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ORIGINAL PAPER

Criminals and the Price System: Evidence from Czech Metal Thieves

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Abstract
Objectives This paper tests the economic theory of criminal behavior. Specifically, it looks at "the carrot" side of the theory, studying how thieves react to changes in monetary gains from crime.
Methods Using a unique crime-level dataset on metal theft in the Czech Republic, we study thieves' behavior in a simple regression framework. We argue that variation in metal prices represents a quasi-experimental variation in gains from crime. It is because (1) people steal copper and other nonferrous metals only to sell them to scrapyard and (2) prices at scrapyards are set by the world market. This facilitates causal interpretation of our regression estimates.
Results We find that a 1% increase (decrease) in the re-sale price causes metal thefts to increase (decrease) by 1–1.5%. We show that the relationship between prices and thefts is very robust. Moreover, we find that thieves' responses to price shocks are rapid and consistent.
Conclusion Our results are in line with the economic model of crime, wherein criminal behavior is modeled as a rational agent's decision driven by the costs and benefits of undertaking criminal activities. Our estimates are also consistent with recent results from the United Kingdom, suggesting these patterns are more general.

Keywords Economics of crime · Rational choice · Gains from crime · Criminal opportunities · Metal theft

Josef Montag: The data and code producing results reported in this paper are available at http://sites.google.com/site/josefmontag or upon request.

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Introduction

Does opportunity make a thief? This paper exploits a quasi-natural experiment in the value of stolen goods in order to test predictions based on the economic theory of crime (Becker 1968; Ehrlich 1973; Posner 1985). This theory views a criminal act as a rational decision: a crime is attempted whenever the expected benefits exceed the costs. The model's main, and most often studied, prediction is that a change in punishment or the probability of apprehension should, if everything else remains the same, result in a change in criminal activity. This is because the cost-benefit ratio reverses for the crimes at the margin. For an overview article see Ehrlich (1996). The origins of the approach can, however, be traced back to Beccaria (1764) and Bentham (1823, 1830).

In economics, the rational model of criminal behavior is generally accepted as the baseline framework for thinking about and analyzing illegal activity. In contrast, its reception in criminology has been less enthusiastic (Matsueda 2013). Loughran et al. (2016) argue that a possible reason for this divide is rather narrow understanding of the economic theory of crime as a theory of "the stick", that is punishment, enforcement, and deterrence. This view may be reinforced by the fact that applied research on the rational choice theory of crime has, indeed, been mostly focused on studying the effects of enforcement and sanctions on deterrence (Matsueda 2013; Piliavin et al. 1986).

The situational crime prevention literature appears to be a significant exception from this pattern. Rational choice is an important element of this school of thought that is more oriented at practical aspects of crime control (Clarke and Cornish 1985; Clarke 2012; Cornish and Clarke 2013; Felson and Clarke 1998). The focus of this literature is on offenders' decision making and the role of criminal opportunities as the fundamental cause of crime. This line of research resulted in a range of policy tools that aim reduce crime through reduction of criminal opportunities (see Clarke 1997).

Ultimately, the question whether a theory is useful, or not, is an empirical one. In this, paper we complement the existing empirical research by testing "the carrot" side of the economic model of crime: we look at how criminals respond to changes in the benefits of a criminal activity. We believe that our work should be informative for criminologists as well as economists as it tests aspects of the theory that have received limited attention so far. This way, the paper extends the range of empirical tests of the rational choice theory of criminal behavior and informs both fields about the usefulness of this framework.

In the deterrence-oriented research, testing the economic model has proved notoriously difficult due to the lack of experimental variation in punishment severity or enforcement intensity (for an overview see Bottoms and von Hirsch 2010). The problem is that changes in policy are likely to reflect changes in criminal activity. Indeed, Tsebelis (1989) model, which treats enforcement as fully endogenous, predicts no equilibrium relationship between the severity of punishment and crime rates—this is because any improvement in the latter results in relaxed enforcement and a subsequent rebound of criminal activity. This may seem to be an extreme prediction. Consider, however, that Montag (2014) investigated the effects of a substantial increase in sanctions for traffic law offenses in the Czech Republic, and found that the immediate effect of such a change was a one third decline in road-traffic-accident-related fatalities. However, a quick rebound followed within the ensuing months and there was no identifiable effect beyond one year after the reform. At the same time, traffic police enforcement activity (though not manpower) declined.

Finding an exogenous source of variation in determinants of the value of criminal activity is thus crucial for empirical research into criminal behavior. To overcome the simultaneity problem, Levitt (1997, 2002) uses political cycles and firefighters, respectively, as instruments for police enforcement. Di Tella and Schargrodsky (2004) exploit sudden changes in the geographic allocation of the police force following a terrorist attack in Buenos Aires. In a similar vein, Klick and Tabarrok (2005) use shocks to police presence in Washington, D.C. following changes in the terror alert levels. All four papers find that increases in police enforcement deter crime.

In this paper, we test the economic theory of crime using exogenous variation in the monetary gains from crime that accrue to the thieves. Earlier literature testing the relationship between gains from crime and criminal behavior was plagued by the difficulty of accurately measuring gains from crime and yielded contradictory results (Chisholm and Choe 2005). In this paper we make use of a clear-cut measure of gains from crime—the market value of the stolen goods. This approach also has the distinct advantage that it directly tests the economic nature of decisions about criminal activity, since changes in the cost-benefit structure of criminal opportunities induced by shocks in the market value of stolen goods are purely monetary in nature. This way, we complement the existing body of literature on deterrence as well as the general literature investigating the effects of economic shocks on crime (Aaltonen et al. 2013; Cook and Zarkin 1985; Cook 2010; Lin 2008), the criminological literature testing the rational choice theory of crime (Loughran et al. 2016; Matsueda et al. 2006; Piliavin et al. 1986), and finally we add to the recent studies on the price-theft hypothesis (Draca et al. 2015; Sidebottom et al. 2014, 2011). This paper may also complement the situational crime prevention research cited above, providing new insights on how opportunities matter for crime.

Specifically, we examine how metal thieves in the Czech Republic respond to changes in the prices of nonferrous metals. After all, the metal is of no value to the thieves, except in as far as it can be sold to a scrapyard. Thus the benefits from a metal theft depend directly on the price of the given metal. At the same time, nonferrous metals are commodities and their prices are determined on the world market, with the majority (more than 75%) of transactions concentrated at the London Metal Exchange (LME).[1] We show that this price information is then directly transferred to scrap markets.[2] We argue, together with Draca et al. (2015) and Sidebottom et al. (2014), that this setup represents a quasi-natural experiment, enabling us to test the causal links postulated by the economic model of criminal behavior and study the properties of the "supply of offenses" (Becker 1968) with respect to gains from crime.[3]

The raw relationship between thefts and prices in our data is shown in Fig. 1, which plots levels and first differences of normalized and deseasoned quarterly series of copper prices at the LME and metal thefts in the Czech Republic. When interpreting the figure, the reader might also consider that the observed increase in metal thefts, including the large downward swing around 2009, took place against general and steady decline in property

[1] See "A Guide to the LME," London Metal Exchange, PDF file, 2014, at http://www.lme.com/~/media/Files/Brochures/A Guide to the LME, last accessed on June 28, 2016. See also Watkins and McAleer (2004).

[2] See also Aruga and Managi (2011), Draca et al. (2015), and Labys et al. (1971).

[3] For more extensive and insightful discussion of the price-theft hypothesis in the realm of non-ferrous metal markets see also Sidebottom et al. (2011).

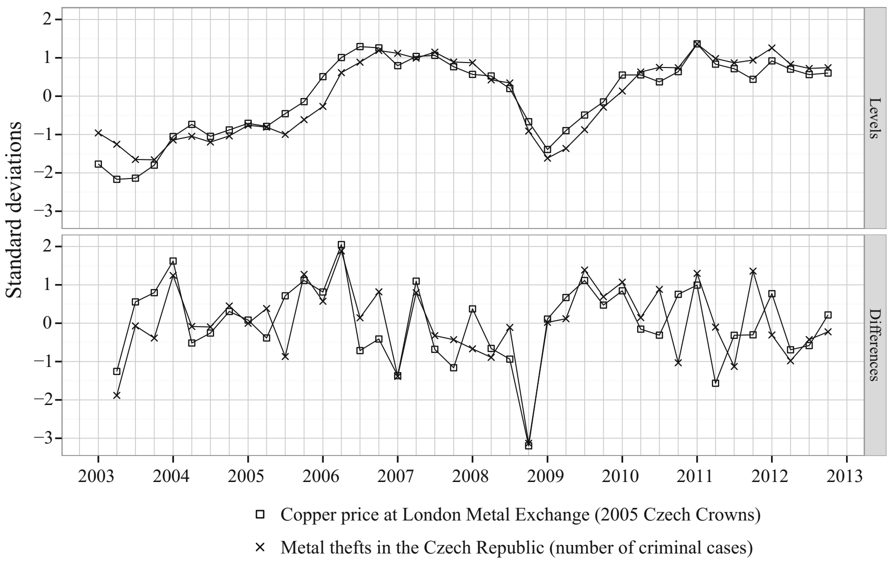


Fig. 1 Copper prices and the number of criminal cases involving nonferrous metals reported to the Czech Police (z-scores of quarterly averages, thefts are lagged by one month). Data are deseasoned, mean centered, and divided by respective standard deviations

crime over the same time period: between 2003 and 2012, the number of property crimes declined by 24.5% and the total damage declined by 46.8% (see Fig. 5 in the Appendix).[4]

Interestingly, the relationship between thefts and the market value of stolen goods has received rather limited research attention. Sidebottom et al. (2011, 2014) have recently studied the relationship between copper prices and the number of police recorded copper cable thefts from the British railway network and found that a 1% change in copper price leads to an increase in thefts by about 3 and 1%, respectively. Most recently, Draca et al. (2015) investigated the relationship between prices and thefts in a panel of different types of stolen property using London Metropolitan Police data. They too found a systematically positive relationship between prices and thefts. For the United States, Posick et al. (2012) found a positive a correlation between metal prices and the number of thefts of metal from commercial and residential dwellings in Rochester, NY.

This paper complements and extends these recent studies. It differs in three main respects: (1) We possess a very detailed crime-level dataset of all nonferrous metal-related thefts that occurred in the Czech Republic during the ten-year period from 2003 until 2012. (2) We offer a more involved analytical approach. Economic theory predicts an equilibrium relationship exists between gains from crime and criminal activity, or the supply of offenses. That relationship also requires the existence of a short-term equilibriating mechanism that corrects deviations from the equilibrium. In econometric terms, the analysis needs to proceed in the co-integration framework (Engle and Granger 1987; Murray 1994). This allows us to directly test the existence of this long-term relationship and study its properties, including the mechanics of short-term adjustments. (3) Last but not least, our detailed data enable us to perform extensive sensitivity analyses and a

[4] This development is consistent with general decline in property crime in Western Europe (Aebi and Linde 2010, 2012; Tonry 2014).

number of robustness checks in order to address sample selection concerns and alternative explanations of our findings.

