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Criminals and the Price System: Evidence from Czech Metal Thieves*

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This paper estimates the elasticity of the supply of offenses with respect to the gains from crime. People steal copper and other nonferrous metals to sell them to a scrap yard. Simultaneously, the prices at scrap yards are set at the world market. We argue, that shocks in metal prices represent a quasi-experimental variation in gains from crime. This allows us to estimate behavioral parameters of supply of offenses and test the economic theory of criminal behavior. Our estimates suggest that the long-run elasticity of supply of metal thefts with respect to the re-sale value of stolen metal is between unity and 1.5. Moreover, the system tends to equilibriate quickly—between 30 and 60 percent of a disequilibrium is corrected the following month and the monthly price elasticity estimates are between 0.9 and unity.

Key words: economics of crime, gains from crime, metal theft, rational model.
JEL classification: K42, Q31, Q32.

1 Introduction

Does opportunity make a thief? This paper exploits a quasi-natural experiment in the values of stolen goods in order to test the predictions of the economic theory of crime (Becker 1968; Ehrlich 1973; Posner 1985).[1] The theory views a criminal act as a rational decision: whenever the benefits exceed the costs, a crime is attempted. The model's

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[1]The origins of the approach can, however, be traced back to Beccaria (1995 [1764]) and Bentham (1823, 2008 [1830]). For an overview article see Ehrlich (1996).

main prediction is that a change in punishment or the probability of apprehension should, everything else the same, result in a change of criminal activity. This is because the cost-benefit ratio reverses for marginal crimes.

Testing the model has proved notoriously difficult for the lack of experimental variation in punishment severity and enforcement. The problem is that policy shocks, such as changes in punishment severity or enforcement, are likely to reflect shocks in criminal activity. In fact, Tsebelis's (1989) model, treating enforcement as fully endogenous, indeed 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, Montag (forthcoming) who investigates the effects of a substantial increase in sanctions for traffic law offenses in the Czech Republic. The immediate effect of the change was a one third decline 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, the traffic police enforcement activity (but not manpower) was declining.

Finding an exogenous source of variation in determinants of the value of criminal activity is thus crucial component in the empirical research of 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 shocks in the geographic allocation of police force following a terrorist attack in Buenos Aires and, in a similar vein, and Klick and Tabarrok (2005) use the shocks to police presence in Washington, D.C. following changes in the terror alert levels. All four papers find that the police deters crime.

In this paper, we test the economic theory of criminal behavior using exogenous variation in gains from crime that accrue to the thieves. This way, we complement the existing body of of literature studying mainly shocks in repression. Our approach has the distinctive advantage that it directly tests the economic nature of decisions about criminal activity. This is because shocks in the market value of stolen goods produce changes in the cost-benefit ratio of associated crimes, which are purely monetary in nature. However, the existing literature testing the relationship between criminal behavior and the gains from crime has been plagued by lack of good measures of gains from crime and yielded contradictory results. Chisholm and Choe (2005) provide an overview of this literature and an excellent discussion of the measurement issues involved. In this paper we make use of a clear-cut measure of gains from crime—that is the market value of the stolen goods.

Specifically, we examine how the metal thieves in the Czech Republic respond to changes in prices of nonferrous metals. For them, the metal is of no value, except that it can be sold to a scrap yard. Thus the benefits from a metal theft depend directly on the price of a specific metal. At the same time, nonferrous metals are commodities and their prices determined at the world market, with most futures transactions taking place at the London Metal Exchange (LME).[2] For copper, which is the most important object of metal thefts we show that this price information is then transferred to other copper markets including scrap markets.[3] We argue that this setup represents a quasi-natural experiment allowing us to test the causal links postulated by the economic model of criminal behavior and estimate the elasticity of the 'supply of offenses' (Becker 1968) with respect to the gains from crime.

Understanding the behavioral background behind metal thefts is also important because this criminal activity represents a serious economic, safety, and security issue. Although many metal thefts may result in little or no damage, this is not true for the entire population. The average value of stolen material per theft in our data is 33,000 CZK ($1,500) and the average damage is about 40,000 CZK ($1,800), approximately a double of the average net monthly wage in the country. 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.[4] Sidebottom, Ashby, and Johnson (forthcoming)

[2]The London Metal Exchange is the world's largest market in options and futures contracts on base and other metals; more than 80 percent of all nonferrous metal futures business is transacted on LME platforms (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.pdf, last accessed October 3, 2014).

[3]See also Aruga and Managi (2011), Labys, Rees, and Elliott (1971), and Watkins and McAleer (2004).

