuition behind this is simple: when wages from legitimate labour increase, the outside option is more attractive and fewer criminals decide to steal. Similarly, equation (6) also shows that an increase in the sanction associated with being caught for stealing the good *1*, S_1, decreases the stolen quantity.

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

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

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

In (7) it is clear that the elasticity of crime with respect to prices 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, we 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 ($S_1 = S_2 = S$) 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*. We return to this point about equal punishments across goods when discussing our empirical specifications in the next section below.[11] Therefore, analogous to the expression for good *1* in (5), the crime-work choice equality for good *2* is:

$$(1 - kC_2)\ P_2 - kC_2\ S = W \tag{8}$$

Thus, after some rearrangement, for the two goods case we can derive:

$$C_1 = [(P_1 - P_2 + kC_2\ (P_2 + S)] / [k\ (P_1 + S\ )] \tag{9}$$

We can then derive a crime-price elasticity for good *1* as

$$(\partial C_1 / \partial P_1)\ (P_1/C_1) = \{(S + P_2)(1\text{-}kC_2) / [k\ (P_1 + S)^2]\}\ (P_1/C_1) \tag{10}$$

In this two-good model, again the crime-price elasticity is always positive. Recall that quantities and in particular kC_2 replaces the probability of being caught π_2, which takes values from 0 to 1.

[11] 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.

Wages do not affect the price elasticity when there are two goods in the society. This is intuitive, as wages affect the choice between crime and legitimate labour but they do not affect the decision between stealing good *1* and *2*, conditional upon the choice to do crime rather than work, provided that legal wages are sufficiently low that render crime profitable for both good *1* and good *2*.[12]

3. Data and Initial Descriptive Analysis

Our analysis matches data on crime to prices, with an aim of estimating empirical crime-price elasticities. We do this in two main ways. We first put together sources of crime data matched to the prices or values of what was stolen for a number of market goods. Second we look specifically at commodity and metal crimes, in part because they have seen a significant rise in prices over the period we study, and also because we can consider plausibly exogenous price variations driven by prices in international commodity markets. Furthermore, in the case of metals we have accurate price data from scrap metal dealers, which are the actual resale prices on offer to criminals.

Crime by Property Type

We draw on two sources 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 look 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

[12] Another result from this model is that a low level of wages is associated with a low overall price elasticity. The intuition is straightforward: when wages are low, say close to zero, almost everyone steals, as the outside option of work is not attractive. In this case an increase in prices cannot shift many from legitimate labour to crime, since most of them already engage in criminal activity.

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 crime shares by one-digit category.

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.[13] 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.

ONS Product Prices

For some of the product groups in the CRIS data we can match the crime counts in each month between January 2002 and December 2012 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.[14] 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

[13] 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.

[14] The data contains information from 1,701 different shops on the prices of 992 different products defined according to the goods classification used by the ONS (where the nomenclature term is item id).

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 we use their calculated price index information, re-setting the base values to January 2002.

Matching MPS and ONS Product Groups

We matched the MPS product codes to the ONS retail price codes by inspecting the label descriptions for the codes across the datasets. This is only feasible for the crimes with market codes in the MPS data and we cannot match the stolen property which is classified to be non-market (around 49.2 percent in terms of crime counts) such as credit cards or personal documents that cannot be priced because they are not tradable in conventional retail or second hand markets. A further "rare/unusual" group (around 3.3 percent of crime counts) contains property types such as those related to animals or weapons that also cannot be feasibly matched to a consistently reported price series.

For the market goods, however, the high level of detail in the ONS price data makes it possible to find credible matches for many two-digit goods categories reported in the MPS property type system. For example, we are able to find separate matches amongst prices for the different types of clothing covered in the MPS data (e.g. menswear, ladies wear, children's) and for different types of electronic, durable and food products.[15] In total, we were able to match 44 crime and goods categories for all months between January 2002 and December 2012, comprising approximately 77.5 percent of the market good crime counts. From this we have formed a balanced panel of crime counts and retail prices across 132 monthly periods. The remaining 22.5 percent could not be matched because of either incomplete crime or price data.[16]

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

[16] 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

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. We can thus form an analogous data set to our MPS crime-consumer goods panel by looking in each year how many items were stolen and we can work out the their average value. Hence this is a direct measure of the value of the item stolen and provides an alternative to our measure based on the retail price index. We do not have as much detail as the MPS data but have been able to put together data in 2002 and 2012 on 22 items, some of which match those in the MPS data, together with their average replacement value.[17] We use this below to draw a comparison with results using the MPS consumer panel.

Metal Crimes

The MPS product coding system features a one-digit group of metal crimes.[18] 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, so we have collected direct data on scrap metal prices. These prices are likely to reflect the true resale value obtained by criminals in the case of metal theft. We collected the data 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 us to match scrap metal prices to the MPS metal crimes. As well as these local, UK-focused scrap metal prices, we are also able to draw on international commodity markets for price information. We obtain

that cannot be easily concorded over time (we found that this was most common in the electronics, furnishing and building materials 1-digit categories).

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

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

international metal commodity prices from the online platform "Index Mundi". All prices are collected at the monthly frequency and are measured in pounds sterling.

Initial Descriptive Analysis

Figure 2 shows trends in the total number of crimes and metal crimes in our 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 50000 in January 2002 to just over 30000 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.

In Table 1 we report some descriptive statistics on the changing composition of thefts by property type as observed in our balanced panel of 44 goods categories. In particular, we look at the change in shares of total thefts per two-digit product and report figures for the top 10 and bottom products over the 2002-2012 period. This indicates some obvious movements that are consistent with changing prices driving crime trends. The fastest growing categories are dominated by either high-tech, high-value electronic goods (mobile phones, power tools) and jewellery-related goods. The products with declining shares are goods where there has been strong downward pressure on prices, such as the case of Audio Players discussed in our introduction.

Figure 3 then 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 plots show the between-good variation across categories in the data, abstracting from within-good changes over time. 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 very 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 well. Closer inspection reveals one difference that is pertinent, 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. We think this probably reflects that higher price mobiles are more likely to be stolen and this is not picked up in the overall average price index, but it would be better reflected when crime victims report replacement costs in the BCS. This apart, however, the main picture is one of striking similarity between the two charts.

4. Empirical Models of Crime and Prices

The descriptive analysis of the previous section is highly suggestive of an empirical connection between changes in crime and changes in prices. In this section, we set out a modelling approach which subjects this initial finding to a more stringent statistical evaluation, including discussion of a number of threats that may be posed to the identification of a positive crime-price elasticity.

Baseline Empirical Models – Consumer Goods Panel

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

$$Log(C_{gt}) = \alpha_g + \beta Log(P_{gt}) + \tau_m + \tau_y + \varepsilon_{gt} \tag{11}$$

where C is the number of crimes (that is, a count of items stolen) and P is the price index for each good (calculated relative to the base level observed at the beginning of the sample in January

2002). α_g is a product-specific fixed effect and to control for common seasonal and annual effects we first include month and year dummies that are denoted by τ_m and τ_y respectively, with ε_{gt} representing the error term. The inclusion of the product, month and year fixed effects ensures that the estimated elasticity β is the within-product elasticity that is identified from changes through time of crime and prices.

We adopt this within-groups specification as we have a long T panel of 132 observations (12 months by 11 years) for our 44 matched crime-price groups. More stringent empirical models can also be estimated and we generalise the estimating equation in several ways. First the fact that we have monthly data over multiple years means we can allow for a full set of time effects by including all month-by-year dummies, τ_t.

We can also generalise further to allow month effects to vary by good g and therefore make the pattern of seasonality fully flexible at the goods level. Incorporating both of these produces the following specification:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \tau_t + \varepsilon_{gt} \tag{12}$$

where τ_t (or τ_{my}) describes every month-year combination and α_{gm} is a fixed effect for each product-month cell. This seasonally adjusted, within-groups model forms our preferred specification as it incorporates a full set of time effects and conditions out goods-specific seasonality.

Issues

These estimating equations capture a number of salient features of the crime-price relationship as described in the simple model of Section 2 and will enable us to subject our initial descriptive findings to a more rigorous evaluation. But, before we consider the estimates that emerge, a number of issues require some discussion.

A first feature to note in terms of the model is that since outside wages (W) and sanctions (S) do not vary across goods then their effects are absorbed into the empirical model's time effects. Note that in the case of sanctions there is a limited sentencing gradient according to the value of thefts in the UK.[19] Secondly, any constant differences in the specific success probability associated with each good (denoted as $(1 - \pi_g)$ in the model) will be absorbed into the goods-specific fixed effect α_g. We can realistically expect this success probability – which can also be interpreted as a general difficulty to steal – as varying across goods according to factors such as: the typical pattern of security or protection afforded to each good; the usual location or placement of the good; the available stock of the good held by consumers; and physical characteristics such as weight and size which will bear on the physical practicality of stealing the good.