Understanding the behavioral background behind metal thefts is also important because this criminal activity represents a serious economic and security issue. Although many metal thefts may result in little or no damage, others are highly damaging. The inflation-adjusted average value of stolen material per theft in our data in 2015 prices is 35,500 CZK ($1,450) and the average damage is about 41,200 CZK ($1,700), more than double the average monthly net wage in the Czech Republic in 2015. Notwithstanding these non-negligible costs, metal theft often results in damage to public infrastructure. Three bridges were recently stolen in the Czech Republic, Turkey, and the United States.[5] Sidebottom et al. (2014) document the large number of live copper cable thefts from the British railway network; these live cables distribute electricity to trains but also to line-side signals. Such crimes not only threaten safety, but also cause substantial delays and costs related to the replacement of stolen material and repairs to damaged equipment; the costs are often disproportionate to the value of the stolen metal. This can be illustrated by three examples from the United States: tornado warning sirens were rendered inoperable because they were stripped of copper wiring; copper wires stolen from a transformer resulted in a power outage (damage $500,000); lastly, loss of crops occurred due to wires being stolen from irrigation wells (total loss of $10 million).[6] Perhaps it is no coincidence that these three events all happened in 2007 and early 2008, while copper prices were at historically high levels. Also, the three bridges mentioned, were stolen between 2011 and 2013, after steel prices returned to their pre-recession levels.

Our results can be summarized as follows. Finding that prices and thefts are, indeed, co-integrated, we are able to estimate the parameters of the long-term equilibrium relationship between gains from crime and the supply of offenses. We find the long-term elasticity of metal thefts with respect to the re-sale value of stolen metal to be between 1 and 1.5. This means that a 1% increase (decrease) in the re-sale price causes metal thefts to increase (decrease) by 1–1.5%. We then recover the parameters of the error-correction mechanism, which animates the real-time adjustments to shocks and determines the rate at which disequilibria, that is deviations from the long-term equilibrium, are corrected. The short-term (monthly) elasticity is estimated around one, close to the long-term estimates. In addition, the system tends to equilibrate quickly—between 30 and 60% of a price shock is predicted to be corrected the following month. We interpret these results as showing that thieves are very responsive to changes in monetary rewards from crime and their behavior is highly consistent over time. Our results are robust to alternative specifications, controlling for general crime trends, enforcement intensity, business cycles, weather, and political cycles. Importantly, we show that our results are not an artifact of a purely

[5] See "Thieves Steal Local Bridge," CBS Pittsburgh, Online, October 7, 2011, at http://pittsburgh.cbslocal.com/2011/10/07/thieves-steal- bridge-in-lawrence-county (last accessed on June 28, 2016); "Czech metal thieves dismantle 10-ton bridge," The Telegraph, Online, April 30, 2012, at http://www.telegraph.co.uk/news/newstopics/howaboutthat/9235705/Czech-metal-thieves-dismantle-10-ton-bridge.html (last accessed on June 28, 2016); and "Thieves Steal Entire Bridge in Western Turkey," Time, Online, March 21, 2013, at http://newsfeed.time.com/2013/03/21/thieves-steal-entire-bridge-in-western-turkey (last accessed on June 28, 2016).

[6] See "Copper Thefts Threaten U.S. Critical Infrastructure," Federal Bureau of Investigation, Criminal Intelligence Section, Online, September 15, 2008, at http://www.fbi.gov/stats-services/publications/copper-thefts (last accessed on June 28, 2016) and resources therein. For policy papers on costs of metal thefts, further background, and potential measures see Bennett (2008, 2012b, 2012a); Kooi (2010); and Lipscombe and Bennett (2012).

mechanical correlation between the volume of recorded crimes and the prices of stolen goods.

Data

The Police Register Data

The crime data analyzed in this paper were drawn from the Statistical Register of Criminality[7] managed by the Police Presidium of the Czech Republic, which records all criminal offenses handled by the police. Czech police maintains a detailed classification of the objects of interest of the criminal and thus we received data from this register relating to all criminal cases in which one of the objects of the crime was a nonferrous metal, in total 44,613 records from the period 2003–2012. The raw data set contains information on the criminal classification of each offense, its location, the date the police learned about the case, up to six objects of the crime coded according to the classification, and whether, how, and when the case ended. Crimes classified as thefts represent 94.8% of all nonferrous metal-related crimes in the data.

We focus on primary metal thefts, that is thefts in which metals were the primary object of the thief's interest. Primary metal thefts represent 80.0% of all thefts in the data, that is, in 20% of cases the primary object was not metal (the two most frequent primary objects in this category were tools and money). As a robustness check, we also report estimates for all metal-related thefts.

However, the database we use has two deficiencies: (1) Notably, one of the criteria for a theft to qualify as a crime is damage in excess of 5000 CZK ($200). Because the data only contains cases known to the police and classified as crimes, this may produce sample selection bias in our results due to a mechanical correlation between metal prices and damage caused, because marginal offenses may become crimes, and enter the data, when prices rise and *vice versa*. Note, however, that the 5000 CZK is a sufficient but not necessary condition. For instance, an offense qualifies as a crime irrespective of the damage if the thief broke into an object or had to overcome an obstacle, such as a fence. Thus, many metal thefts recorded by the police probably qualify as crimes irrespective of the damage caused. In fact, 34.6% of the thefts in our data involved a break-in. We exploit this information later to check the robustness of our results. (2) The second deficiency of our data is that it does not contain any information as to which particular metal was stolen. This is because the police classification only contains a general item "nonferrous metals, products, and scrap thereof."

Which Metals?

To proceed without knowing the exact mix of stolen metals, we first had to determine the relevant price index to measure the gains from metal thefts. The existing sources suggest that copper is probably the most frequently stolen of the nonferrous metals (Bennett 2008, 2012b; Kooi 2010; Posick et al. 2012; Sidebottom et al. 2011, 2014). Copper price is thus the first candidate.

[7] "Evidenčně? statistický systém kriminality" in Czech.

Table 1 Metal thefts in the media: number of articles mentioning individual metals

	Aluminum	Copper	Lead	Nickel	Tin	Zinc	All metals except copper
Mean	52.17	89.52	1.90	1.07	2.72	0.83	58.68
Median	53.00	92.50	1.00	0.00	2.00	0.00	60.00
Correlation with primary metal thefts	0.04	0.89^{*}	−0.01	0.11	-0.19^{+}	0.24^{*}	0.03
	(0.41)	(21.36)	(−0.09)	(1.17)	(−2.14)	(2.71)	(0.35)

The unit of observation is a month, data range from January 2003 to December 2012. Primary metal thefts are those with non-ferrous metals as the primary object of the thief's interest. Data source: Anopress.cz. *t*-statistics are in parentheses: $^{+}p<0.05$, $^{*}p<0.01$

In order to verify this assumption, we retrieved all newspaper articles that mentioned a metal theft related to aluminum, copper, lead, nickel, tin, and zinc, using media monitoring service Anopress.cz. The means and medians of monthly number of articles reporting thefts of these metals are reported in Table 1. Based on this evidence, the most frequently stolen metal is indeed copper, followed by aluminum; other metals seem to play a much lesser role. We then estimated the Pearson correlation coefficient between the number of primary metal thefts in the police data and the number of mentions of respective metal theft in media in monthly time series from 2003 and 2012. As reported at the bottom of Table 1, for aluminum the estimate is $r = 0.04$ (*t*-statistic 0.41, *p* value 0.68), whereas for copper it is $r = 0.89$ (*t*-statistic 21.36, *p* value <0.001). When all metal thefts in media except copper are added together, the correlation with the police data is $r = 0.03$ (*t*-statistic 0.35, *p* value 0.72). From this, we believe, it is safe to conclude that copper is the most relevant price component and we therefore use copper price as a measure of the value of metal theft opportunities and our main explanatory variable.

However, to the extent that a "true price" relevant for the thieves would rather be a price index, possibly with time-varying weights, as thieves may be able to substitute between individual metals to be stolen depending on their market valuation, using only copper introduces a measurement error which is negatively correlated with copper price. Intuitively, a decrease in copper price would alter thieves' optimum mix of stolen metals and the weight of copper in the index should decrease; yet our price index keeps it fixed at 100%. Keeping the measure fixed thus results in our overestimating the changes in the value of theft opportunities, leading to conservative bias in our regressions. As a robustness check we use an index consisting of copper and aluminum prices, obtaining somewhat higher point estimates compared to our baseline models.

Local Prices and the World Market

Next, we wanted to ascertain whether the prices Czech metal thieves work with are driven by the world market. For this purpose we contacted and personally visited a number of scrapyards in order to obtain historical price data. In the end we were only successful in one case, a scrapyard in Hradec Králové, which is a town with a population of 90,000 located about 100 km east of Prague.[8] The dataset covers the period from July 2006 to April 2011 and

[8] The reason why the other yards could not provide us with the data, which their personnel gave most often, was simply that the prices change very frequently and they do not keep records. However, the personnel often stated that their prices are determined by the market.

contains the prices of copper (sheets and wires), aluminum (sheets and pieces), lead (pieces), and zinc (sheets). We aggregated the data to obtain monthly average prices and merged it with the monthly metal prices at the LME, available from the World Bank's GEM Commodities database, multiplied by the exchange rate. We then ran simple regressions of the scrapyard prices on the LME prices (all in logs). The results, reported in Table 2, show that the world and scrapyard prices of copper are very closely related: a 1% change in copper price at the LME is predicted to change prices at the Czech scrapyard by 1.03% (s.e. 0.04, r^2 0.97), which is not statistically different from one—that is a 1% change in world price translates into a 1% change in the local scrapyard price in the same direction.

Another useful way to test the relationship between local and world prices is to test whether the series are cointegrated, which is a sign of a stable long-term relationship (see Sect. 3 below). Such relationship would occur if scrapyards are part of the world market, so that their prices mirror the world prices. Cointegration is examined by testing whether the residuals from regressions in Table 2 are non-stationary using the Augmented Dickey–Fuller test. For copper, the non-stationarity is rejected at 1% level. For other metals, however, the relationship between world and local prices is less tight. To summarize, the results of this exercise increase our confidence that copper prices from the LME can be safely used as a proxy for the prices Czech metal thieves work with. These findings are also consistent with findings in Aruga and Managi (2011), Draca et al. (2015), and Labys et al. (1971).

Final Dataset

To obtain the estimation dataset, we aggregate the police data to the monthly level and merge it with the average monthly metal prices at the LME available from the World Bank's GEM Commodities database. The prices are then multiplied by the CZK/USD exchange rate and divided by the Czech Consumer Price Index to obtain real prices. To control for potential confounding factors, we merge the data with series on property crimes, stolen bicycles, the monthly unemployment rate, the quarterly average gross wage index (we intrapolate wage data to obtain monthly series), monthly averages of the Standard & Poor's 500 Index, air temperature, and rainfall.