[4]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 October 5, 2014); "Czech metal thieves dismantle 10-ton bridge," The Telegraph, Online, April 30, 2012, at http://www.telegraph.co.uk/news/

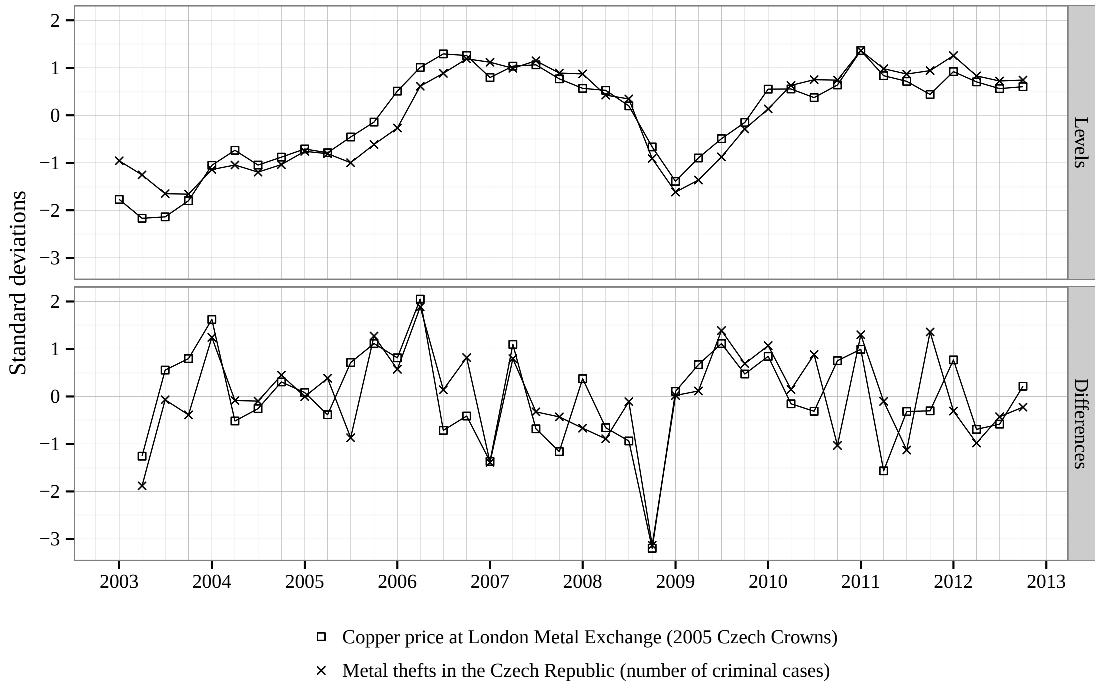

Figure 1: Copper prices and the number of criminal cases involving nonferrous metals reported to the Czech Police (quarterly averages, thefts are lagged by one month). Data are deseazoned, demeaned, and divided by respective standard deviations.

document the large number of "live" copper cable thefts from the British railway network; live cables distribute electricity to trains but also to line side signals. Apart from threats to safety, these crimes result in large damage not only in stolen material and delays, but also in replacement and repair cost; these costs are often disproportionate to the value of stolen metal. In the United States: tornado warning sirens were rendered inoperable because they were stripped of copper wiring; power outage resulted from copper wires being stolen from a transfomer (damage $500,000); lastly, loss of crops occurred due to wires being stolen from irrigation wells (total loss of $10 million).[5]

Perhaps, it is not a coincidence that the last three events happened in 2007 and early 2008 while copper prices were at historically high levels. And, the three bridges were

newstopics/howaboutthat/9235705/Czech-metal-thieves-dismantle-10-ton-bridge.html (last accessed on October 5, 2014); 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 October 5, 2014).

[5]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 October 5, 2014) and resources therein. For policy papers on costs of metal thefts, further background, and potential measures see Bennett (2008, 2012a,b); Kooi (2010); and Lipscombe and Bennett (2012).

stolen between 2011 and 2013 after the copper prices returned to the levels from mid 2000s. The relationship between thefts and prices in our data is shown in Figure 1, which plots levels and first differences of normalized and deseazoned quarterly series of copper prices at the London Metal Exchange and metal thefts in the Czech Republic. From the top panel it is apparent that prices and thefts are tightly correlated. Because, one may be worried that the correlation is driven by some third variable, such as business cycle, the bottom panel plots first differences of the two series. Differencing removes the common component, however the co-movement is still apparent in the two series.

We are not the first to examine the relationship between metal prices and thefts. Sidebottom, Belur, Bowers, Tompson, and Johnson (2011) and Sidebottom, Ashby, and Johnson (forthcoming) study the relationship between copper prices and the number of police recorded copper cable thefts from the British railway network and find elasticities of thefts with respect to copper price to be around three and unity, respectively. Similarly, Posick, Rocque, Whiteacre, and Mazeika (2012) report a positive a correlation between metal prices and the number of instances of stolen metal from commercial and residential dwellings in Rochester, NY.

This paper complements and extends these earlier studies. It differs in three main respects: (i) We posses a very detailed crime-level dataset of all nonferrous metal-related thefts in the Czech Republic, which occurred during the ten-year period from 2003 until 2012.[6] (ii) We offer a more involved analytical approach. Specifically, economic theory predicts that there exists an equilibrium relationship between gains from crime and criminal activity, that is the supply of offenses. Such a relationship, simultaneously, requires the existence of a short-run 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). (iii) Last, our data allow us to perform extensive sensitivity analyses and perform number of robustness checks in order to address concerns and alternative explanations of our findings.