The product fixed effects α_g also play role when considering measurement issues that might arise with respect to our price data. The preferred measure of P outlined in the model would be re-sale value, that is, the amount of money a criminal can obtain for a stolen good. The price we use (retail prices as given by the ONS) is obviously an imperfect proxy for this. The fraction of analogous retail value that a criminal can recoup for a good will depend on a range of factors such as: traceability, the size of potential resale markets, and product durability. However, if we think of the relationship between retail prices and re-sale value as following a simple linear markdown function, such as $Resale_{gt} = (1 - \lambda)\ Retail_{gt}$, then this makes the re-sale price faced by criminals some constant fraction $1 - \lambda$ of the retail price we measure. If this markdown is

[19] The UK's Sentencing Guidelines for theft provide scope for sentences to vary with the value of theft being considered (Sentencing Council 2014). These 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. These bands and associated sentences are changed infrequently and can therefore be treated as fixed for the purposes of the monthly analysis presented in this paper. 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 for it to affect our estimated elasticities. Hence we treat sanctions as being fixed and homogenous across goods.

stable over time then it will be differenced out by the product fixed effects in all of the specifications outlined above. As a result, our within groups estimate using retail prices will capture the underlying changes in re-sale value that drive the crime participation decision.

This assumption that non-price heterogeneity is constant or only slowly changing through time does have implications for the interpretation of our estimated β parameter for prices. If we think that non-price factors such as the success probability $(1-\pi_g)$ or the re-sale depreciation factor λ could vary at the same frequency as the price effects then this could be a source of omitted variable bias. That is, our measured price changes could also be picking up correlated effects related to unmeasured changes in success probabilities or the state of the resale market. It is therefore important to establish the time profile of the price effects in order to judge whether these effects could be plausibly conflated with goods-specific omitted variables in this way.

Dynamic Specifications - Consumer Goods Panel

It is straightforward to extend the above empirical model to incorporate dynamics. Firstly, a lagged dependent variable can, following the usual logic, be included to account for persistence and as a proxy for additional omitted factors that could be correlated with crime:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \delta Log(C_{g(t-1)}) + \tau_t + \varepsilon_{gt} \tag{13}$$

In this dynamic setup, the long-run crime-price elasticity is $\beta/[1-\delta]$.[20] Dynamics can also be introduced in terms of extra lags in prices, to allow for the possible adjustment of crime to price shocks over several prior periods, as follows:

$$Log(C_{gt}) = \alpha_{gm} + \beta Log(P_{gt}) + \sum_{k=1}^{K} \gamma_k Log\left(P_{g,(t-k)}\right) + \tau_t + \varepsilon_{gt} \tag{14}$$

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

[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 long-T structure of our panel.

The specification in (14) is helpful for validating the argument presented above regarding 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. Practically, 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. We return to this discussion of confounders in the results section where we also discuss other sources of time-varying confounders, in particular the biases that could result from endogenous reporting behaviour by victims of crime.

Instrumental Variable (IV) Approach

While the above framework for the consumer goods panel can deal with a large range of possible omitted confounders, we also extend our research design to deal with the potential influence of good-specific demand shocks over time. By this we mean 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 our 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. We show the plot of the 12-month differences for these goods in Figure A1 and the period-to-period tracking is clearly apparent. However, the concern about unspecified sources of bias still applies, so to address this we 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, our 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 we use the oil price. We map metals directly to their associated world commodity prices. For metals we also have directly measured local UK scrap metal prices, which ameliorate concerns of using retail price indexes for new goods as a measure of the resale value that could be recouped by the criminal.[21]

Practically, our approach can be interpreted as a quasi-experiment such that 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 our 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.

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

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

$$\begin{aligned} \Delta_{12}Log(C_t) &= \delta_1 + \theta_1\Delta_{12}Log(WP_t) + \psi_1 t + \omega_{1t} \\ \Delta_{12}Log(P_t) &= \delta_2 + \theta_2\Delta_{12}Log(WP_t) + \psi_2 t + \omega_{2t} \end{aligned} \tag{15}$$

which can be combined to give a structural form as:

$$\Delta_{12}Log(C_t) = \delta_3 + \theta_3\Delta_{12}Log(P_t) + \psi_3 t + \omega_{3t} \tag{16}$$

where the instrumental variable (IV) estimate of the crime-price elasticity is the ratio of the reduced form coefficients, where $\theta_3 = \theta_1/\theta_2$.

5. Results – Consumer Goods Panel

Baseline Models – Consumer Goods Panel

Columns (1) to (3) of Table 2 report the results of estimating crime-price elasticities from the balanced panel of 44 consumer goods products. 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 that 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, it seems that crime is 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).[22] The elasticity is a little higher for thefts, at 0.413 compared to 0.254 for (burglary+robbery), but both are significant and positive showing important price sensitivities, and we are not able to formally reject the null hypothesis that they are equal to one another. For the rest of the analysis we therefore consider all crimes.

It is well known that crime is highly persistent and so we allow for this via inclusion of a lagged dependent variable 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 / [1-0.692]). Thus the estimates are robust to crime dynamics. Put a different way, inclusion of the detailed product by month and year by month fixed effects has already netted out a large part of the possible influence of crime persistence on the estimated elasticity.[23]

Figure 4 shows the full set of plots for individual goods elasticities where we have estimated separate elasticities at the 1-digit level. All are positive and significant price elasticities are apparent across a wide range (the majority) of categories. But there is some evidence of heterogeneity as a subset of goods are seen to be highly price sensitive with estimates of elasticities just above unity.

[22] We aggregate burglary and robbery since the number of robberies is relatively small, representing 6 percent of total items stolen.

[23] In a further robustness check, we re-estimated the 44-good model as 12-month differences, rather than the seasonally adjusted within-groups model. The estimated elasticity remains strongly significant and positive, although falls a little to an estimate and associated standard error of 0.194 (0.042).

Price Dynamics – Consumer Goods Panel

Given the structure of the models we have 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 we have made. As discussed, 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 that we use 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.

In Table 3 we show estimates of the lag structure of prices in our 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 models 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 very sharp, short-run pattern to account for the price effect we measure in our 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 here 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 our 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 therefore also attenuate any price-related effects on crime. In addition to the measurement error that arises from using retail rather than direct resale prices, this suggests that our 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 are more likely to report the incident. Since our MPS data is based on reported crime this source of bias is relevant. We therefore turn to the British Crime Survey data that contains information on reported and non-reported thefts to determine some bounds for the potential influence of endogenous reporting on the crime-price relationship.

British Crime Survey

We have put together data on the number of stolen items and their value for 2002 and 2012 from BCS reported victimizations. This data allows us to both study the sensitivity of crime reporting to the value of stolen items as well as provide estimates of the basic crime-price relationship using an alternative data source.

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 is shown in Figure 5. The Figure shows that the relationship between reported and non-reported crime to be steady over the 2002 to 2012 period. 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 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 we view this as strong corroboration of our core findings.

6. Results – Commodity and Metal Crimes

Instrumental Variable (IV) Estimates

The results presented in our 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. Sophisticated consumer goods such as electronics are particularly susceptible to this problem since they are subject to sometimes rapid changes in quality that are correlated with changing consumer demand patterns.

To rule this kind of behaviour out, we set up a quasi-experimental design where price movements in international commodity markets shift the corresponding domestic UK prices of a subset of related goods. Hence the changes in price we identify 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 we consider are homogenous in their quality over time thereby shutting down this particular source of confounding demand shocks.

The descriptive statistics for our 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 our 44-good consumer goods panel which typically feature a high level of gold content.[24] Since fuel is only reported as a separate crime category by the MPS from 2005 onwards we report means for this good across 96 months rather than the 132 months observed for all other goods. The numbers in the Table show

[24] These 2-digit categories (with MPS property type codes in parentheses – see the Appendix) are: Necklace/Pendant (JA), Ring (JB), Bracelet/Bangle (JD) and Earrings (JE).

that the number of jewellery crimes was fairly constant over time changing by -0.5 percent per year, but that this is a relative rise compared to the -3.5 percent annual fall in all crimes. At the same time, the jewellery price and the world gold price grew significantly. Fuel crimes grew rapidly at over 20 percent a year and the associated prices also significantly rose.

Turning to the metal crimes in the lower panel of the Table, we see significant increases over time in both crime and prices. All metal crimes rose by 11 percent a year between 2002 and 2012. Copper crimes grew by an extraordinary 29 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 12 percent a year and the copper scrap price by 15 percent a year. The world prices (a composite for all metals from Index Mundi and the world copper price) showed similarly strong rises.

Plots over time of local and world prices are shown in Figure 6 for jewellery and fuel and in Figure 7 for all metals and copper make the nature of the price increases clear across goods. 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). There were large level shifts in metal and copper prices in the mid-2000s and prices were sustained at a high level as demand for many types of metal from countries like China and India continued. Gold prices experienced a well-known trend increase and drifted upwards with some sharp fluctuations over the 2002-2012 period.

However, the most important feature of these plots for our research design is the tight relationship between local and global prices. The plots for jewellery and fuel prices in Figure 6 are expressed in terms of indexed values and show a general pattern of strong co-movement with some asymmetries in timing and, in the case of the jewellery-gold price relationship, a difference in trend growth rates. The 12-month seasonal difference plots also shown in Figure 6 show a very tight tracking between local and world prices, with a correlation of 0.49 for jewellery/gold and 0.77 for fuel/oil.

For the metals commodities (shown in Figure 7) we have 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. We show some formal evidence on this 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 local scrap and international metal prices.[25]

Given this background of strong local and world price correlations, we can now turn to the statistical relationship between crime and prices for our commodity-related goods. Figure 8 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.

[25] 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.