In 2008, the Ministry of the Environment amended the directive that regulates the operation of establishments dealing with waste, including scrapyards.[9] The amendment introduced a new article that completely prohibits scrapyards from buying specified items (artistic objects, funerary art or religious objects, industrial machinery, traffic signs, manhole covers, and electronic equipment) or their components from physical persons and paying for them in cash. This was apparently the government's reaction to a number of publicized cases of objects of this nature being stolen, and later often found in scrapyards. Because the amendment was effective from January 1, 2009, we include a dummy variable that is turned on therefrom. We also include trend that is interacted with this dummy to allow for a potential change of the effect of this amendment over time. This amendment was the only relevant policy intervention that was introduced during the period covered by our data.[10] Because a new Criminal Code was introduced in 2010, we also create an

[9] The amendment was published on December 22, 2008 as Directive no. 478/2008.

[10] Although metal theft has been a continuous public concern and proposals for an intervention were discussed frequently in media and politics, it was only in March 2015 that scrapyards were prohibited from buying scrap metals and other items for cash. A referee noted that scrapyards became obliged to identify sellers and keep a record of individual transactions. However this obligation was already present the

Table 2 The world market and metal prices at a Czech scrapyard

Scrap yard prices (logs)	Copper		Aluminum		Lead	Zinc
	Sheets (1)	Wires (2)	Sheets (3)	Pieces (4)	Pieces (5)	Sheets (6)
LME prices (logs)						
Copper	1.03*	1.03*				
	(0.04)	(0.04)				
Aluminum			1.45*	1.35*		
			(0.34)	(0.31)		
Lead					0.97^{+}	
					(0.48)	
Zinc						1.03^{+}
						(0.47)
Constant	-0.44^{+}	-0.44^{+}	-2.48^{+}	−1.95	−0.75	−1.10
	(0.19)	(0.19)	(1.26)	(1.16)	(1.65)	(1.76)
Observations	58	58	58	58	58	58
Adjusted R^2	0.97	0.97	0.72	0.78	0.55	0.71
Augm. Dickey–Fuller t. (p value)	<0.01	<0.01	0.22	0.34	0.30	0.22

The unit of observation is a month, data range from July 2006 to April 2011. Heteroskedasticity and autocorrelation robust standard errors (Newey and West 1987) are in parentheses: $^{+}p<0.05$, $^{*}p<0.01$

indicator variable which is switched on from January 1, 2010 when the law became applicable. Finally, in order to control for the political cycle, which may produce demand-side shocks (Levitt 1997), we create dummies for pre- and post-election years for parliamentary and regional elections. Table 3 summarizes our estimation dataset.

Methodology and Results

Our empirical model of criminal activity is straightforward: Let y_t be the number of primary metal thefts and p_t the average copper price, respectively. Both variables are observed at the monthly level, where t denotes a year-month. As a candidate regression consider

$$\log y_t = \beta_0 + \beta_1 \log p_t + \boldsymbol{\beta}_2' \boldsymbol{x}_t + \epsilon_t, \tag{1}$$

where log denotes the natural logarithm, $\boldsymbol{x}_t$ is a vector of control variables, βs are parameters to be estimated, and ϵ_t is the residual. The coefficient of interest is β_1. Because thefts and prices are in logs, β_1 estimates the percentage change in thefts corresponding to

Footnote 10 continued
Directive 383/2001, which is the general directive that regulates the operation of establishments dealing with waste, that was effective from January 1, 2002 (a year before our the first year of our data). In particular, scrapyards were required to keep a record of the kind and amount of the items bought as well as the name, address, and the serial number of the Identity Document of the seller. This obligation applied to a list of items that contained all nonferrous metals as well as their mixtures and cables.

Table 3 Summary statistics

	Mean	St. Dev.	Min	Median	Max
Metal thefts (primary)					
Thefts	282.0	134.7	61	280	516
Damage per theft (1000 CZK)	41.2	11.4	21.9	39.5	88.5
Stolen value per theft (1000 CZK)	35.5	9.9	17.1	34.1	74.0
Detection rate (% in 30 days)	25.7	4.7	14.8	25.2	38.4
Copper price (CZK/kg)	131.9	40.3	57.3	141.3	213.0
Number of stolen bicycles	526.0	236.4	167	540.5	1 050
Damage per stolen bicycle (1000 CZK)	16.8	1.6	9.5	16.7	21.5
Number of property crimes	18 419.2	1 760.7	13 668	18 376.5	22 376
Damage per property crime (1000 CZK)	48.4	9.4	21.4	48.3	101.8
Real wage index $\times 100$	132.7	9.2	116.3	135.2	149.5
Unemployment rate (%)	8.2	1.3	5.0	8.5	9.9
Standard & Poor's 500 Index	1 204.4	180.0	757.1	1 212.1	1 539.7
Air temperature (°C)	8.3	7.5	-6.0	8.2	21.4
Rainfall per day (mm)	1.9	1.0	0.03	1.8	4.8
Waste directive amendment (=1)	0.4	0.5	0	0	1
New criminal code (=1)	0.3	0.5	0	0	1
Parliamentary elections					
Year before (=1)	0.2	0.4	0	0	1
Year after (=1)	0.2	0.4	0	0	1
Regional elections					
Year before (=1)	0.3	0.5	0	0	1
Year after (=1)	0.2	0.4	0	0	1
Number of observations	120				

The unit of observation is a month, data range from January 2003 to December 2012

a 1% change in prices, that is the elasticity of supply of metal thefts with respect to copper price. This can be most easily seen by looking at a small change in price, denoted Δp, and the implied change in the number of thefts, denoted Δy, while keeping everything else constant. Then regression (1) implies

$$\log(y + \Delta y) = \beta_0 + \beta_1 \log(p + \Delta p) + \boldsymbol{\beta}_2' \boldsymbol{x} + \epsilon, \tag{2}$$

omitting time subscripts for clarity. Subtracting Eq. (1) from Eq. (2) yields

$$\log(y + \Delta y) - \log y = \beta_1 \log(p + \Delta p) - \beta_1 \log p,$$

which can be written as

$$\log \frac{y + \Delta y}{y} = \beta_1 \log \frac{p + \Delta p}{p}$$

and is equivalent to

$$\log\left(1+\frac{\Delta y}{y}\right)=\beta_1\log\left(1+\frac{\Delta p}{p}\right),$$

which for small Δp converges to

$$\frac{\Delta y}{y}=\beta_1\frac{\Delta p}{p}$$

that, solving for β_1, finally gives

$$\beta_1=\frac{\frac{\Delta y}{y}}{\frac{\Delta p}{p}}.$$

Because we are estimating Eq. (1) in a time series framework, one has to be careful to check whether the data are stationary, and if not whether they are cointegrated.[11] The Augmented Dickey–Fuller test of nonstationarity of the log metal thefts series produces test statistic -2.51 (p value 0.36) whereas for the first-differenced series the statistic is -5.47 (p value <0.01). For the series of log copper prices the test yields statistic -2.40 (p value 0.41) whereas for the first differenced series it is -4.30 (p value <0.01). This suggests that both y_t and p_t are indeed nonstationary and integrated of order one, since their first differences are stationary.

Equation (1) is then a valid estimator only if y_t and p_t are cointegrated of order zero (Engle and Granger 1987; Murray 1994). This happens if there is a linear combination of the series that is stationary and can be ascertained by testing whether the residual series ϵ_t from regression (1) is nonstationary.[12] We therefore supplement our regression results with Augmented Dickey–Fuller (ADF) tests of nonstationarity of the residuals.

The Supply of Offenses

Specifications (1) through (6) in Table 4 report alternative estimates of regression (1) with p values of ADF tests of nonstationarity of residuals reported at the bottom. With one exception, nonstationarity of the vector of residuals is always rejected at the 5% level. This is evidence of the existence of a long-term equilibrium relationship between copper prices and metal thefts, which can be estimated using the levels estimator (1) (Davidson and MacKinnon 2003). Because Durbin–Watson tests always reject the absence of autocorrelation of residuals, as reported at the bottom of Table 4, the reported standard errors were computed the using Newey and West (1987) estimator, which is robust to heteroskedasticity and autocorrelation.

Specification (1) reports the results of a simple regression of metal thefts on copper price, linear trend, and a full set of month dummies to control for seasonal regularities and the number of days in a month. The coefficient estimate on copper price suggests that the price elasticity of the supply of offenses is 1.25, and with the estimated standard error of 0.21 this is statistically significant at an arbitrary level. Taken at face value, this estimate means that a 1% change in copper price leads to a change in metal thefts by 1.25% in the same direction.

[11] See Murray (1994) for an excellent non-technical introduction into nonstationary processes and cointegration.

[12] See Davidson and MacKinnon (2003, ch. 14.6) for an overview and discussion of testing for cointegration.

Table 4 Levels estimates of the effect of copper prices on nonferrous metal thefts

	OLS estimates						Dynamic OLS estimates					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log copper price	1.25*	1.33*	1.02*	1.21*	1.20*	1.07*	1.36*	1.49*	1.25*	1.02*	1.02*	1.19*
	(0.21)	(0.17)	(0.14)	(0.11)	(0.11)	(0.12)	(0.19)	(0.14)	(0.11)	(0.22)	(0.23)	(0.41)
Log stolen bicycles		0.25	0.07	0.16	0.21	0.07		0.53	-0.29	-0.48	-0.44	0.02
		(0.29)	(0.26)	(0.18)	(0.16)	(0.19)		(0.30)	(0.33)	(0.39)	(0.41)	(0.50)
Log property crimes		1.59^{+}	1.78*	0.89	0.82^{+}	1.09		1.90	2.67*	-0.26	−0.30	0.08
		(0.77)	(0.62)	(0.46)	(0.40)	(0.57)		(1.13)	(0.94)	(1.23)	(1.26)	(1.41)
Waste directive amendment (=1, since 2009)			−0.95*	−0.56*	−0.57*	−0.69*			−0.84*	−0.58	−0.56	−0.50^{+}
			(0.19)	(0.16)	(0.20)	(0.11)			(0.19)	(0.30)	(0.30)	(0.21)
Waste Directive amendment × year			0.51*	0.98*	1.01*	1.03*			0.81^{+}	0.92*	0.92*	0.87
			(0.18)	(0.21)	(0.19)	(0.22)			(0.33)	(0.27)	(0.28)	(0.58)
Lagged detection rate (% in 30 days)			−0.01	−0.0004	0.001	0.01			−0.03	−0.02	−0.02	0.01
			(0.01)	(0.01)	(0.005)	(0.01)			(0.02)	(0.01)	(0.01)	(0.02)
New criminal code (=1, since 2010)			0.27*	0.31*	0.32*	0.18*			0.12	0.18	0.18	0.18
			(0.10)	(0.06)	(0.07)	(0.06)			(0.10)	(0.10)	(0.10)	(0.13)
New criminal code × year			−0.51*	−0.73*	−0.80*	−0.86*			−0.72*	−0.38	−0.38	−0.81
			(0.18)	(0.18)	(0.19)	(0.17)			(0.28)	(0.45)	(0.48)	(0.69)
Unemployment rate (%)				−0.21*	−0.21*	−0.17*				−0.12	−0.12	−0.14
				(0.05)	(0.04)	(0.06)				(0.08)	(0.08)	(0.13)
Real wage index × 100				0.03	0.02	0.01				0.09	0.08	0.0004
				(0.02)	(0.01)	(0.01)				(0.06)	(0.06)	(0.08)
Log S&P 500				−0.13	−0.08	0.05				−0.24	−0.23	0.24
				(0.30)	(0.27)	(0.27)				(0.45)	(0.48)	(0.60)
Log rainfall					0.03	0.02					0.01	0.01
					(0.02)	(0.02)					(0.02)	(0.02)