[6] Sidebottom, Ashby, and Johnson's (forthcoming) data cover the period from January 2006 until April 2012 and include only thefts of cables from the British rail network.

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-run equilibrium relationship between gains from crime and the supply of offenses. Then we recover the parameters of the error-correction mechanism, which animates the real-time adjustments to shocks and determines the rate at which disequilibria are corrected. We find the long-run elasticity of metal thefts with respect to the re-sale value of stolen metal to be around unity. The short-run (monthly) elasticity is estimated between 0.9 and unity. In addition, the system tends to equilibriate quickly—between 30 and 60 percent of a shock is predicted to be corrected the following month. These results are robust to alternative specifications, controlling for general crime trends, enforcement intensity, business cycle, weather, and political cycle. Importantly we show that our results are not an artifact of a purely mechanical correlation between the volume of recorded crimes and prices of stolen goods.

2 Data

Crime data analyzed in this paper were drawn from the Registration-Statistical System of Criminality database[7] managed by the Police Presidium of the Czech Republic. The database records all criminal offenses handled by the police. We have received data on all criminal cases in which one of the objects of the crime were nonferrous metals, in total 44,613 records from the period 2003–2012. The raw data set contains information on criminal classification of each offense, its location, the date the police learned about the case, the primary and secondary object of the crime, as well as whether, how, and when the case ended. We focus on primary metal thefts, that is thefts with metals being the primary object of interest of the thief.[8]

However, the database we have received has two deficiencies: (i) Notably, one of criteria for a theft to qualify as a crime is a damage in excess of 5,000 CZK. Because the

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

[8]Crimes classified as thefts represent 94.8 percent of all nonferrous metal-related crimes in the data. Primary metal thefts represent 80.0 percent of thefts in the data, that is, in 20 percent of cases the primary object was not metal (the two most frequent primary objects in this category are tools and money). As a robustness check, we report also estimates with all metal-related thefts.

data contains only cases known to the police and classified as crimes, this may produce selection bias in our results due to a mechanical correlation between metal prices and the damage, because marginal offenses may simply become crimes, and enter the data, when prices rise and *vice versa*. Note, however, that the 5,000 CZK is sufficient but not necessary condition. For instance, an offense qualifies as a crime 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 a crime irrespective of the damage. In fact, 34.6 percent of thefts in our data involved a break-in. We exploit this information later to check the robustness of our results. (ii) There is no information as to which particular metal was stolen. To proceed without knowing the mix of stolen metals, we first had to determine the relevant price index. The previous literature suggests that copper is probably the most often stolen nonferrous metal (Bennett 2008, 2012a; Kooi 2010; Posick et al. 2012; Sidebottom et al. 2011 Sidebottom, Ashby, and Johnson forthcoming). Copper price is thus the first candidate.

In order to verify this contention we have retrieved all mentions of metal theft related to aluminum, copper, lead, nickel, tin, and zinc using a media monitoring service Anopress.cz. Means and medians of monthly counts of articles reporting thefts of these metals are reported in Table 1. Based on this evidence, the most often stolen metal is copper followed by aluminum; other metals seem to play a much lesser role. We then estimated Pearson correlation coefficient between the number of 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 $r = 0.02$, whereas for copper it is $r = 0.87$ (t-statistic 19.15). From this, we believe, it is safe to conclude that copper is the most relevant price component and we therefore use copper price as the 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, using only copper introduces in either pure measurement error or an error which is negatively

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

	Aluminum	Copper	Lead	Nickel	Tin	Zinc
Mean	52.17	89.52	1.90	1.07	2.72	0.83
Median	53.00	92.50	1.00	0.00	2.00	0.00
Correlation with primary metal thefts	0.02	0.87*	−0.04	0.14	-0.19^{+}	0.23^{+}
	(0.27)	(19.15)	(−0.43)	(1.53)	(−2.15)	(2.56)

Note: The unit of observation is a month, data range from January 2003 to December 2012. Primary metal thefts are those with non-ferrous metals being the primary object of interest of the thief. Data source: Anopress.cz. t-statistics are in parentheses: $^{+}p < 0.05$, $^{*}p < 0.01$.

correlated with copper price.[9] Both types of measurement error should result in biasing our coefficients towards zero, making our estimates conservative.

Next, we wanted to ascertain whether prices faced by Czech metal thieves are driven by the world market. For this purpose we have been able to collect daily data on metal prices from a scrap yard in Prague. The dataset covers the period from July 2006 to April 2011 and contains prices of copper (sheets and wires), aluminum (sheets and pieces), lead (pieces), and zinc (sheets). We then aggregated the data to obtain monthly average prices and merged it with monthly metal prices at the London Metal Exchange, available from the World Bank's GEM Commodities database, multiplied by the exchange rate. We then run simple regressions of scrap yard prices on LME prices (all in logs). Results, reported in Table A1 in the Appendix, show that copper prices are very closely related: one percent change in copper price at LME is predicted to change prices at the Czech scrap yard by 1.03 percent (s.e. 0.04, r^2 0.97), which is not statistically different from unity. This finding is consistent with earlier results in Aruga and Managi (2011). From this exercise we conclude that copper prices from LME can be safely used as proxy for prices faced by Czech metal thieves.