Statistical estimates 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 0.56 in column (1) but also that (as the above charts show) there are differential trends in crime and prices that render this insignificant if a trend is included (in column (5)). However, the reduced form crime and price regressions (in columns (2) and (3) without a trend and in columns (6) and (7) with a trend) turn out to be strong. They show a significant and positive connection between crime and world prices and between UK prices and world prices. The latter first stage regression has high F-statistics. Thus the IV estimates in the trend free and trend included estimates uncover a strong and significant jewellery-crime price elasticity that exceeds unity (in column (4) of 1.25 and in column (8) of 1.48).

We also find significant crime-price elasticities for fuel as the regression estimates reported in Panel B of Table 6 show. 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 first-stage F statistics are very significant. The IV estimates turn out to be a little lower than the OLS estimates, and are between 0.63 and 0.66, thus showing there to be a sizable fuel crime-price elasticity.

We conduct a similar analysis for metal commodities with the plots of crime against the associated change in scrap metal price shown in Figure 9. For all metals and for copper, the price and crime series track each other well, with some jumps in places, and are highly correlated. 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 goods studied in the consumer goods panel. Consistent with the rapid and high level of price transmission evident in the Figure 7 plots, 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.[26] 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. We therefore see this as 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.

One concern could be that the metal elasticities that we estimate 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-

[26] We have also estimated crime-price elasticities for lead and aluminium crimes. For lead (for example, as in the case of "lifted from the roof of a Holy Named church"), we had to confine ourselves to the looking at data only for the second half of our 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, we uncovered similarly high magnitude IV elasticities 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. We report the full estimates in the Appendix in Table A2 with associated plots comparable to Figures 7 and 9 in Figures A2 and A3.

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, we estimate that 45-60 percent of metal crimes are infrastructure-related in our sample[27] with the remainder comprised of commercial businesses, where reporting rates are typically high.[28]

However, as a robustness check against the ‘gold rush’ effects we conducted an exercise 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. We begin by running 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. We then iteratively extend the sample one month at a time, incorporating observations before 2008 until we reach the T = 120 (seasonally differenced) full sample by going back as far as January 2003. This allows us to see the influence on the crime-price elasticity of incorporating the potential ‘gold rush’

[27] 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.

[28] 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.

observations between 2005 and 2007. The coefficient and confidence interval plots shown in Figure 10 do not reveal any explosive sensitivity to the inclusion of each sub-period – in all cases we see 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.[29]

In summary, in both cases (all metals and copper) we do not detect evidence that suggests the estimates are affected by either explosive 'gold rush' effects biasing the elasticities upwards or strong adaptation effects as potential victims change their behaviour. Note also here 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.

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 economic incentives. In particular, evidence of price responsiveness sheds light on one route whereby the returns to crime emphasised in the standard Becker/Ehrlich model may work. If the value of loot changes, because it becomes more or less attractive to potential criminals as its price changes, then it alters the relative return to crime available for stealing different goods.

[29] The recursive elasticities in Figure 10 are from estimates using the IV metal crime / scrap price specification from column (8) of Table 7.

Thus, crime may rise if prices rise (and vice versa). Also, the mix of crimes done by criminals may then be shaped by price variations. If this mix changes through time then it is also possible that crime trends may be affected by price changes. For example, witness the very significant upsurge in metal crimes that we have shown occurred at the same time as the price of metals were exogenously driven up by world markets.

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 considered in these discussions.

Whether there is a contribution of changing prices to crime trends is interesting if (as we find) there is evidence of a positive crime-price elasticity. This could mean that part of any crime drop could be explained by a falling real value of goods that were traditionally stolen by criminals. Furthermore, since the structure of consumer prices is highly correlated across countries, prices are a plausible 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 global crime trends.

We have constructed an empirical counterfactual exercise to look at this in a very simple way. Over our period of study, total crime falls by 3.5 percent per year between 2002 and 2012 (see Figure 2 and Table 5 above). Since our empirical analysis detects evidence of a significant crime-price elasticity, we can undertake a counterfactual exercise to ask what the crime fall would have been had the relative structure of prices stayed the same in real terms. We do this in practice in a simple, mechanical manner by considering price growth for the goods in our consumer panel as compared to overall price growth.

The average price of the stolen items in our 44-goods panel rose by 1.4 percent per year on average between 2002 and 2012. The overall CPI rose by 2.9 percent per year over the same time period, so that in real terms the value of the goods stolen by criminals had been falling (by 1.5 percent a year). 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 our elasticity of 0.35 predicts a 0.53 percent a year fall in crime, or 15 percent of the overall crime drop.

If instead of comparing to prices of all goods, we benchmark the 1.4 percent a year average price rise to the 2.7 percent a year growth in average wages in London (the legal alternative) between 2002 and 2012, we come up with a prediction of 13 percent of the overall crime drop.[30] Benchmarking to growth in the London 10th percentile weekly wage - since one might think the 10th percentile weekly wage is a more appropriate comparison for individuals on the margins of crime - predicts a slightly bigger 0.81 percent a year fall, or 23 percent of the overall crime drop.[31]

In terms of magnitudes we view this as a sizable contribution given that crime is shaped by a whole range of factors, of which the changing value of loot is one. In this context of multiple factors shaping crime trends see, for example, Levitt's (2004) account of ten possible factors that could account for the US crime fall, of which he argues four matter and six do not. Interestingly, changing prices, or the changing value of stolen goods more generally, not being one of the ten

[30] Average weekly wages in London rose from £550 in 2002 to £697 in 2012 (based on Annual Survey of Hours and Earnings data).

[31] The bigger contribution is because the 10th percentile actually rose by a little more than average (probably because the minimum wage kept its value better than the average in the downturn and Great Recession period) going from £124 a week in 2002 to £169 in 2012, or up by 3.6 percent a year.

candidate explanations remains an understudied, if not an entirely missing, feature of research on the crime drop.

The estimated contribution to falling crime could form a lower bound for two reasons, crime specialization and revenues from crime. First, crime specialization due to adjustment costs might not allow criminals to adapt to changing prices and switch easily from DVD burglars to mobile phone pickpockets, as construction workers cannot simply shift to nurses, even if market opportunities are better for the latter in both cases. Though some goods have become more attractive, we might still observe some criminals specialising on the less attractive ones, due to their product-specific crime skills. Second, if potential criminals do substitute into more lucrative alternatives as relative prices change, then they may do less crime as the returns rise (in parallel discussion to the labour supply literature, crime participation would be lower if the income effect dominates). This means that the well-documented drop in crime refers to the quantity and not the total revenue (quantity X prices) from crime, which might relate more to the societal costs associated with crime, as prices are missing from most of the existing studies.

So far we have considered the magnitudes of crime responses on average. For some goods, however, the observed price falls have been very sizable. The example we highlighted at the start of the paper was the very rapidly falling real price of audio-visual goods. Between 2002 and 2012 their nominal price fell by a huge 9 percent per year on average, as compared to the average price rise of 1.4 per year in the consumer goods panel, and the overall CPI rising by an average 2.9 percent per year. Asking whether the real price fall (of 11.9 = 9.0 + 2.9 percent a year) for this particular group contributed to falling crime produces a more definitive answer – conducting the counterfactual exercise for audio-visual goods reveals that 38 percent of the crime drop of 8 percent a year is attributable to lower prices.[32]

Finally, consider the case of metals, where we saw the rapid price increases and the very sharp upsurge in metal crime and where we estimated a strong sensitivity of crime to price changes. Price growth for all metals was an annual 12 percent (see Table 5), or 9.1 percent above CPI inflation. Multiplied by the estimated IV elasticity of 1.49 this predicts a metal crime increase of 13.5 percent a year, and so accounts for all of the actual rise of 11.1 percent a year. For copper, a real price increase of 12.4 percent a year combined with the estimated elasticity of 1.81 predicts a 22.4 percent a year increase, or 76 percent of the 29.3 percent a year increase in copper crimes.

8. Conclusions

In this paper, we study how changes in the prices of goods that criminals may steal affect criminal behaviour. We consider this to offer a direct test of whether shifts in economic incentives, working through movements in returns to crime driven by price changes, impact on crime. We estimate 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.

We obtain price elasticities for two sets of goods, the former a consumer panel of 44 stolen goods categories that we match to price data over time, the latter for metal and commodity related goods where we have scrap metal prices and can consider prices 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 a just over a third. We view this as a lower bound, for a number

[32] This comes from multiplying the 11.9 percent real price drop by the good-specific elasticity of 0.248, which predicts a crime fall of 3.0 percent a year (or 38 percent of the total crime fall of 8 percent a year).

of reasons we discuss in the main body of the paper. But even at this level as the average price increase for these goods has not risen by as much as overall price inflation, thus showing a real fall, we find that this explains around 20 percent of the aggregate fall in burglaries, thefts and robberies seen in our data. The 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 have been rising as their prices have been rising by much more than price inflation, we show there to be sizable crime-price elasticities, for metals in excess of unity, and that rising world commodity prices over the time period we study played a big role in the rise of these crimes.

Therefore to conclude, we find that crime is responsive to goods price changes. The evidence of price responsiveness implied by the significant crime-price elasticities we uncover is very much in line with the way in which changing returns to crime in the standard Becker/Ehrlich model are formulated as a driver of crime. More generally, we view our findings as offering strong evidence that changing economic incentives matter for criminality from a different perspective than that offered in the economics and criminology literatures to date.