Table 4 continued

	OLS estimates						Dynamic OLS estimates					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Air temperature (°C)					0.02^{+}	0.02					−0.001	0.001
					(0.01)	(0.01)					(0.01)	(0.01)
Parliamentary elections												
Year before						-0.10^{+}						-0.22^{+}
						(0.05)						(0.10)
Year after						0.05						−0.03
						(0.05)						(0.07)
Regional elections												
Year before						−0.08						−0.06
						(0.05)						(0.06)
Year after						−0.03						−0.02
						(0.06)						(0.11)
Constant	−0.56	−18.03*	−17.53*	-10.01^{+}	-8.80^{+}	-10.75^{+}	−1.12	-23.47^{+}	−24.45*	−0.26	0.08	−1.62
	(0.96)	(6.46)	(5.36)	(4.55)	(4.10)	(5.41)	(0.91)	(10.26)	(9.08)	(12.07)	(12.35)	(12.96)
Month effects and linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOLS variables	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120	120	119	119	119	119	115	115	114	114	114	114
Adjusted R^2	0.81	0.83	0.90	0.93	0.94	0.94	0.88	0.90	0.94	0.96	0.95	0.96
Augm. Dickey–Fuller t. (*p* value)	0.080	0.024	0.021	< 0.01	< 0.01	< 0.01	0.099	0.013	< 0.01	< 0.01	< 0.01	< 0.01
Durbin–Watson test (*p* value)	0.000	0.000	0.000	0.000	0.001	0.006	0.000	0.000	0.000	0.000	0.000	0.005

The outcome variable is the logarithm of the average number of thefts involving nonferrous metals as the primary object per day in a month. Data range from January 2003 to December 2012. DOLS specifications include first-differences of all integrated explanatory variables and two leads and lags of these differenced variables (Saikkonen 1991; Stock and Watson 1993). *p* values of Augmented Dickey–Fuller below 0.01 are reported as < 0.01. Heteroskedasticity and autocorrelation robust standard errors (Newey and West 1987) are in parentheses: $^{+}\,p<0.05$, $^{*}\,p<0.01$

In order to control for general crime trends and potential substitution between metal theft and other criminal activities due to shocks in the (relative) value of metal theft opportunities (as opposed to substitution between legitimate and illegitimate activity), specification (2) includes the number of property crimes and the number of stolen bicycles in each month, both are in logs.[13] Although the available empirical evidence on substitution across criminal activities is inconclusive,[14] we hypothesize that stealing a bicycle is a relatively close alternative to metal theft; since bicycle thefts are comparable to metal thefts in terms of the sophistication required as well as in terms of the frequency and the damage caused (see Table 3). Bicycle thefts are unlikely, though, to be (directly) driven by metal prices, since bicycles are typically stolen to be resold on the used bicycle market rather than to a scrapyard. Controlling for property and bicycle thefts does not appreciably change the estimated elasticity, however.

Specification (3) adds a dummy for the 2008 waste directive amendment prohibiting scrapyards from buying certain items from physical persons and paying for them in cash (see Sect. 2.4) and its interaction with linear trend. The amendment appears to have had a negative immediate effect on metal thefts but the positive sign on trend suggests this effect was fading over time. We however prefer not to speculate about the causal interpretation of this result since the empirical set up of this paper is not appropriate for such inference. In order to account for possible shocks in the two most important "demand" factors: the probability of getting caught and the punishment, we also include a lagged detection rate, that is the percentage of thieves detected by the police in the previous period, and a dummy for the 2010 Criminal Code and its interaction with linear trend. The coefficient estimates on these controls should nevertheless be read with caution as the detection rate may be influenced by criminal activity, as cases "compete" for police resources, and the new Criminal Code did not bring about any substantive change in the treatment of thefts. As a result of controlling for these factors, but mainly due to the amendment, the coefficient estimate on log copper loses about one fourth of its value, compared to specification (2), but remains statistically as well as substantively significant.

To control for general economic shocks that may affect metal thefts, specification (4) includes the unemployment rate, the real wage index, and the Standard & Poor's 500 index. These controls are potentially problematic, as economic shocks are likely to affect demand for metals and thus metal prices. This is consistent with the negative and statistically significant coefficient estimate on unemployment, which is the opposite sign from what one would expect if criminal activity is countercyclical (Aaltonen et al. 2013; Cook 2010; Cook and Zarkin 1985; Lin 2008). This suggests we are "overcontrolling" in this specification and the price elasticity of metal thefts is underestimated. However if we instead control for the business cycle then the estimated elasticity is equal to 1.21 and is

[13] The two series are plotted in Fig. 5 in the Appendix. We note that it is not clear whether property crime should be controlled for or not. It is possible that offenders may substitute metal thefts and other property, depending on their relative valuation. In that case, property crimes would be affected by copper prices, and regressions controlling for property crimes would underestimate the effect of prices on metal thefts. Note, however, that the average number of property crimes per month in our data is 18,400 while the average number of metal thefts is 280, so the bulk of variation in property crime will probably be unrelated to substitution from metal thefts (see Table 3). More importantly, one might argue that not including property crimes would lead to overestimating the effect of prices on thefts, as new metal thefts may represent substitutes for other opportunities and not new crimes. We lean towards the latter approach and prefer the regressions controlling for property crimes and bicycle theft in order to net out these potential substitution effects and control for general crime trends. We further delve the issue of substitution in Sect. 4.4.

[14] See, e.g., Ayres and Donohue (2003); Cameron (1987); Detotto and Pulina (2013); Koskela and Viren (1997); Levitt (1998); and Lott and Mustard (1997).

highly statistically significant. Less controversially, specifications (5) and (6) control for weather shocks and the political cycle. Weather does not alter results but controlling for pre- and post-election years results in a small decline in the estimate of the elasticity to about 1.07. This result is not statistically different from our estimates in specifications (4) and (5).

Because levels estimators in small samples may be biased and are inefficient, we have also estimated dynamic OLS (DOLS) models that have been shown to yield unbiased estimates of the cointegrating relationship (Saikkonen 1991; Stock and Watson 1993). The DOLS estimates are obtained by augmenting the levels estimators with the first differences of the explanatory variables and two leads and lags of differenced explanatory variables.[15] We re-estimate DOLS models for specifications (1) through (6) in Table 4. The results are reported in columns (7) through (12) and the estimates of elasticities are qualitatively similar to the simple levels models estimates, albeit slightly higher in four out of six cases. To summarize, we provide a range of estimates and leave it to readers to assess which model is preferable. The results of the 12 alternative regression estimates reported in Table 4 strongly suggest that the price elasticity of the supply of metal thefts is greater than zero and most likely lies between 1 and 1.5. A 1% increase (decrease) in the re-sale price causes metal thefts to increase (decrease) by 1–1.5%.

The results of our analysis of the long-term equilibrium relationship between copper prices and metal thefts are summarized in Fig. 2. The solid line connects the predicted number of thefts as a function of copper prices, using the coefficient on Log copper price and the Constant from specification (12) in Table 4. Dots are the residuals from that regression anchored by these predicted values. The points lying on the supply curve are the equilibrium levels of metal theft corresponding to different copper prices. The vertical distance between each of the dots and the supply curve is the estimated difference between the equilibrium number of thefts and the thefts realized in that period, or the "disequilibrium thefts." This empirical supply of offenses by Czech metal thieves appears to match the standard supply curve derived theoretically in microeconomics textbooks.

Short-Term Corrections

Cointegration evidences a long-term equilibrium relationship between copper price and metal thefts. This means that necessarily a mechanism must exist to absorb shocks and correct transitory deviations from that equilibrium (Engle and Granger 1987; Murray 1994). This error-correction mechanism (ECM) can be expressed as

$$E(y_t - y_{t-1}) = \gamma_1 \epsilon_{t-1} + \boldsymbol{\gamma}_2'(\boldsymbol{x}_{t-1} - \boldsymbol{x}_{t-2}), \tag{3}$$

where ϵ_{t-1} is the distance between the realized level of y and its equilibrium value in the period $t-1$. In plain words, the expected change in y in the current period depends on its deviation from the equilibrium at the beginning of the period and real shocks in the previous period. The coefficient γ_1 is then the error-correction term capturing the speed with which the system equilibriates and is predicted to have a negative sign. The vector $\boldsymbol{\gamma}_2$ captures the short-term reaction of y to shocks in the explanatory variables. Because the residual series from levels regressions estimate the equilibrium error in each period, Eq. (4) can be estimated directly as

[15] The choice of leads and lags follows Stock and Watson (1993) who, in their Monte Carlo simulations, used two leads and lags for samples of size 100; our sample size is 120. Using different a number of leads and lags yields qualitatively similar results (see Sect. 4.5).