To obtain the estimation dataset, we aggregate the police data to the monthly level and merge it with average monthly metal prices at the London Metal Exchange available from the World Bank's GEM Commodities database. Prices are then multiplied by the CZK/USD exchange rate and divided by the Czech consumer price index to obtain real

[9]Intuitively, a drop 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 percent. As a robustness check we used an index consisting of copper and aluminum prices, but there is no appreciable change in results.

Table 2: Summary statistics

	Mean	St. Dev.	Min	Median	Max
Metal thefts (primary):					
Thefts	282.0	134.7	61	280	516
Damage per theft (1000 CZK)	36.1	10.1	21.2	34.4	82.0
Stolen value per theft (1000 CZK)	31.1	8.3	16.9	30.4	61.6
Detection rate (% in 30 days)	25.7	4.7	14.8	25.2	38.4
Copper price (CZK / kg)	107.5	32.8	46.7	115.1	173.6
Number of stolen bicycles	526.0	236.4	167	540.5	1050
Number of property crimes	18419.2	1760.7	13668	18376.5	22376
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	1204.4	180.0	757.1	1212.1	1539.7
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
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				

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

prices. To control for potential confounding factors, we merge the data with series on property crimes, stolen bicycles, monthly unemployment rate, index of quarterly average gross wage (we intrapolate wage data to obtain monthly series), monthly averages of Standard & Poors 500 Index, territorial air temperature, and rainfall. Because a new Criminal Code was introduced in 2010, we also create an indicator variable which is switched on from January 1, 2010. Finally, in order to control for political cycle we create dummies for pre- and post-election years separately for regional and parliamentary elections. Table 2 summarizes the final dataset.[10]

3 Methodology and Results

Our empirical model of criminal activity is straightforward: Let y_t be the natural logarithm of the number of primary metal thefts and p_t the natural logarithm of monthly average copper price, respectively. Both variables are observed at monthly level, where t

[10]The data and code are available from the authors upon request.

denotes a year-month. As a candidate regression consider

$$y_t = \beta_0 + \beta_1 p_t + \boldsymbol{\beta_2 x_t} + \epsilon_t, \tag{1}$$

where $\boldsymbol{x_t}$ 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, it estimates the elasticity of supply of metal thefts with respect to copper price. Because both y_t and p_t are non-stationary and integrated of order one, equation (1) is a valid estimator only if y_t and p_t are cointegrated of order zero (Engle and Granger 1987; Murray 1994).[11] 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]

3.1 The Equilibrium Relationship

Specifications (1) through (6) in Table 3 report alternative estimates of regression (1) with p-values of augmented Dickey-Fuller (ADF) tests of nonstationarity of residuals for each specification are reported at the bottom. With one exception, nonstationarity is always rejected at 5 percent level. This suggests the existence of long-run equilibrium relationship between copper prices and metal thefts, which can be estimated using the levels estimator (1). Because Durbin-Watson tests always reject the absence of autocorrelation of residuals, as reported at the bottom of Table 3, reported standard errors were computed the using Newey and West's (1987) estimator, which is robust to heteroskedasticity and autocorrelation.

Specification (1) reports results of a simple regression of metal thefts on copper price and a full set of month dummies to control for seasonal regularities and number of days in a month. The coefficient estimate on copper price suggests the price elasticity of supply of offenses is 1.34 and with the estimated standard error of 0.14 it is statistically significant

[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).