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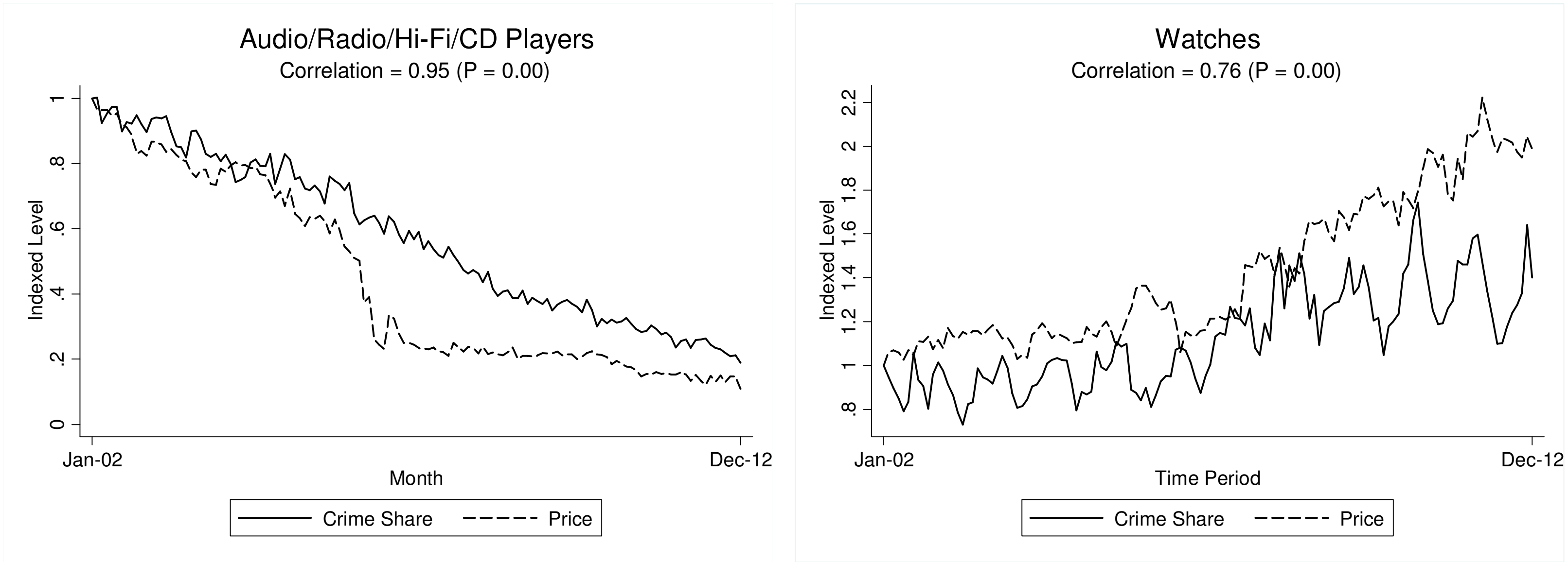
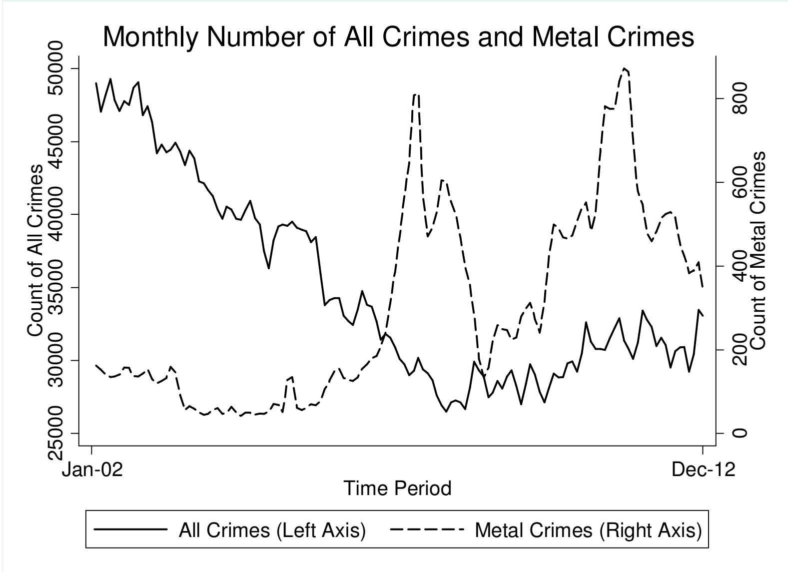
Figure 1: Examples of Changes in Crime Shares and Prices

(a) (b)



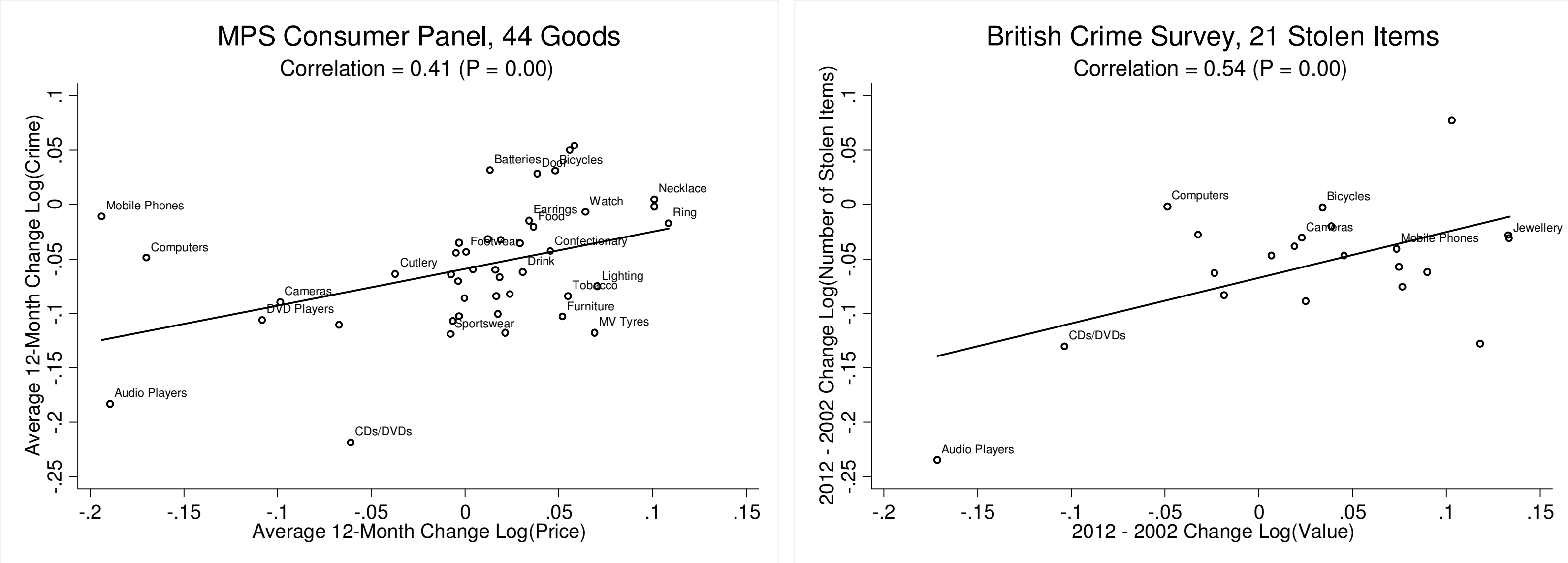
Notes: Indexed change in the share of total items stolen by these two types of goods on a monthly basis from January 2002 to December 2012. The initial crime share for audio players in January 2002 is 0.19 while for watches it is 0.05 (where the shares add up to 1.00 across the 44 categories in our 44 consumer goods product panel).

Figure 2: 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.

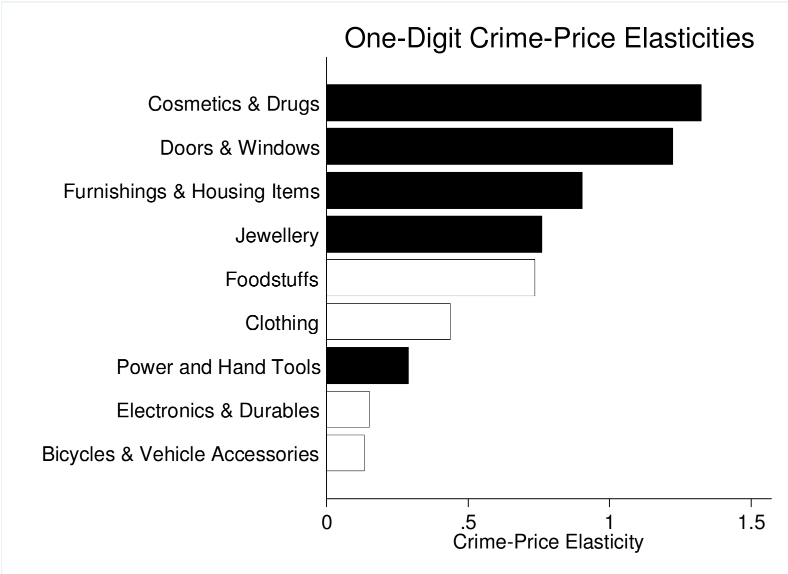
Figure 3: Average 12-Month Changes in Log(Crime) and Log(Prices) For Matched MPS Panel - Changes in Log(Crime) and Log(Value) For British Crime Survey, 2002-2012



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.