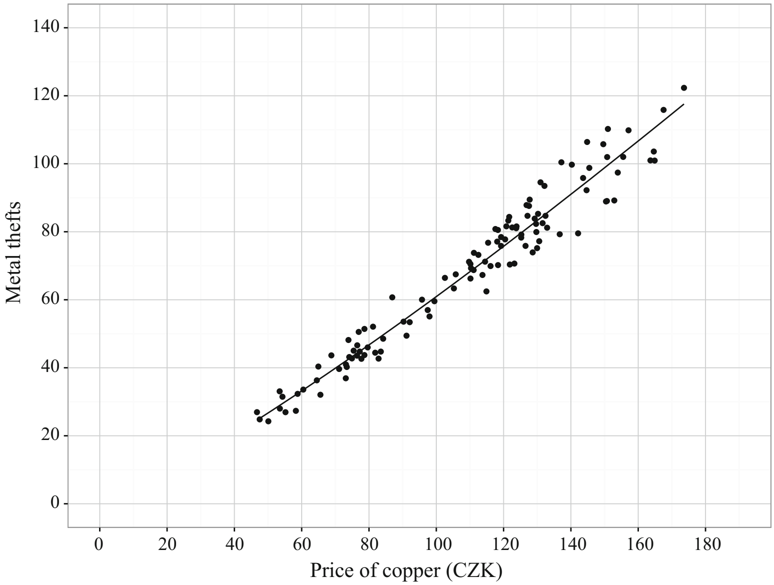


Fig. 2 The empirical supply of offenses. The *solid line* connects the predicted number of thefts corresponding to different prices, using the coefficient on Log copper price and the Constant from specification (12) in Table 4. *Dots* are the regression residuals anchored by these predicted values

$$y_t - y_{t-1} = \gamma_1 \hat{\epsilon}_{t-1} + \boldsymbol{\gamma}_2'(\boldsymbol{x}_{t-1} - \boldsymbol{x}_{t-2}) + e_t, \tag{4}$$

where $\hat{\epsilon}_t$ is the residual series from regression (1) and e_t is an error term.[16]

Table 5 reports the results of ECM models analogous to specifications (1) through (5) and (7) through (11) in Table 4. The ECM models do not include controls for the waste amendment, the new Criminal Code and pre- and post-election years, as there would be no sensible interpretation of coefficients estimates on differenced dummies in ECM regressions. The first row reports estimates on the respective error correction terms. For models (1) through (5) in Table 5 the equilibrium error term is the residual series from the respective regressions in Table 4. Models (6) through (10) include the residual series from the respective DOLS models. Both sets of estimates yield comparable results. The coefficient estimates for the error-correction term are between −0.21 and −0.63 and are always highly statistically significant. These numbers suggest that between one fifth to two thirds of a disequilibrium is corrected within one month. The second row of Table 5 reports estimates of the short-term (monthly) price elasticity of the supply of metal thefts. The results for models with residuals from simple OLS models suggest that the short-term elasticity is between 0.5 and 0.8. However, these estimates are only marginally statistically significant. We note that, to the extent that DOLS levels models are preferable, ECM models that include equilibrium error terms estimated by DOLS should be preferred as well. These models yield estimates of short-term elasticity between 0.9 and 1 and all these estimates are highly statistically significant. The short-term elasticities are almost as high

[16] Note that $\hat{\epsilon_t}$ is an estimate of ϵ_t containing measurement error. Therefore, our estimates of γ_1 will be biased towards zero. We are grateful to Giovanni Mastrobuoni for pointing this out to us.

Table 5 Error-correction models of copper prices and nonferrous metal thefts

	Estimates with residuals from OLS models					Estimates with residuals from dynamic OLS models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged residuals from levels models	−0.27*	−0.26*	−0.21*	−0.40*	−0.43*	−0.30*	−0.33*	−0.38*	−0.63*	−0.54*
	(0.05)	(0.04)	(0.08)	(0.11)	(0.09)	(0.05)	(0.05)	(0.10)	(0.14)	(0.12)
Lagged differences										
Log copper price	0.52	0.55	0.85^{+}	0.54	0.61^{+}	0.97*	1.00*	0.98*	0.89*	0.93*
	(0.36)	(0.32)	(0.36)	(0.33)	(0.26)	(0.31)	(0.32)	(0.34)	(0.31)	(0.26)
Log stolen bicycles		−0.29*	−0.23	−0.20	−0.04		-0.28^{+}	-0.29^{+}	-0.27^{+}	−0.11
		(0.10)	(0.12)	(0.11)	(0.11)		(0.11)	(0.12)	(0.12)	(0.12)
Log property crimes		0.09	0.02	0.08	0.07		0.20	0.21	0.20	0.17
		(0.21)	(0.25)	(0.20)	(0.18)		(0.20)	(0.22)	(0.18)	(0.16)
Lagged detection rate (% in 30 days)			0.001	0.001	0.002			0.001	0.001	0.002
			(0.003)	(0.002)	(0.003)			(0.003)	(0.003)	(0.003)
Unemployment rate (%)				0.02	−0.02				0.02	−0.01
				(0.06)	(0.06)				(0.05)	(0.05)
Real wage index × 100				0.01	−0.005				0.0000	−0.01
				(0.01)	(0.01)				(0.01)	(0.01)
Log S&P 500				0.61^{+}	0.70^{+}				0.33	0.41
				(0.31)	(0.34)				(0.31)	(0.30)
Log rainfall					0.01					0.01
					(0.01)					(0.01)
Air temperature (°C)					0.02*					0.02*
					(0.01)					(0.01)
Constant	0.52*	0.39*	0.41*	0.37*	0.53*	0.52*	0.40*	0.39*	0.38*	0.54*
	(0.07)	(0.07)	(0.08)	(0.10)	(0.09)	(0.07)	(0.07)	(0.08)	(0.10)	(0.09)
Month effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 continued

	Estimates with residuals from OLS models					Estimates with residuals from dynamic OLS models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Observations	118	118	117	117	117	115	115	114	114	114
Adjusted R^2	0.71	0.71	0.69	0.70	0.75	0.71	0.72	0.70	0.71	0.75
Augm. Dickey–Fuller t. (p value)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.012	< 0.01	< 0.01	< 0.01	< 0.01
Durbin–Watson test (p value)	0.902	0.980	0.377	0.982	0.860	0.256	0.493	0.368	0.759	0.689

The outcome variable is the month-to-month difference of the logarithm of the average number of metal thefts per day. Data range from January 2003 to December 2012. DOLS specifications include residuals from respective DOLS models in Table 4. p values of augmented Dickey–Fuller below 0.01 are reported as <0.01. Heteroskedasticity and autocorrelation robust standard errors (Newey and West 1987) are in parentheses: $^{+}p<0.05$, $^{*}p<0.01$

as our long-term estimates, suggesting that thieves are quick to respond to price shocks and their behavior is highly consistent over time.

Our estimates of the dynamic mechanisms that absorb price and other shocks, maintaining the long-term equilibrium relationship between copper prices and metal thefts, are illustrated in Fig. 3. We consider an unexpected 10% increase in the price of copper and use the estimated coefficients from specifications (12) and (10) in Tables 4 and 5, respectively, to estimate the corresponding change in long-term equilibrium and the short-term reaction to such a shock. Assuming that prior to the shock, thefts were in equilibrium, which we set to the average number of thefts in the data (282), a higher price increases the equilibrium level of thefts, because thieves prefer to "supply" more thefts at higher prices (see Fig. 2). In reaction to higher copper price, thieves therefore increase stealing but slightly (eight thefts) less than what would be needed to reach the new equilibrium (318 thefts), as the short-term elasticity is smaller than the long-term elasticity. This results in a disequilibrium—that is, the level of stealing is lower than the predicted long-term equilibrium that corresponds with the new price level—and a correction is needed. In the next month, thieves will increase thefts by about one half of the difference between the equilibrium level thefts and thefts realized in the previous month, halving the disequilibrium. Each following month they will increase thefts by 0.54 of the remaining disequilibrium. In month 4, the disequilibrium is smaller than one theft.

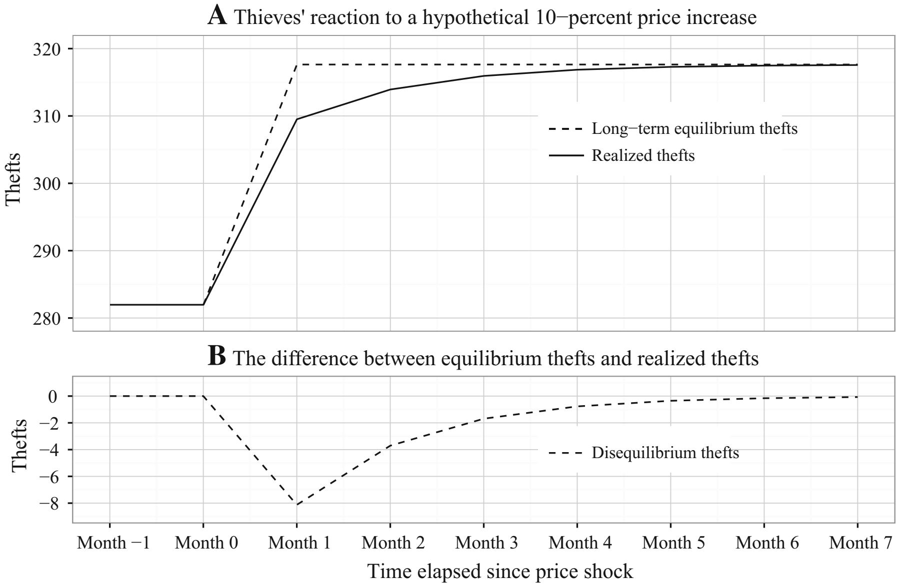


Fig. 3 Modeling a reaction to a price shock. Initially (Month 0 and before), thieves are in an arbitrary equilibrium (we choose the average level of metal thefts, that is 282), meaning that, for a given copper price, they have no incentives to change the amount of stealing. Then an unexpected 10% increase in copper price takes place during Month 1. This increases the long-term equilibrium level of thefts to 317.6 [$= \exp(\log 282 + 0.1 \times 1.19)$], using the estimated coefficient on Log copper price from specification (12) in Table 4. In reaction to higher copper price, thieves increase stealing but only to 309.5 [$= \exp(\log 282 + 0.1 \times 0.93)$], using the estimated coefficient on Log copper price from specification (10) in Table 5, which is 8.1 thefts less than the equilibrium. Therefore in Month 2, thieves will increase thefts by 4.4 ($= -8.1 \times -0.54$), using on the estimated coefficient on Lagged residuals from specification (10) in Table 5, halving the disequilibrium. Each following month they will increase thefts by 0.54 of the remaining disequilibrium. In month 4, the disequilibrium is smaller than one theft

Fig. 4 Damage distributions by year, logarithmic scale (damage below 10 CZK coded as 10 to save space). ▶ Plots are overlaid with jitter, with each point representing damage associated with an individual metal theft. Contours of violins represent kernel densities, with bandwidth selected according to the Sheather and Jones (1991) algorithm (Jones et al. 1996). Slanted crosses mark means. The *upper* and *lower* "hinges" of boxplots correspond to the 25th and 75th percentiles. The upper (lower) whisker extends from the hinge to the highest (lowest) value that is within $1.5 \times IQR$ of the hinge, where IQR is the distance between the 25th and 75th percentiles. The notches extend $1.58 \times IQR/\sqrt{n}$, where n is the number of observations, roughly a 95 % confidence interval for comparing medians (McGill et al. 1978). The 5000 series in the bottom plot denotes the value of the damage associated with a hypothetical theft with damage worth 5000 CZK-damage in 2003 prices. The value of that damage in the following years was computed assuming that the value of stolen copper is 80% of the damage (i.e. 80% of the damage was adjusted to reflect the changes in copper price and 20% was adjusted by the consumer price index)