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

Table 3: Levels estimates of the effect of copper prices on nonferrous metal thefts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log copper price	1.34*	1.40*	1.34*	1.05*	1.05*	0.90*	1.41*	1.49*	1.47*	1.09*	1.10*	1.00*
	(0.14)	(0.13)	(0.13)	(0.10)	(0.09)	(0.13)	(0.10)	(0.13)	(0.11)	(0.17)	(0.17)	(0.30)
Log stolen bicycles		0.47^{+}	0.07	0.31	0.31	0.32		0.65*	0.08	0.23	0.27	0.22
		(0.22)	(0.25)	(0.16)	(0.17)	(0.17)		(0.20)	(0.28)	(0.29)	(0.29)	(0.22)
Log property crimes		0.51	1.51*	1.28*	1.21*	0.89*		0.71	1.82*	0.95	0.95	−0.33
		(0.42)	(0.59)	(0.34)	(0.36)	(0.32)		(0.53)	(0.66)	(0.90)	(0.92)	(0.85)
Lagged detection rate (% in 30 days)			−0.01	0.003	0.005	0.01			−0.01	0.005	0.005	0.04^{+}
			(0.01)	(0.01)	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)	(0.01)
New Criminal Code (=1)			0.30^{+}	0.49*	0.50*	0.37*			0.30*	0.42^{+}	0.41^{+}	0.15
			(0.13)	(0.12)	(0.12)	(0.10)			(0.11)	(0.18)	(0.19)	(0.13)
Unemployment rate (%)				−0.14*	−0.14*	−0.11*				−0.11*	−0.11*	−0.07
				(0.03)	(0.03)	(0.03)				(0.04)	(0.04)	(0.04)
Real wage index$\times$100				−0.005	−0.01	0.001				−0.001	−0.001	0.01
				(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.01)
Log S&P 500				0.44	0.42	0.58^{+}				0.35	0.32	0.47
				(0.25)	(0.26)	(0.26)				(0.38)	(0.40)	(0.65)
Log rainfall					0.02	0.03					0.01	0.01
					(0.02)	(0.02)					(0.02)	(0.02)
Air temperature (° C)					0.02^{+}	0.02^{+}					−0.004	−0.004
					(0.01)	(0.01)					(0.01)	(0.01)
Parliamentary elections:												
Year before						−0.09^{+}						−0.27*
						(0.04)						(0.07)
Year after						−0.01						−0.01
						(0.06)						(0.05)
Regional elections:												
Year before						−0.10						−0.05
						(0.06)						(0.04)
Year after						−0.13^{+}						−0.11^{+}
						(0.06)						(0.05)
Constant	−0.64	−8.43^{+}	−15.72*	−15.13*	−14.23*	−12.56*	−1.02^{+}	−12.00^{+}	−19.29*	−11.69	−11.65	−2.11
	(0.63)	(4.26)	(5.53)	(4.43)	(4.44)	(3.88)	(0.47)	(6.03)	(6.22)	(10.58)	(10.84)	(9.15)
Month effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOLS	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120	120	119	119	119	119	115	115	114	114	114	114
Adjusted R^2	0.80	0.82	0.85	0.92	0.92	0.93	0.88	0.90	0.92	0.94	0.94	0.96
Augm. Dickey-Fuller t. (p-value)	0.047	0.037	0.068	< 0.01	< 0.01	< 0.01	0.078	0.020	< 0.01	< 0.01	< 0.01	< 0.01
Durbin-Watson test (p-value)	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.000	0.000	0.000	0.047

Note: 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 two leads and lags of first-differenced integrated explanatory 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: $^{+}p < 0.05$, $^{*}p < 0.01$.

at an arbitrary level. In order to control for general crime trends, specification (2) includes log of the number of stolen bicycles in a month and the number of property crimes (both time series are plotted in Figure A1 in the Appendix). Bicycle thefts are comparable criminal activity to metal thefts in terms of required sophistication as well as in terms of the damage. But bicycle thefts are unlikely to be (directly) driven by metal prices for bicycles are typically stolen to be resold in used bicycle market rather than to a scrap yard. Controlling for property and bicycle thefts, however, does not appreciably change the estimated elasticity, however. Specification (3) adds lagged percentage of detected thieves and a dummy for the 2010 Criminal Code. The coefficient estimates on these controls should be read with caution as the detection rate is likely to be influenced by criminal activity and the new Criminal Code did not bring any substantive change in the treatment of thefts. Notwithstanding those concerns, the coefficient estimate on log copper price is almost the same as in specification (1) and is not statistically different from estimate in specification (2). 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. As a result, the estimate on copper price decreases to 1.05 and with standard error 0.10 remains highly statistically significant. Note, however, that these controls are problematic, as economic shocks are likely to affect demand for metals and thus metal prices. This is consistent with the negative coefficient estimate on unemployment and positive estimate on S&P 500, that is opposite signs than one would expect if business cycle was negatively correlated with criminal activity. This suggest, we are 'overcontrolling' in this specification and the price elasticity of metal thefts is underestimated. Less controversially, specifications (5) and (6) control for weather shocks and political cycle. Weather does not alter the results but controlling for pre- and post-election years results in a small decline in the estimate of the elasticity to about 0.90, but this result is not statistically different from 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 better estimates of the cointegrating relationship (Saikkonen 1991; Stock and Watson 1993).

Reported DOLS estimators are obtained by augmenting the levels estimators with first differences of explanatory variables and two leads and lags of differenced explanatory variables.[13] We re-estimate DOLS models for specifications (1) through (6) in Table 3. The results are reported in columns (7) through (12) and the estimates of elasticities are qualitatively similar, albeit are slightly higher, to the simple levels models estimates. To summarize, we provide a range of estimates and leave it to readers to assess which model is preferable. Yet, the results of 12 alternative regression estimates reported in Table 3 strongly suggest that the price elasticity of supply of metal thefts is certainly greater than zero and most likely lies between unity and 1.5.

3.2 Short-Run Corrections

Cointegration evidences a long-run equilibrium relationship between between copper price and metal thefts. This requires that there is a mechanism correcting transitory deviations from that equilibrium (Engle and Granger 1987; Murray 1994). The error-correction mechanism (ECM) can be written as

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

where ϵ_{t-1} is the distance between the realized y_{t-1} and its equilibrium value in the previous period. In words, the change in y is given by its preceding deviation from the equilibrium 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 negative sign. The vector $\boldsymbol{\gamma}$ captures short-run reaction of y to shocks in explanatory variables. Because the residual series from levels regressions estimate the equilibrium error, equation (3) can be estimated as

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

[13]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 number of leads and lags yields qualitatively similar results (see Table 5).