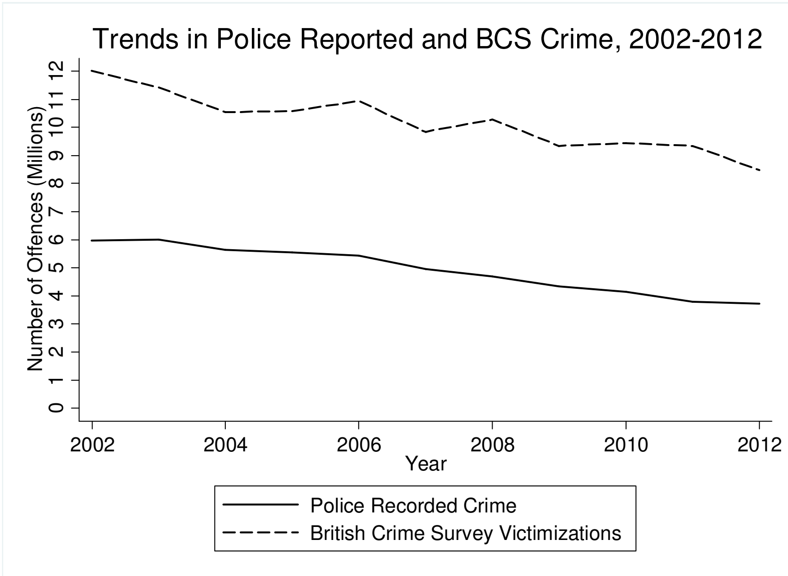
Notes: Change in log(number of stolen items) and log(value) for the 21 consistently reported item groups available across the two BCS cross-sections for 2002-2012. Some labels (mostly on relatively small crime categories) have been omitted for space reasons.

Figure 4: One-Digit Product Group Elasticities – Matched MPS Panel, 2002-2012



Notes: Price elasticities calculated for one-digit product group goods categories (see Appendix Table A1 for more detail on product group classifications). Calculated for the one-digit group from a full seasonally adjusted, within-groups specification with month-year time effects (i.e. comparable to column (3) of Table 2). Black bars indicate statistical significance at the 5 percent level or better. Robust standard errors used for inference.

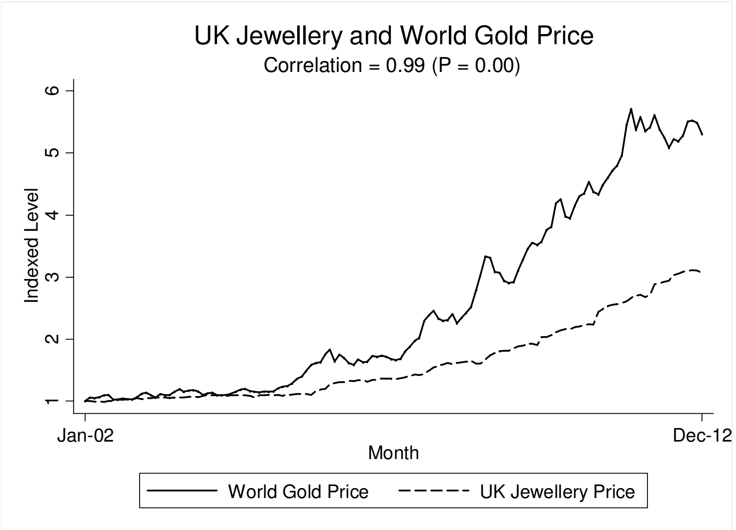
Figure 5: Police Recorded Crime and British Crime Survey Victimizations, 2002-2012



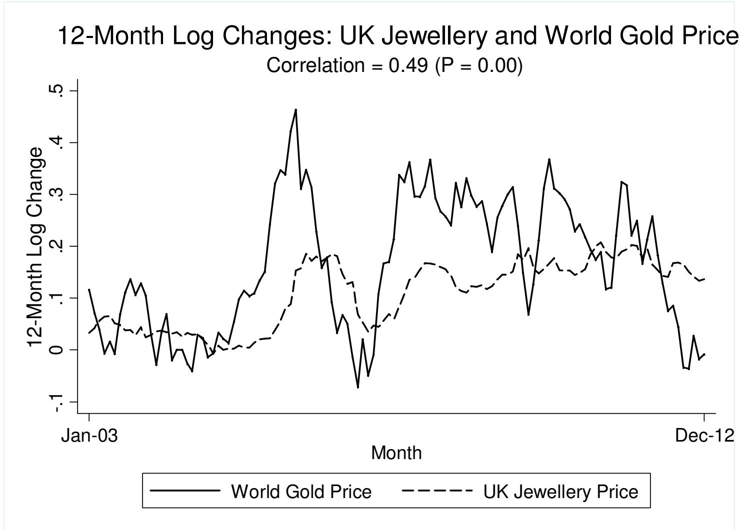
Notes: The number of criminal incidents reported to the police (solid line) compared to survey-based victim-reports from the British Crime Survey (dashed line).

Figure 6: UK and World Prices for Jewellery (Gold) and Fuel (Oil), 2002-2012

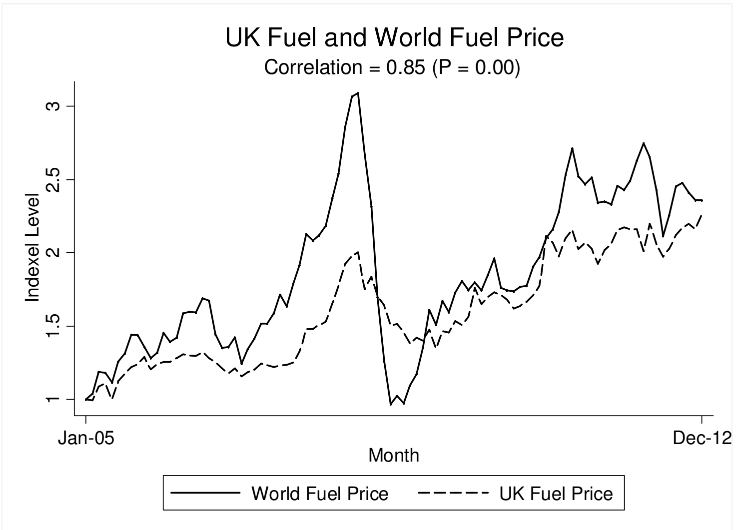
(a)



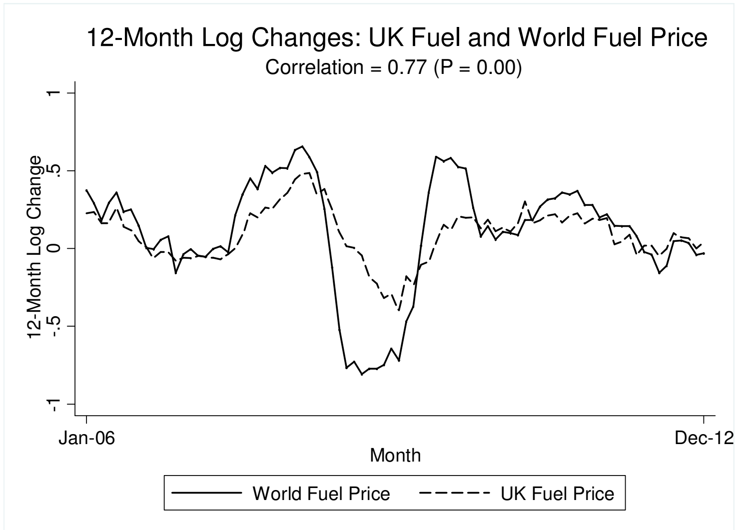
(b)



(c)