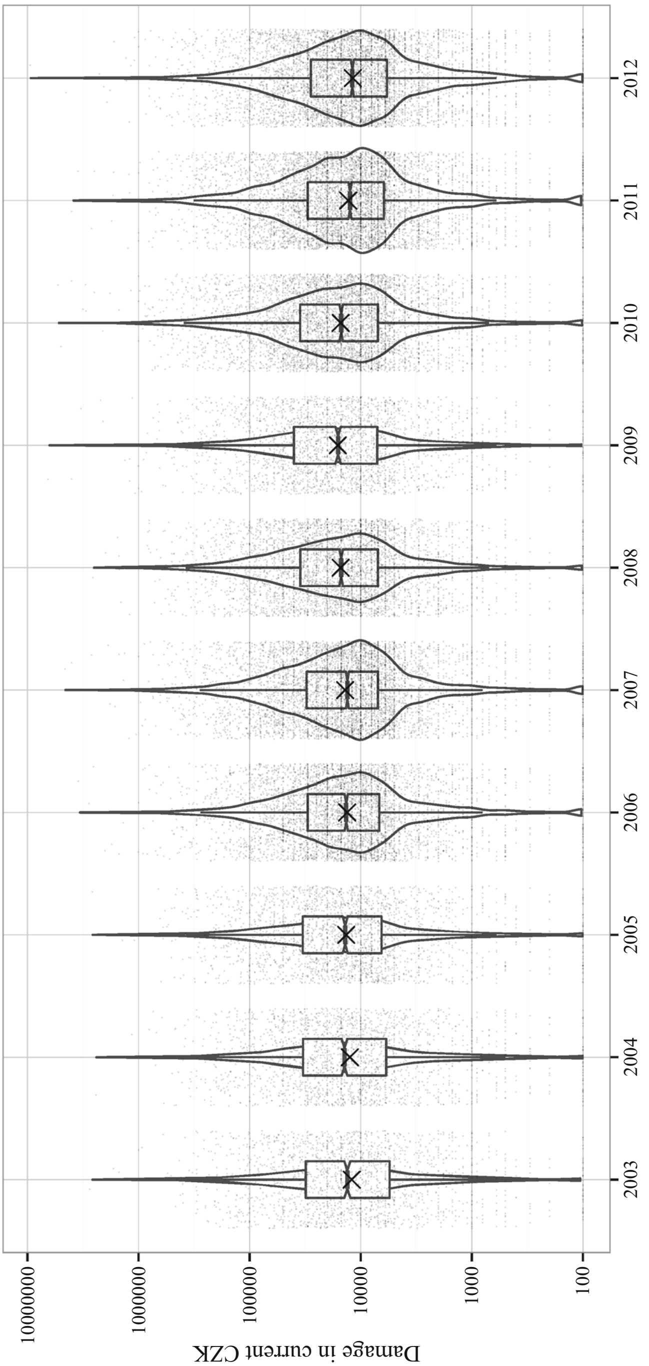
Because the median monthly change in copper price in our data is $<4\%$, the disequlibria caused by price changes will generally be smaller and corrections faster. However even the most violent price shocks such as the maximum 26.4% drop in copper price in October 2008, will produce only temporary distortions of thefts from their equilibrium levels.

Alternative Explanations and Robustness Checks

Gauging Selection Concerns

As noted in Sect. 2, one of the criteria for an offense to be qualified as a crime is that the damage is "non-negligible," which in practice means it should exceed 5,000 CZK. This has two potentially important implications: (1) Because the cost of committing a crime is discontinuous at the threshold, individuals have incentives to avoid exceeding it. As a result, a rise in the copper price may lead to an increased number of "sub-crime" level thefts. Unless some other crime-qualifying condition is met, these thefts do not qualify as crime and are not recorded in the crime database. This may imply that our estimates of the elasticity of supply of offenses may be too conservative. (2) More worrying, however, is the fact that the value of the stolen material as well as the damage that metal thefts cause are linked to metal prices—if metal prices rise, a specific theft is likely to be associated with greater damage and *vice versa*. This is problematic because it means the number of crimes may change purely mechanically as offenses at the margin become crimes when prices rise. This would in turn mean that we would be overestimating criminals' reactions to prices.

Being conservative and assuming that prices are fully reflected in the claimed damage and thieves have no control over the extent of the damage they cause, then if thieves do not react to prices, one would expect that the distribution of damage caused simply shifts up and down with prices. Damage distributions by year are plotted in Fig. 4. The boxplots are overlaid with jitter, with each point representing damage associated with an individual metal theft. Darker parts of the plot suggest a higher frequency of thefts at the respective damage level. It is visually apparent that years with a higher number of recorded crimes saw a rise across the whole spectrum of damage, rather than simply a shift upwards. Also means and medians are quite stable across years and the lower hinges are always above the 5000 CZK threshold, suggesting that over 75% of crimes in the data result in damage above the threshold. Thus, it is unlikely that prices interacting with the threshold explain


Damage in current CZK
10000000
1000000
100000
10000
1000
100
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012

the almost 250% increase in thefts between 2003 and 2011 (the years with minimum and maximum number of metal thefts, respectively).

Nevertheless, this graphical evidence cannot rule out the concern that our main estimates overstate the effect of prices on crime. If the mechanical relationship between copper price and damage is important, there should be a positive relationship between the copper price and the average damage per crime. To test this prediction formally, we regress the log of average damage per crime on copper price and other explanatory variables using the specifications from Table 4. The results are reported in block A of Table 6 and suggest that the relationship is actually negative, although it is mostly small and statistically significant in only three out of 12 specifications.[17] Block B reports coefficients on log copper price in specifications where the outcome is replaced by the log average value of stolen goods per theft. The results are qualitatively very similar; the relationship between copper price and the average value of stolen material is predominantly negative. This finding may seem surprising and, perhaps, counterintuitive. However, a possible explanation is that marginal crimes are likely to be those with low value and marginal thieves are likely to be those with low-value theft opportunities. Put differently, high-value thefts are likely to be undertaken at a wide range of copper prices. So, if the copper price increases, new thefts, if any, will more often be low-value thefts. And if the copper price goes down, low-value theft opportunities will be abandoned, as they are no longer worth it.

To further probe this issue, we exploit the fact that the 5000 CZK threshold is a sufficient but not necessary condition for an offense to qualify as a crime. We thus reestimate the models from Table 4 with the outcome variable computed as the monthly number of metal thefts with damage below 5000 CZK. For these thefts the damage threshold had no impact. If the mechanical relationship between copper price and damage is important, this measure should clearly undervalue the change in thefts due to the change in prices, as it mechanically excludes thefts that exceed the 5000 CZK margin. If that were the case, these estimates of price elasticity could be interpreted as conservative. Consistent with our predictions, the estimates of the effect of copper prices on metal theft with damage below the threshold in block C are somewhat smaller than our baseline estimates in Table 4, except in specifications (10) and (11). However, the patterns and magnitudes of both sets of estimates are comparable and the differences in coefficients are not statistically significant. Similar results are found when the outcome is defined as the number of metal thefts with a value of stolen goods <5000 CZK and zero CZK, as reported in blocks D and E, respectively. Interestingly, the estimates for thefts with no loot tend to be higher than the baseline, supporting our hypothesis that marginal thefts are those of low value.

In block F we reestimate our baseline models with the outcome defined as the log of the number of thefts involving break-in (about one third of all metal thefts). These offenses qualify as crimes regardless the size of the resulting damage so that the 5000 CZK threshold is irrelevant. The estimates of the elasticity of break-in thefts are slightly smaller than the baseline models, except for the last three DOLS specifications, but these differences are not statistically significant. To summarize, these results are inconsistent with the interpretation that the relationship between copper prices and metal thefts in our data is an artifact of the mechanical relationship between copper price and the number of metal thefts that qualify as crimes.

[17] Note that using the 10% level, the Augmented Dickey–Fuller tests fail to reject nonstationarity of residuals from specifications (1), (7) and (8), so these results should be interpreted with caution.

Table 6 Gauging the selection concerns and further robustness checks

	OLS estimates						Dynamic OLS estimates					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Outcome replaced by log of mean damage	−0.14	−0.20^{+}	−0.05	−0.14	−0.13	0.12	−0.23^{+}	−0.26*	−0.09	−0.54	−0.53	0.05
	(0.10)	(0.08)	(0.08)	(0.12)	(0.11)	(0.19)	(0.11)	(0.08)	(0.13)	(0.41)	(0.42)	(0.54)
	[0.28]	[0.09]	[0.01]	[0.01]	[0.01]	[0.01]	[0.65]	[0.34]	[0.01]	[0.01]	[0.01]	[0.01]
B: Outcome replaced by log of mean stolen value	−0.12	−0.18*	−0.10	−0.19	−0.19	0.15	−0.20*	−0.22*	−0.11	−0.65	−0.65	0.07
	(0.06)	(0.06)	(0.09)	(0.13)	(0.12)	(0.17)	(0.07)	(0.06)	(0.13)	(0.42)	(0.42)	(0.58)
	[0.52]	[0.32]	[0.01]	[0.01]	[0.01]	[0.01]	[0.54]	[0.32]	[0.01]	[0.01]	[0.01]	[0.01]
C: Total damage less than 5,000 CZK[a]	0.96*	1.13*	0.88*	1.18*	1.16*	0.88*	1.12*	1.29*	1.11*	1.29*	1.30*	1.16^{+}
	(0.28)	(0.20)	(0.13)	(0.19)	(0.19)	(0.19)	(0.28)	(0.18)	(0.11)	(0.28)	(0.33)	(0.47)
	[0.32]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]	[0.45]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
D: Value of stolen material less than 5,000 CZK[b]	1.06*	1.18*	0.88*	1.16*	1.16*	0.90*	1.22*	1.38*	1.12*	1.09*	1.11*	1.14*
	(0.25)	(0.19)	(0.13)	(0.16)	(0.16)	(0.18)	(0.24)	(0.17)	(0.13)	(0.27)	(0.27)	(0.41)
	[0.21]	[0.05]	[0.03]	[0.02]	[0.02]	[0.01]	[0.32]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
E: Value of stolen material equal to zero[c]	1.44*	1.50*	1.12*	1.22*	1.24*	0.83*	1.72*	1.92*	1.82*	1.13*	1.20*	1.72^{+}
	(0.31)	(0.26)	(0.26)	(0.28)	(0.28)	(0.25)	(0.27)	(0.20)	(0.23)	(0.44)	(0.40)	(0.78)
	[0.05]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.11]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]
F: Only thefts involving break−in[d]	1.00*	1.10*	0.86*	0.98*	0.97*	0.85*	1.09*	1.23*	1.04*	1.11*	1.11*	1.47*
	(0.24)	(0.20)	(0.13)	(0.06)	(0.06)	(0.08)	(0.24)	(0.19)	(0.12)	(0.21)	(0.19)	(0.31)
	[0.24]	[0.12]	[0.01]	[0.01]	[0.01]	[0.01]	[0.16]	[0.05]	[0.01]	[0.01]	[0.01]	[0.01]
G: Outcome replaced by log of stolen bicycles[e]	−0.16	−0.12	−0.003	0.02	−0.004	−0.11	−0.15	−0.09	0.02	−0.19*	−0.18*	−0.28*
	(0.12)	(0.12)	(0.07)	(0.08)	(0.08)	(0.10)	(0.14)	(0.14)	(0.07)	(0.07)	(0.06)	(0.09)
	[0.26]	[0.44]	[0.01]	[0.01]	[0.01]	[0.01]	[0.20]	[0.52]	[0.01]	[0.01]	[0.01]	[0.01]
H: DOLS models with single leads and lags							1.33*	1.47*	1.21*	1.42*	1.42*	1.44*
							(0.19)	(0.14)	(0.11)	(0.16)	(0.16)	(0.15)
							[0.21]	[0.06]	[0.01]	[0.01]	[0.01]	[0.01]