Table 4: Error-correction models of copper prices and nonferrous metal thefts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged residuals from levels models	−0.28*	−0.28*	−0.34*	−0.41*	−0.40*	−0.30*	−0.32*	−0.38*	−0.59*	−0.49*
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)	(0.07)	(0.08)	(0.13)	(0.11)
Lagged differences:										
Log copper price	0.49	0.48	0.46	0.53	0.62*	0.97*	1.00*	0.98*	0.88*	0.93*
	(0.29)	(0.28)	(0.26)	(0.29)	(0.22)	(0.29)	(0.28)	(0.34)	(0.30)	(0.23)
Log stolen bicycles		-0.30^{+}	−0.20	-0.24^{+}	−0.09		−0.27	-0.29^{+}	-0.27^{+}	−0.11
		(0.12)	(0.11)	(0.11)	(0.12)		(0.14)	(0.12)	(0.10)	(0.11)
Log property crimes		0.20	−0.08	−0.05	−0.04		0.17	0.18	0.16	0.16
		(0.28)	(0.18)	(0.20)	(0.20)		(0.29)	(0.14)	(0.16)	(0.16)
Lagged detection rate (% in 30 days)			0.002	0.0002	0.001			0.001	0.001	0.001
			(0.002)	(0.002)	(0.003)			(0.003)	(0.002)	(0.003)
Unemployment rate (%)				−0.01	−0.05				0.02	−0.01
				(0.05)	(0.06)				(0.04)	(0.04)
Real wage index × 100				0.02	0.002				−0.0000	−0.01
				(0.01)	(0.01)				(0.01)	(0.01)
Log S&P 500				0.61^{+}	0.68				0.33	0.40
				(0.31)	(0.41)				(0.23)	(0.30)
Log rainfall					0.01					0.01
					(0.01)					(0.01)
Air temperature (° C)					0.02*					0.02*
					(0.01)					(0.005)
Constant	0.52*	0.39*	0.41*	0.34*	0.50*	0.52*	0.41*	0.39*	0.38*	0.53*
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)	(0.07)
Month effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Error correction terms from DOLS	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Observations	118	118	117	117	117	115	115	114	114	114
Adjusted R^2	0.71	0.71	0.73	0.72	0.76	0.71	0.71	0.71	0.72	0.75
Augm. Dickey-Fuller t. (p-value)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Durbin-Watson test (p-value)	0.858	0.986	0.507	1.000	0.838	0.250	0.433	0.447	0.758	0.517

Note: 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 3. 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: $^{+}p < 0.05$, $^{*}p < 0.01$.

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

Table 4 reports the results of ECM models analogous to specifications (1) through (5) and (7) through (11) in Table 3.[14] The first row reports estimates on the respective equilibrium error terms. For models (1) through (5) in Table 4 the equilibrium error term is the residual series from the respective regressions in Table 3. Models (6) through (10) include the residual series from respective DOLS models. Both sets of estimates yield comparable results however. The coefficient estimates on the error-correction term are between -0.28 and -0.59 and are always highly statistically significant. These numbers suggest that a disequilibriating shock is corrected within two to four months. The second row of estimates reported in Table 4 reports estimates of short-run (monthly) price elasticity of supply of metal thefts. The results for OLS models suggest that the short-run elasticity is around 0.5, with one exception, however, these estimates are only marginally statistically significant. Models with error term from DOLS specifications produce the estimates of short-run elasticity between 0.9 and unity and all estimates are highly statistically significant. We note that, to the extent DOLS levels models are preferable, ECM models that include equilibrium error terms estimated by DOLS should be preferred as well.

3.3 Gauging the Selection Concerns

As noted in Section 2, one of the criteria for an offense to be qualified as crime is that the damage is 'non-negligible', which in practice means it should exceed 5,000 CZK. Recall also that the 5,000 CZK is sufficient but not necessary condition. This has two potentially important implications: (i) Because the cost of committing a crime is discontinuous at the threshold, individuals have incentives to avoid exceeding it. As a result, rising price of copper may lead to increased number of 'sub-crime' level thefts. Unless some other crime-qualifying condition is met, these thefts do not qualify as crime and thus are not recorded in the crime database. This may imply that our estimates of elasticity of supply of offenses may be too conservative. (ii) More worryingly, however, as

[14] Note that ECM models do not include dummies for the new Criminal Code and pre- and post-election years for there would be no sensible interpretation of coefficients estimates on differenced dummies in ECM regressions.

the damage from metal thefts and the value of stolen material are linked to metal prices—if metal prices rise a specific theft is likely to be associated with larger damage and *vice versa*. This is problematic because 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 the reaction of criminals to prices.