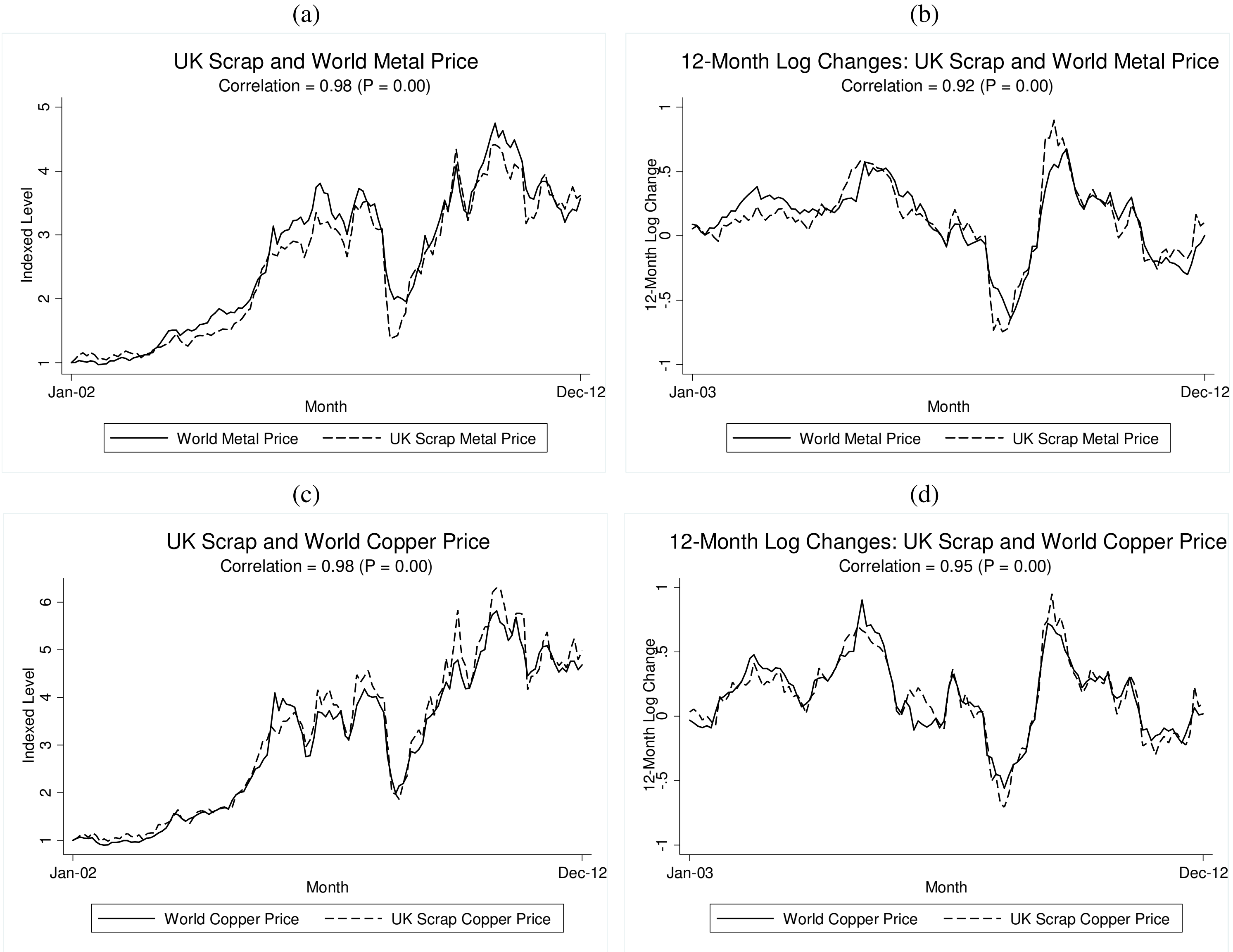


(d)



Notes: The left figures show indexed levels (January 2002 = 1 for (a), January 2005 = 1 for (b)). The right figures show analogous 12-month differenced plots.

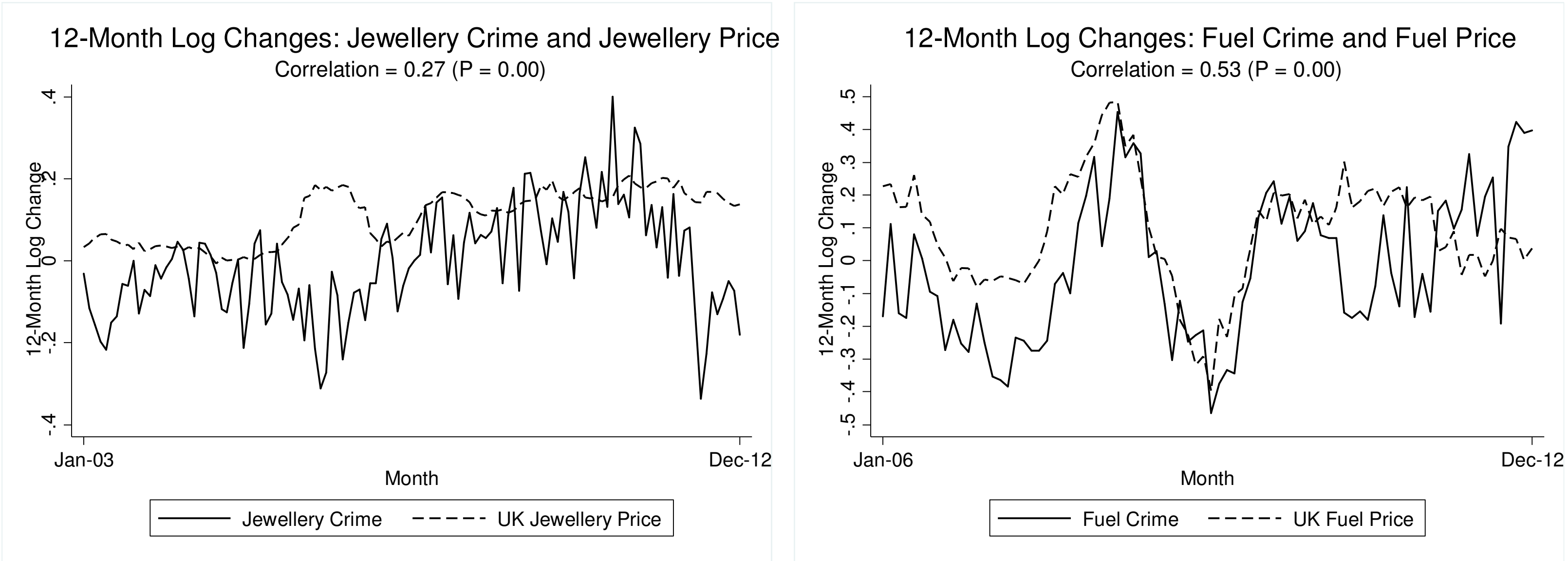
Figure 7: UK Scrap Metal Prices and World Metal Prices



Notes: The left figures show indexed levels (January 2002 = 1). The right figures show analogous 12-month differenced plots. The UK price is the scrap metal price reported by industry trade media outlet letsrecycle.com. World prices come from Index Mundi.

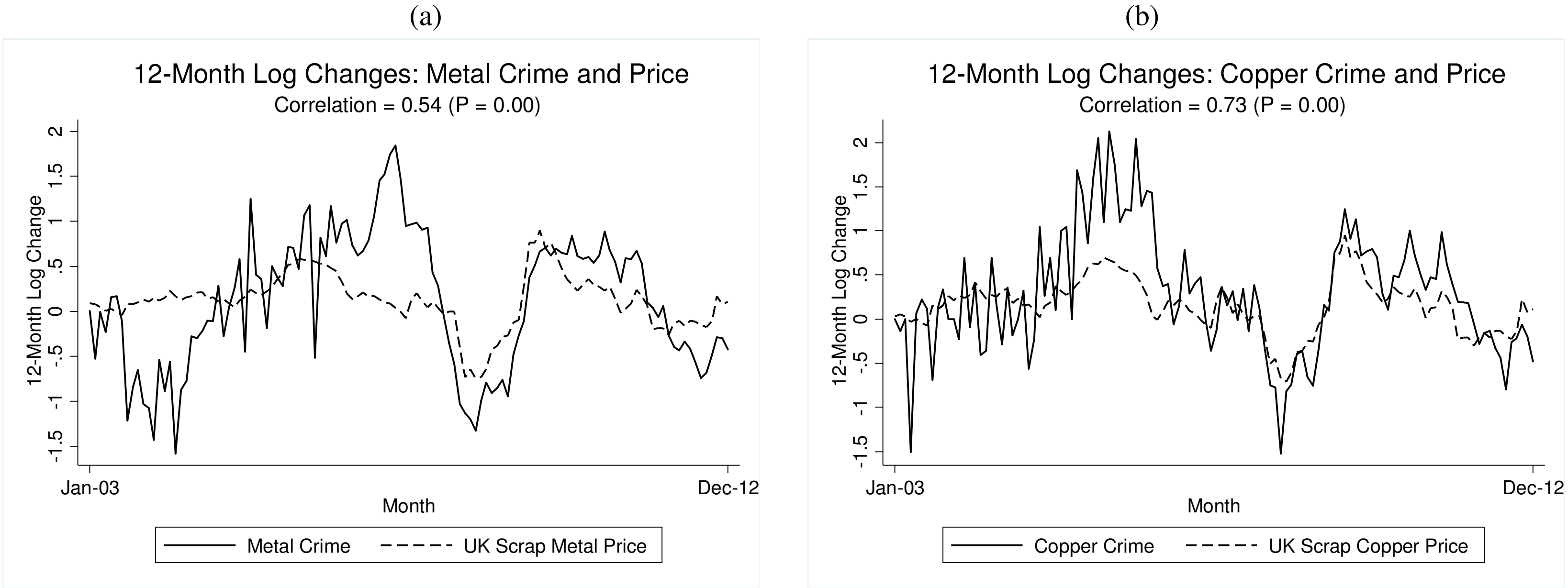
Figure 8: 12-Month Changes in Log(Crime) and Log(Prices), Jewellery and Fuel, 2002-2012

(a) (b)



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

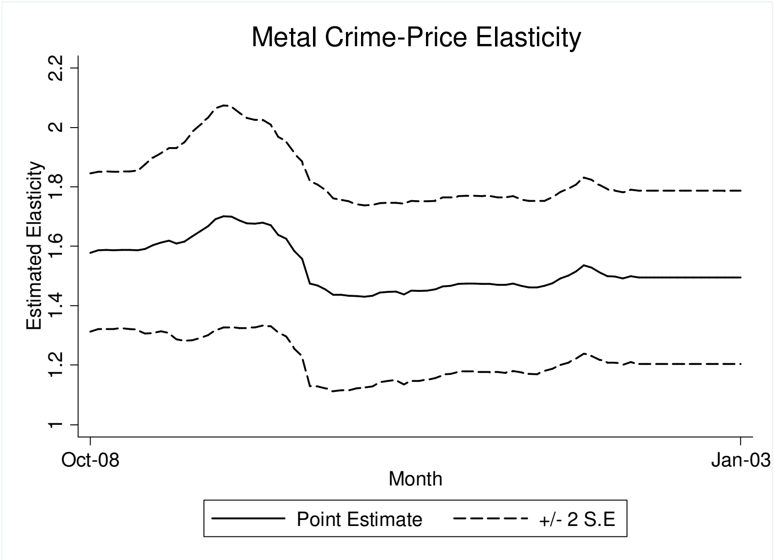
Figure 9: 12-Month Changes in Log(Metal Crime) and Log(Scrap Metal Prices), 2002-2012