Table 6 continued

	OLS estimates						Dynamic OLS estimates					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
I: DOLS models with three leads and lags							1.40*	1.52*	1.29*	0.73	0.75$^+$	1.15
							(0.17)	(0.12)	(0.11)	(0.40)	(0.35)	(0.60)
							[0.11]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
J: DOLS models with four leads and lags							1.45*	1.59*	1.31*	0.97$^+$	1.09$^+$	1.26*
							(0.17)	(0.14)	(0.12)	(0.40)	(0.45)	(0.41)
							[0.27]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]
K: Log copper replaced by price index[f]	1.40*	1.48*	1.14*	1.33*	1.32*	1.22*	1.51*	1.63*	1.40*	1.10*	1.11*	1.37*
	(0.21)	(0.17)	(0.14)	(0.12)	(0.12)	(0.14)	(0.17)	(0.14)	(0.11)	(0.23)	(0.27)	(0.43)
	[0.06]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.08]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
L: Outcome replaced by log of all metal−related thefts[g]	1.06*	1.13*	0.89*	1.11*	1.10*	0.96*	1.17*	1.27*	1.10*	0.91*	0.92*	1.04*
	(0.17)	(0.14)	(0.12)	(0.10)	(0.10)	(0.11)	(0.15)	(0.11)	(0.10)	(0.27)	(0.27)	(0.34)
	[0.05]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.07]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Observations	120	120	119	119	119	119	115	115	114	114	114	114

Table reports alternative estimates of models (1) through (12) from Table 4. Only the estimates of the effect of copper price on thefts are reported; detailed results are available upon request. Heteroskedasticity and autocorrelation robust standard errors (Newey and West 1987) are in parentheses: $^+p<0.05$, $^*p<0.01$. Square brackets report p values of Augmented Dickey–Fuller tests for each model (values below 0.01 are reported as 0.01). [a] The outcome is the logarithm of the number of metal thefts with total damage below 5000 CZK. [b] The outcome is the logarithm of the number of metal thefts with a value of stolen material below 5000 CZK. [c] The outcome is the logarithm of the number of metal thefts with a value of stolen material equal to zero. [d] The outcome is the logarithm of the number of metal thefts which involved break-in and thus qualified as crimes regardless of the damage. [e] The outcome is the logarithm of the number of bicycle thefts classified as crime. Specifications are identical to those in Table 4, except bicycle thefts are dropped from the explanatory variables. [f] Log of copper price is replaced by the logarithm of price index consisting of aluminum and copper with weights fixed at 1/3 and 2/3, respectively. The choice of weights was motivated by patterns in Table 1. [g] The outcome is the logarithm of the number of all thefts involving nonferrous metals, that is all thefts where one of the objects was metal

Reverse Causality, Market Shares, and Endogenous Enforcement

We argue, together with Draca et al. (2015) and Sidebottom et al. (2014), that variation in metal prices constitutes a natural experiment involving metal thieves. This is because metal prices are set on the world market, in which stolen metal is unlikely to play an important role. In microeconomic parlance, thieves are price-takers.

To gauge this assumption, consider that the total value of stolen metal in 2012 (the last year of our data) was \$12.13M and assume that theft volumes are similar around the world. Dividing this number by the Czech Republic's share on world population (0.15%) we obtain a rough estimate of the world total volume of metal theft of \$8.08B. The total volume of copper trade at the LME in 2012 was 35.87 M of 25-tonne lots.[18] Multiplied by the average copper price in 2012 of \$7.96/kg, we obtain the total value of traded copper at \$7.13T. Thieves' market share in copper trade at the LME would then be 0.11%, or about one thousandth. This estimate must be certainly taken with a grain of salt, it nonetheless gives the sense of proportions, suggesting that thieves' market share is rather small. Note also that while one may still contest that there is an endogenous element in world copper prices with respect to the activity of metal thieves, albeit small, this would mean that the observed relationship between metal prices and thefts in the data would be weaker than the true causal effect of price change on thefts, making our results conservative.

Another criticism of our results might point to endogeneity of enforcement (see e.g. Cook 1986; Cook and MacDonald 2011; Tsebelis 1989). When thefts surge, individuals and the police have greater incentives to invest into preventing thefts and pursuing offenders. Apart from the clearance rate included in our regressions, we do not have data on numbers of police allocated to solving metal thefts, neither do we possess data on private spending on crime prevention. Additionally, protective technologies, such as CCTV or security alarm, are improving over time and their costs decline. Including time trend in our regressions may serve as a proxy, albeit imperfect, for such factors. We however note that endogenous enforcement and not controlling for the availability of protective technologies may bias our results in the direction going against our hypothesis, making our results, again, conservative.

Prices as a Measure of the Value of Stolen Material

A possible concern may be that metal prices do not exactly reflect the value of stolen metal that accrue to the thief. Scrapyards may know the "usual suspects" and take a cut of their gains.[19] As a result, sale prices for the thieves would then be lower than the standard scrapyard prices. This may also happen when someone is selling objects that scrapyards are barred from buying (such as manhole covers, traffic signs, or headstones). We believe, however, that this would be a problem if the size of the cut was a function of prices (or the supply of thefts). Suppose that this is the case and scrapyards are able to take a bigger cut when the supply of stolen copper goes up. Then, we could still estimate the effect of prices on thefts, which is weakened by this ability of scrapyards to cut into the price. This phenomenon would therefore most likely work against our hypothesis, yielding a conservative bias in our results.

[18] See "2012 trading volumes," Online, at https://www.lme.com/metals/reports/monthly-volumes/annual/2012/ (last accessed on July 7, 2016).

[19] We are grateful to Nikolas Mittag for raising some of these points.

In reality, in order to be able to cut into prices, scrapyards would have to exert some market power. Indeed, scrapyards in the Czech Republic are not entirely free-entry businesses and their start-up costs are probably non-zero. Their operation is regulated by a special law on waste and adjacent government directives, so that scrapyards need to satisfy a number of safety-related and other requirements. Additionally, a license issued by regional-level government is required for their operation. However, searching for "scrapyards" ("sběrné dvory" in Czech) on Firmy.cz, the most comprehensive online database of Czech businesses, produces almost 450 establishments; in Prague, the capital with population of 1.3 million, there are 42 listed scrapyards. Because not all scrapyards necessarily have their profile listed, the true number of scrapyards is probably higher. This suggests that this market is highly competitive. Competition should limit scrapyard's ability to take cuts in prices beyond what would be cost-justified (from the yards' point of view).[20]

An analogous argument applies to the concern that we equate prices with gains from theft, which ignores the cost of stealing and transporting the goods. This again would only be a problem if the costs were a function of criminal activity, which is entirely possible. If marginal costs increase in the number of thefts, our changes in prices will overstate the changes in gains from crime, making the results in this paper conservative.

Substitution Across Criminal Activities

Understanding, whether the price-theft relationship in our data represents a net variation in criminal activity (i.e. substitution between legitimate and illegitimate activity), or rather shifts in the allocation of effort across alternative crimes (substitution between alternative illegitimate activities, without an overall change in crime), is relevant from the substantive as well as policy perspectives. This question is closely linked to the displacement hypothesis, the main criticism levied against the situational crime prevention literature (Cornish and Clarke 1987). The idea is that criminal activity is somehow given and changes in the value of individual criminal opportunities only lead criminals to commit different crimes elsewhere.[21]

To address this concern, we control for general crime trends and potential substitution across criminal opportunities by including property crime and bicycle thefts as explanatory variables in our regressions. However, one might argue, that these variables also contain a noise that is unrelated to substitution effects, if any. As a result, potential substitution effects may not properly controlled for.[22]

Other researchers have investigated substitution between criminal activities in response to crime-specific shocks in deterrence, mainly stemming from changes in arrest rates (Cameron 1987; Koskela and Viren 1997; Levitt 1998). Their results however need to be interpreted cautiously, because thieves may not directly observe arrest rates and the

[20] For discussion of market forces and dynamic aspects of illicit trade see also d'Este (2014). Looking at the effects of pawnshop availability on property crime in the US, he finds an elasticity of property thefts to pawnshops of between 0.8 and 1.5.

[21] In a review of 102 studies, Guerette and Bowers (2009) find no systematic evidence of displacement of criminal activity following an intervention. About one fourth of studies find some displacement, yet it is never complete. However, about the same number of studies found diffusion of benefits.

[22] We are grateful to David de Meza for pointing this out to us and suggesting a more direct test we report below. See also the discussion in footnote 13.

resulting shocks in the relative value of criminal opportunities (Levitt 1998). Our situation is different, since shocks in the market value of stolen material affect the relative value of metal theft directly and observably. Thus, our setting is better suited for identification of substitution between criminal activities.

A direct way to test the substitution hypothesis is simply to regress the substitute criminal activities on copper prices. Since we only possess data on bicycle thefts, which is plausibly a substitute to metal theft, we reestimate regression (1) with the log of bicycle thefts as the outcome variable. Note that bicycle thefts and metal thefts are relatively comparable crimes in terms of frequency and magnitude of events (see Table 3); bicycle thefts are almost twice as frequent, but the average damage in our data is 16,800 CZK, or about 40% of the average metal theft damage. The results are reported in block G of Table 6. The estimates are mostly negative, which is consistent with the substitution hypothesis. In DOLS specifications that control for business cycle (unemployment, wages, and S&P 500), the estimated cross-elasticity is between -0.18 and -0.28 and statistically significant. However in most cases, the point estimates are smaller than this, not statistically significant, and often close to zero. When the largest estimate from block G is taken at face value, substitution between bicycle theft and metal theft may explain about 20–25% ($\approx 0.28/1.19$) of the price elasticity of copper thefts in our data in terms of the total damage, using the elasticity from specification (12) in Table 4.

Further Robustness Checks

The remainder of Table 6 offers additional specification checks. Blocks H, I, and J report the results of DOLS models from Table 4 with alternative numbers of leads and lags (one, three, and four) of differenced explanatory variables. The results are similar to the baseline DOLS estimates and the differences in coefficients are not statistically significant. To check the sensitivity of our results to our choice of price index, we then replace the log copper price with the log of composite prices, consisting of the LME prices of aluminum and copper with weights of 1/3 and 2/3, respectively. This choice was motivated by the results in Table 1, which suggest that these two metals constitute the bulk of metal thefts. The estimates of elasticity, reported in block K, are about 5–20 log points higher across the 12 specifications, but the differences are largely not statistically significant. This is consistent with our assertion, that using only copper price in our main specifications leads to conservative estimates (see Sect. 2.2). Lastly, in block L we replace the outcome variable, the log of the number of primary metal thefts, by the number of all thefts involving metals. That is, we include thefts whose primary object was something other than metal. The estimates of price elasticity for such metal thefts with respect to copper price are about 10–20 log points smaller, and four out of 12 estimates are smaller than one, but the distance is not statistically significant.