The direction and extent of the actual bias depends on four main factors: the weight of stolen material on the total damage; the weight of crimes around the threshold on total criminal activity; whether and how are price changes incorporated in determination of the size of the damage; and the amount of control thieves have about the damage they cause. Being conservative and assuming that thieves can well chose the size of the damage and that prices are fully reflected in the claimed damage, the first two factors are the most important. Because the average damage per theft is 37,000 CZK and the average value of stolen goods is 30,500 CZK, the weight of stolen material on total damage is around 80 percent (see Table 2).[15]

Because our data include crimes with damage below the 5,000 CZK threshold, that is crimes for which another crime-qualifying criterion (e.g. breaking into and object) was met, we may further investigate, whether our main finding can be 'explained away' by selection into the sample. If this was the case, one would expect discontinuity in the distribution of metal theft-related damages. Figure 2 therefore plots distributions of damages from recorded crimes in respective years. Looking at the estimates of probability density and probability mass functions at the two top panels of the figure, respectively, there is no apparent discontinuity at the 5,000 CZK threshold. While it is possible that prices affect the rate at which metal thefts qualify as crimes, it is unlikely that this factor explains almost 250 percent increase in thefts between 2003 and 2011 (the years with minimum and maximum number of metal thefts, respectively). A more complete picture is provided in the bottom panel with boxplots of damages for individual years. First, boxes are always above the 5,000 CZK threshold suggesting that over 75 percent of crimes in

[15]This figure seems, however, quite high, considering, that the total damage includes all the cost resulting from theft, including replacement of stolen material, labor, as well as forgone income, if applicable. The raw metal thus probably represents a smaller portion of the costs. Nonetheless, it is the reported damage that relevant for the determination whether a theft is to be prosecuted as a crime.