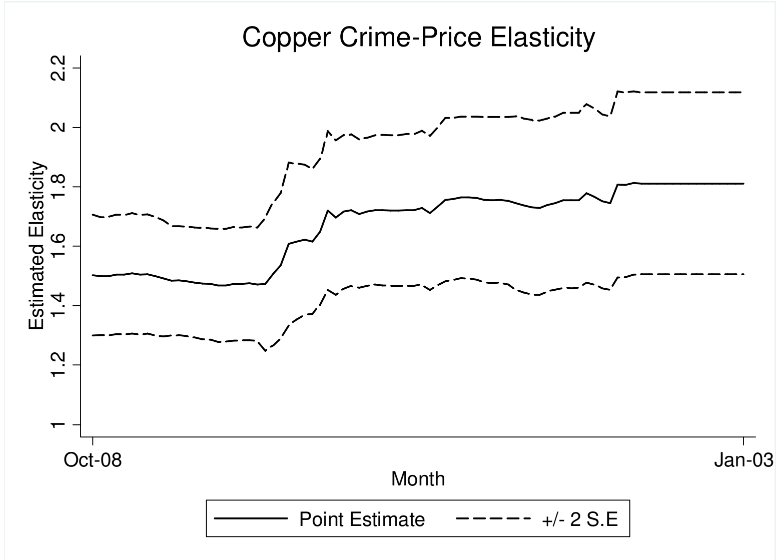
Notes: 12-month changes in Log(Crime) and Log(Scrap Metal Price) for all metals and copper.

Figure 10: 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	1.9	5.1
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	-2.9	0.6
EB	TV/Video/DVD/Projectors	-1.9	2.3
SB	Optical Equipment	-1.0	1.8
TB	Hand Tool – Mechanical	-0.8	1.0
AA	Ladieswear	-0.6	2.6
GD	Drink – Alcoholic	-0.6	2.2
DA	Cosmetics / Drugs	-0.6	3.3
AB	Menswear	-0.5	3.3
AD	Toiletries	-0.5	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)	0.348	0.348	0.346	0.413	0.254	0.106
	(0.130)	(0.132)	(0.138)	(0.155)	(0.123)	(0.047)
Lagged Dependent Variable						0.692
						(0.061)
Long-Run Elasticity						0.342
						(0.140)
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)	0.346	0.193	0.165	0.164
	(0.138)	(0.138)	(0.086)	(0.085)
$\text{Log(Price)}_{(t-1)}$		0.156	0.087	0.085
		(0.101)	(0.077)	(0.078)
$\text{Log(Price)}_{(t-2)}$			0.099	0.091
			(0.080)	(0.045)
$\text{Log(Price)}_{(t-3)}$				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	0.018	0.421	0.518
	(0.026)	(0.023)	(0.216)	(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 good enough 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. and the products with matched crime and price data. 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)	-3.5	1.4	-
Jewellery	-0.5	10.8	16.3
Fuel	21.8	10.0	14.3
B. Metal Crimes			
All Metals	11.1	12.0	12.6
Copper	29.3	15.3	15.7

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 world price attached to jewellery is the gold price and the world price attached to fuel is the oil price. The top row reports the numbers for the 44-category consumer goods panel for purposes of comparison.

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)	0.563			1.248	-0.205			1.479
	(0.168)			(0.395)	(0.314)			(0.898)
Δ_{12}Log(World Price)		0.304	0.244			0.191	0.129	
		(0.089)	(0.037)			(0.104)	(0.026)	
F-Statistic			43.90				24.39	
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			0.626	0.708			0.657
	(0.096)			(0.110)	(0.098)			(0.106)
Δ_{12}Log(World Price)		0.229	0.365			0.240	0.366	
		(0.050)	(0.046)			(0.052)	(0.046)	
F-Statistic			63.77				62.20	
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. Robust 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			1.320	1.427			1.493
	(0.114)			(0.143)	(0.133)			(0.143)
Δ_{12}Log(World Price)		1.333	1.010			1.587	1.063	
		(0.151)	(0.050)			(0.148)	(0.051)	
F-Statistic			412.85				422.13	
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			1.756	1.700			1.812
	(0.128)			(0.146)	(0.136)			(0.154)
Δ_{12}Log(World Price)		1.752	0.997			1.811	0.999	
		(0.134)	(0.040)			(0.136)	(0.042)	
F-Statistic			636.99				578.61	
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. Robust standard errors in parentheses.

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

(1) One Digit Code	(2) Description	(3) Number of Two Digit Products	(4) Share of Total Crime (Full Period)	(5) Share of Total Crime (2002)	(6) Share of Total Crime (2012)	(7) Share Matched (Within One Digit)
A	Clothing	10	0.036	0.040	0.034	0.877
B	Publications	4	0.003	0.004	0.002	0.802
C	Currency and Official Documents	13	0.261	0.288	0.210	na
D	Cosmetics and Drugs	4	0.017	0.172	0.015	0.972
E	Electronic and Electrical	21	0.194	0.191	0.232	0.804
F	Weapons	5	0.001	0.001	0.000	na
G	Food and Drink (inc Alcohol)	7	0.024	0.024	0.026	0.862
H	Furnishing & Household Accessories	22	0.018	0.026	0.012	0.665
J	Jewellery	10	0.060	0.055	0.083	0.887
K	Personal Bags and Cases	8	0.101	0.107	0.086	na
L	Leisure Equipment / Vehicle Accessories	19	0.056	0.038	0.072	0.505
M	Metal Commodities	7	0.003	0.001	0.006	1.000
N	Personal and Vehicle Documents	12	0.091	0.089	0.080	na
P	Office and Art Materials	8	0.004	0.005	0.003	na
R	Building Materials	16	0.002	0.001	0.002	0.525
S	Photographic and Scientific Equipment	5	0.030	0.029	0.024	0.309
T	Building Tools	10	0.030	0.037	0.036	0.816
V	Pets and Animals	7	0.000	0.000	0.000	na
W	Public Property, Fuel and Miscellaneous	15	0.071	0.050	0.078	0.148
	Overall Statistics					
	(1) Share Matched (balanced panel)		0.368			
	(2) Share Non-Matched (unbalanced)		0.108			
	(3) Share Rare / Unusual		0.033			
	(4) Share Non-Market		0.492			

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 we use 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 across both the Consumer Goods and Commodities panels; (2) Share Non-Matched (unbalanced), the share of goods with incomplete data on either crime or prices; (3) Share Rare / Unusual, goods such as animals, objects of art and weapons that cannot be feasibly matched to a price series, and (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. 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	Ladieswear	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 how we have matched the 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 our 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)	0.507 (0.028)	-0.104 (0.147)	0.321 (0.046)	0.129 (0.101)	0.878 (0.040)	1.122 (0.204)	0.966 (0.037)	0.887 (0.120)
Log (World Prices)$_{(t-1)}$		0.633 (0.145)		0.207 (0.087)		-0.253 (0.192)		0.082 (0.113)
Number of Observations	131	131	96	96	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.

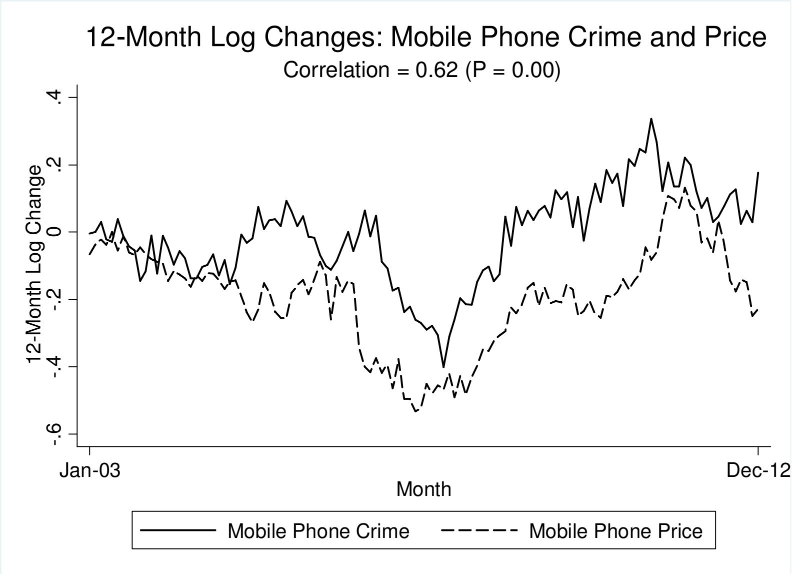
Table A4: Metal Crime-Price Elasticities, Lead and Aluminium, 2002-2012

	(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)	1.884			2.170
	(0.233)			(0.233)
Δ_{12}Log(World Price)		2.274	1.048	
		(0.203)	(0.061)	
F-Statistic			292.06	
Time Trend	Yes	Yes	Yes	Yes
Number of Observations	66	66	66	66
B. Aluminium				
Δ_{12}Log(Scrap Price)	1.526			1.606
	(0.218)			(0.256)
Δ_{12}Log(World Price)		1.990	1.239	
		(0.337)	(0.080)	
F-Statistic			239.78	
Time Trend	Yes	Yes	Yes	Yes
Number of Observations	120	120	120	120