Discussion

Consistency with Recent Results from the United Kingdom

Two recent studies also analyzed the relationship between metal prices and metal thefts using data from the United Kingdom that covered time periods overlapping with our data. How consistent are their findings with our results from the Czech Republic?

Sidebottom et al. (2014) study data on copper cable theft from the British rail network covering January 2006 through April 2012. They estimate a first-difference regression of metal thefts on copper price, other railway theft, unemployment, and lagged metal thefts, all in logs (see their Table 3, p. 694). This regression is similar to our ECM model (9) in Table 5. Their estimate of the short-term elasticity of thefts with respect to copper price is 1.00 (s.e. 0.41), this is very close to our estimate of 0.89. Using our data, we ran a first-differenced regression that is more similar to theirs, of thefts on lagged copper prices, property and bicycle thefts, unemployment, and lagged thefts, which gave us short-term elasticity estimate of 1.19 (s.e. 0.34). When we run this regression on a subset of data covering the same time period as Sidebottom et al. (2014) data, the estimated elasticity is 1.31 (s.e. 0.36). Thus, estimates on Czech data are slightly higher but not statistically different from theirs.

The second study is by Draca et al. (2015), who analyze monthly data from London's Metropolitan Police Service covering metal thefts between 2002 and 2012. Unlike us, they have information on the type of metal stolen, so they can match prices of different metals with corresponding thefts. They, among other things, estimate 12-month-difference instrumental variable (IV) regressions, without and with a linear trend, of metal thefts on scrapyard metal prices. They instrument scrapyard prices with world prices and also report the corresponding OLS regressions of thefts on scrapyard and world prices, respectively (see their Table 7, p. 60). However, their OLS and IV estimates of the elasticity of metal thefts with respect to metal prices are substantively as well as statistically very similar, ranging from 1.32 (s.e. 0.11) to 1.49 (s.e. 0.14). These results are comparable in magnitude to our baseline estimates (1) and (7) in Table 4. In specifications (2) and (6), they also report corresponding (reduced-form) regressions of metal thefts on world prices, without and with a trend, reporting estimates of 12-month elasticities of 1.33 (s.e. 0.15) and 1.59 (s.e. 0.15), respectively. Running identical regressions in our data, we obtain estimates of 12-month price elasticity of thefts with respect to world copper prices of 1.39 (s.e. 0.20) and 1.46 (s.e. 0.17). In summary, Czech thieves react to changes in the value of their potential loot in the same manner and with similar consistency and responsiveness as their English colleagues.

Relevance for Criminology and Limitations

As mentioned in the Introduction, Loughran et al. (2016) point out that limited acceptance of rational theory of criminal behavior in criminology may have to do with its misperception as a theory about punishment and deterrence. This view may have been supported by the fact that economists have, indeed, focused mainly on "the stick" side of the theory. However, this focus is probably not just the profession's obsession with punishment and deterrence, rather the reason is that public policies and resources are primarily targeted at deterrence and economists have been simply trying to understand their efficacy.

Our contribution, together with the research of Draca et al. (2015) and Sidebottom et al. (2014), correct this lack of tests on "the carrot" side. One can now safely state that the economic theory of crime has now been tested—in different quasi-experimental setups—on both sides and has withstood. The main finding of these papers, showing a strong and consistent response of thieves to the value of criminal opportunities, in turn provides empirical backing for the situational crime prevention and policies that aim to reduce crime through reduction of criminal opportunities (Clarke 1997).

Loughran et al. (2016) have recently tested both aspects of the theory simultaneously. They analyze data on self-reported offending together with perceived measures of costs and non-monetary (psychological and reputational) benefits from crime in a longitudinal sample of adolescent felons from two US counties (one in Arizona and one in Pennsylvania). Estimating fixed effects models for three different types of crime (theft and robbery, drug-related, violent), they found a positive relationship between self-reported offending and the benefits from committing a crime and a negative relationship between the expected punishment and crime. They also found that legal earnings increase if the expected punishment increases and that earnings decrease if the benefits from crime increase. Analogous conclusions have been reached earlier in a widely cited study by Matsueda et al. (2006).

But finding consistency of human behavior with a theory doesn't speak to its relative importance *vis-á-vis* competing approaches. While it is beyond the scope of this article to undertake such assessment thoroughly, we offer a couple of observations that we think are of some relevance for this question. First, our empirical results might be used to gauge the relative strength of rational model of crime. When we look at our most parsimonious model reported in column (1) of Table 4, one can see that 81% of variation in metal-related crime is explained by changes in the value of stolen metal, seasonal effects, and linear trend. Most explanatory power, however, accrues to copper prices: when we regress only thefts on copper prices, the resulting r^2 is 0.72. The corresponding models (1) and (6) in Table 5, estimating thieves' short-term reactions, account for 71% of variation in monthly changes in metal thefts. Taken at face value, about one third of variation in criminal activity is left for other theories to be explained. Of course, this number cannot be extrapolated too far as it comes from a very specific criminal activity (although Draca et al. 2015, show that thieves' reaction to changes in the value of loot is similar for other objects of theft, such as mobile phones and bicycles and Loughran et al. 's 2016, results extend to violent and drug-related crimes). Nonetheless, it suggests, that, for understanding criminal behavior, the economic model of crime is highly relevant.

Second, these papers have a serious limitation in that they do not tell much about why and how people become, or cease to be, criminals. To what extent is the variation in criminal activity explained by the "usual suspects" optimizing across criminal opportunities and to what extent do better illegal opportunities attract otherwise law-abiding citizens into crime? This is hard to tell when looking only at criminals, or crime statistics, as we do in this paper. However, to the extent criminals are found to behave rationally, changes in costs and benefits of crime as well as changes in benefits from legal work should change their allocation of time between legal and illegal activities. Therefore, increasing the severity of punishment, decreasing the benefits from crime, or increasing the benefits of legitimate work should push rational criminals into legal activity and *vice versa*. This is what Loughran et al. (2016) have found. Of course, the relative importance of these factors and the effects of alternative policies are an empirical question. The take-home message from this research is that incentives do matter and that the benefits from crime as well as opportunities in the legal job market can play an important role in determining the extent of a criminal activity.

The Big Picture

But does this reasoning extend to the whole population? An extreme prediction of the rational theory is that everyone would commit a crime, provided the benefits are high enough (and the costs low). This seems far-fetched. However there is anecdotal evidence from formerly communist countries in Eastern Europe that is consistent with this prediction. Due to their orientation on heavy industry, lack of private businesses, and absence of competitive forces in their centrally planed economic systems, these countries were characteristic with scarcity and low quality of consumer goods. This led to shortages and development of shadow economy including black markets with goods stolen from the state. According to some accounts, stealing was widespread in these economies, which is illustrated by the saying from then Czechoslovakia: "If you don't steal, you are robbing your family" (Crampton 2002, p. 252).

Stealing was not driven by shortages only, but also by ample opportunities—a result of swelled, yet weakly protected, state ownership: "Stealing is that when a person steals personal belongings from another [...] taking away or 'procuring' of material which more or less does not belong to anybody [...] is definitely not stealing" (Brown 2008, p. 72). Although crime data from communist era are unreliable, so that time comparison is problematic, some accounts suggest that in Russia stealing further increased after the collapse of Soviet Union as a result of state failures in enforcement and rigged privatization.[23]

In this context, the consistency between our current findings for the Czech Republic with the results from the United Kingdom—despite differences in culture, language, history, and especially post World War II development—is even more striking. We interpret this anecdotal evidence, together with our results and the body of research on economic theory of crime, as demonstrating that legal opportunities together with costs and benefits of crime are important determinants of acquisitive crime. This means that a prosperous economic system generating opportunities to earn a decent living is necessary for crime control.

Conclusion

The rational choice theory has one important advantage. It allows us to think of criminal behavior in a similar manner as when we are studying the behavior of people engaging in lawful activities, enabling us to make use of the well developed toolbox of decision theory and microeconomics. In addition, the rational choice and the importance of criminal opportunities form the backbone of the situational crime prevention literature, which has led to development of an array of policy tools that aim to reduce crime through reduction of criminal opportunities (Clarke 1997, 2012; Cornish and Clarke 2003; Felson and Clarke 1998; Wortley 2001). It is therefore important to understand to what extent the rational model explains criminal activity.

We have subjected the supply side of the rational theory of crime to an extensive test in a quasi-experimental set-up. We interpret our results as robustly consistent with the economic theory—the supply of thefts is upward sloping and our estimates suggest that Czech metal thieves are highly responsive to changes in returns to crime. Finally, we stress that our results closely match the earlier results in Sidebottom et al. (2014) as well as recent findings by Draca et al. (2015) from the United Kingdom—a country with different legal

[23] See "In Russia, Stealing Is a Normal Part of Life," Los Angeles Times, Online, September 21, 1998, at http://articles.latimes.com/1998/sep/21/news/mn-25012 (last accessed on June 28, 2016).

system, language, ethnic composition, as well as recent history—suggesting that these patterns are more general. We must conclude that opportunity makes the thief.

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Appendix

See Fig. 5.

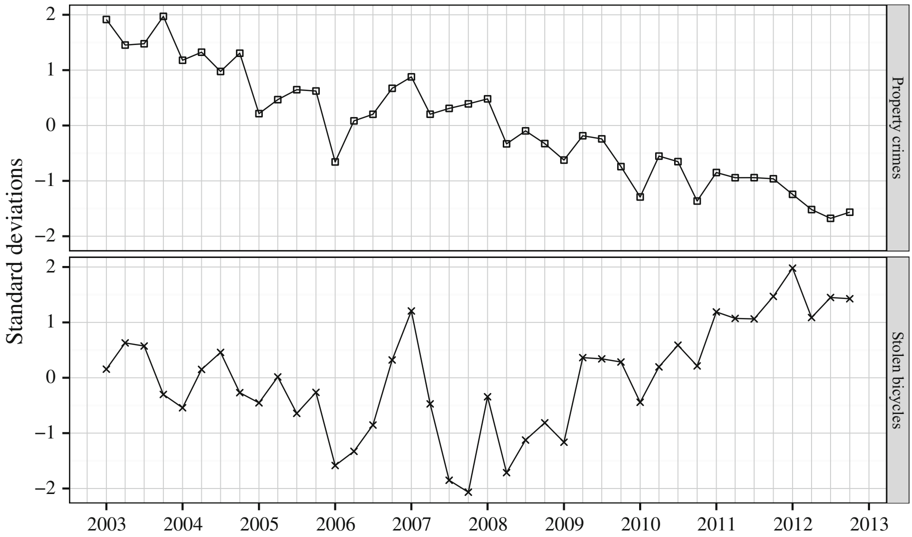

Fig. 5 Property crime and bicycle theft (that qualify as crime) reported to the Czech Police (z-scores of quarterly averages). Data are deseasoned, mean centered, and divided by respective standard deviations

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