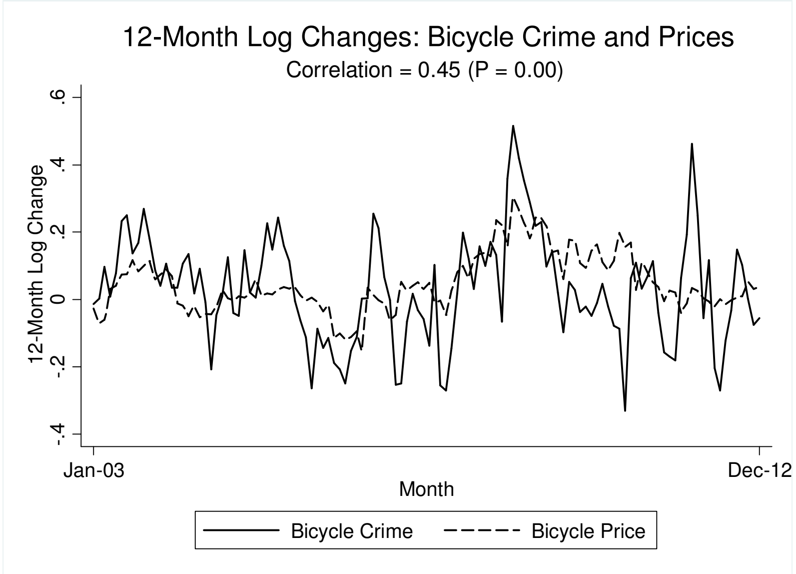
Notes: OLS and instrumental variable (IV) estimates of the models relating 12-month changes in lead and aluminium crimes to 12-month changes in scrap metal prices for each, where the corresponding world metal commodity price is used as the instrument. All models include a time trend and are therefore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

Figure A1: 12-Month Changes in Log(Crime) and Log(Prices), Mobile Phones and Bicycles, 2002-2012

(a)

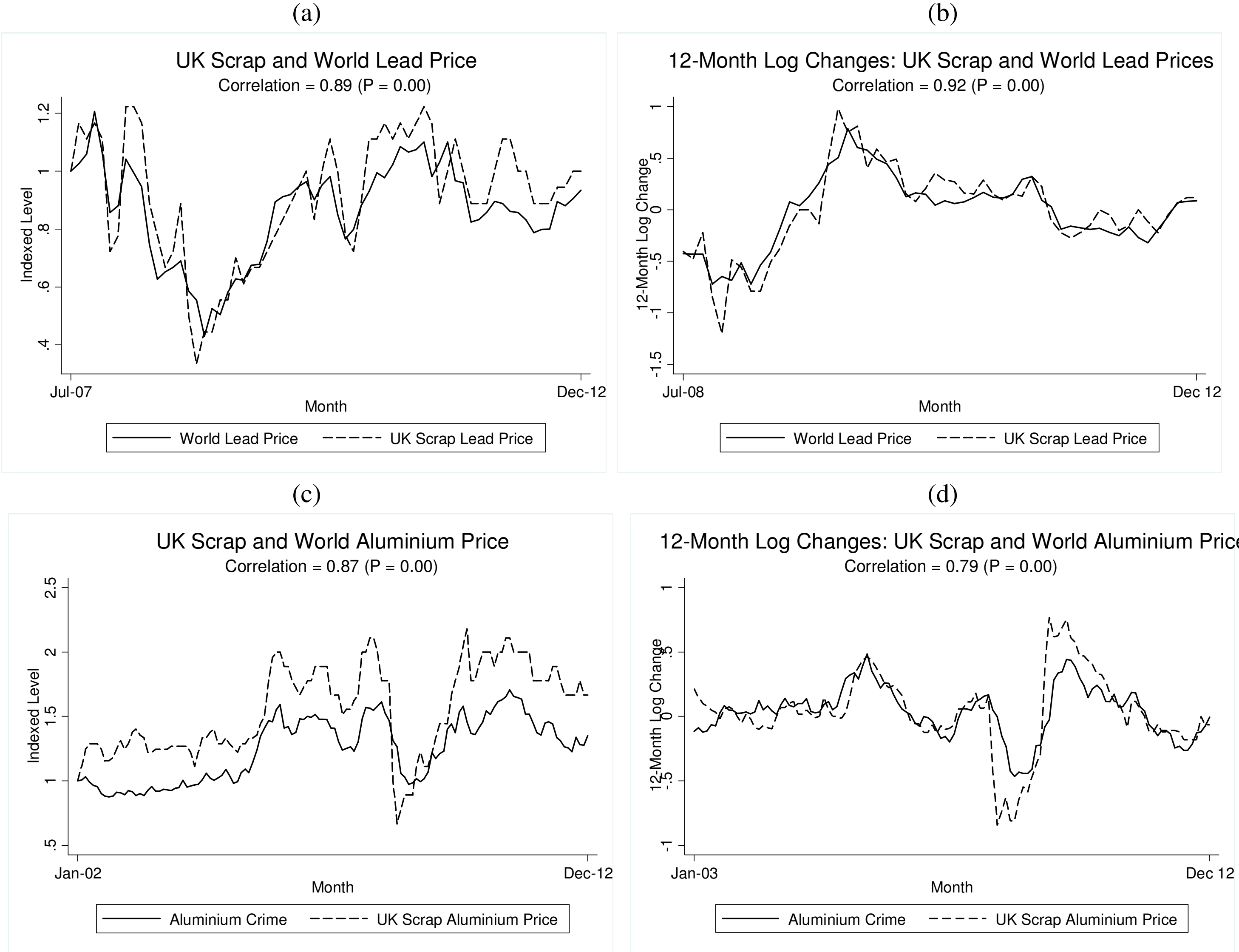


(b)



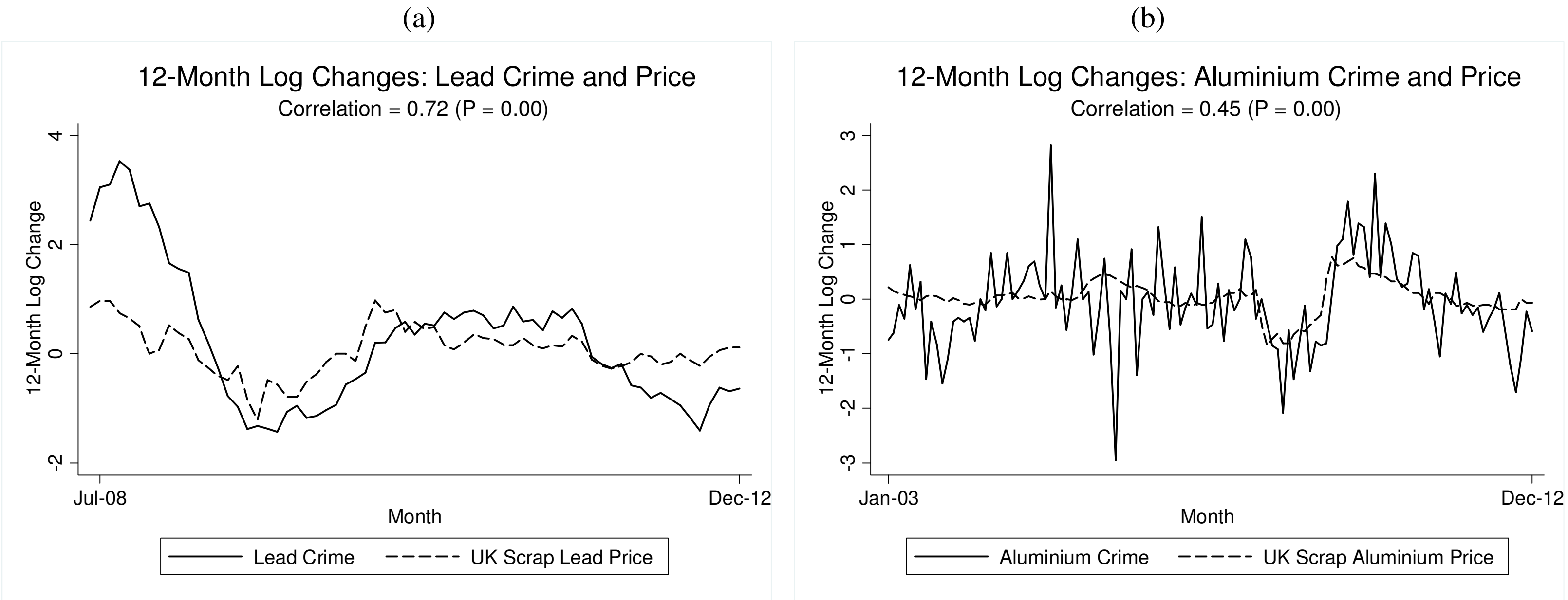
Notes: 12-month changes in Log(Crime) and Log(Price) for mobile phones and bicycles.

Figure A2: UK Lead and Aluminium and World Lead and Aluminium Prices



Notes: The left figures show indexed levels (July 2007= 1 for (a), January 2002 for (b)). The right figures show analogous 12-month differenced plots. The UK price is the scrap metal price reported by industry trade media outlet letsrecycle.com. World prices come from Index Mundi.

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.