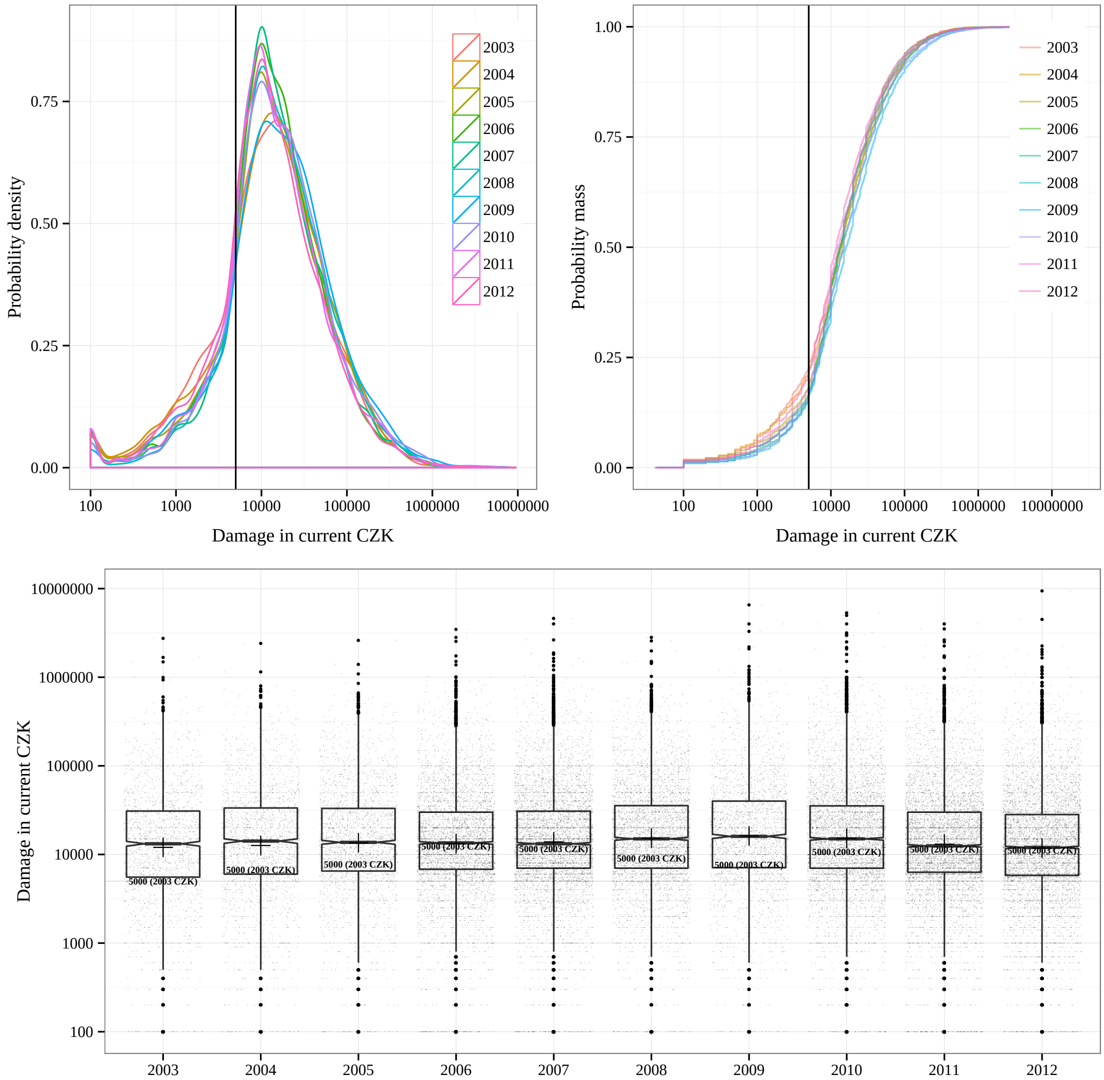

Figure 2: Damage from individual metal thefts (damage below 10 CZK is coded as 10 to save space). The 5,000 (2003 CZK) series in the bottom plot denotes the value of the damage associated with a hypothetical theft with damage worth 5,000 CZK-damage in 2003 prices. The value of that damage in following years was computed assuming that the value of stolen copper is 80 percent of the damage (i.e. one half of the damage was adjusted to reflect the changes in copper price and the other was adjusted by the consumer price index). The upper and lower ‘hinges’ 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 percent confidence interval for comparing medians (McGill, Tukey, and Larsen 1978).

the data result in a damage above the threshold. Boxplots are overlaid with jitter with each point represents a damage associated with an individual metal theft. Darker parts of the plot suggest higher frequency of thefts at the respective damage level. It is visually apparent that years with higher number of recorded crimes have experienced a rise across the whole spectrum of damages, rather than shift upwards.

Yet, this graphical evidence cannot rule out the concern that our main estimates overstate the effect of prices on crime. Note that 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 specifications from Table 3. Results are reported in block A of Table 5 and suggest that the relationship actually negative, although it is substantively small and statistically significant only in four out of 12 specifications.[16] Block B reports coefficients on log copper price in specifications where the outcome is replaced by log average value of stolen goods per theft. The results are, however, qualitatively very similar; the relationship between copper price and average value of stolen material is consistently 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, large-value thefts are likely to be undertaken under a wide range of copper prices. So, if copper price increases, new thefts, if any, will be more often low-value marginal thefts. And if copper price goes down, low-value theft opportunities will not be exploited for they are no longer worth it. This result thus supports our claim, that thieves react to changes in the value of criminal opportunities.

To further probe this issue, we reestimate the models from Table 3 with the outcome variable being computed as the monthly average number of metal thefts with damage below 5,000 CZK. 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 have exceeded the 5,000 CZK margin. If

[16]Note that, using 10 percent level, the augmented Dickey-Fuller tests fail to reject nonstationarity of residuals from specifications (1) and (7), so those results should be interpreted with caution.

Table 5: Gauging the selection concerns and further robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Outcome replaced by log of mean damage	−0.08	−0.18^{+}	−0.17^{+}	−0.06	−0.05	−0.04	−0.12	−0.26*	−0.35*	−0.32	−0.34	−0.04
	(0.07)	(0.07)	(0.07)	(0.15)	(0.14)	(0.19)	(0.09)	(0.09)	(0.07)	(0.30)	(0.37)	(0.40)
	[0.38]	[0.16]	[0.19]	[0.01]	[0.01]	[0.01]	[0.65]	[0.44]	[0.46]	[0.01]	[0.01]	[0.01]
B: Outcome replaced by log of mean stolen value	−0.13^{+}	−0.17*	−0.18*	−0.15	−0.15	−0.16	−0.17^{+}	−0.23*	−0.29*	−0.41	−0.44	−0.17
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.18)	(0.08)	(0.07)	(0.07)	(0.26)	(0.26)	(0.38)
	[0.56]	[0.36]	[0.35]	[0.01]	[0.01]	[0.01]	[0.57]	[0.38]	[0.42]	[0.02]	[0.02]	[0.01]
C: Value of stolen material less than 5,000 CZK[a]	1.21*	1.20*	1.12*	0.95*	0.96*	1.16*	1.27*	1.21*	1.25*	1.49*	1.53*	1.65*
	(0.15)	(0.13)	(0.12)	(0.26)	(0.27)	(0.27)	(0.15)	(0.16)	(0.13)	(0.40)	(0.39)	(0.38)
	[0.14]	[0.04]	[0.07]	[0.01]	[0.01]	[0.01]	[0.32]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
D: Total damage less than 5,000 CZK[b]	1.22*	1.23*	1.15*	0.90*	0.91*	0.99*	1.32*	1.31*	1.35*	1.19*	1.22*	1.07*
	(0.17)	(0.15)	(0.13)	(0.20)	(0.21)	(0.25)	(0.15)	(0.18)	(0.11)	(0.37)	(0.38)	(0.33)
	[0.10]	[0.04]	[0.05]	[0.01]	[0.01]	[0.01]	[0.22]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
E: Only thefts involving break-in[c]	1.40*	1.24*	1.16*	0.77*	0.75*	0.64*	1.48*	1.28*	1.23*	0.94*	0.96*	0.80*
	(0.19)	(0.15)	(0.13)	(0.09)	(0.08)	(0.14)	(0.20)	(0.19)	(0.11)	(0.18)	(0.16)	(0.23)
	[0.06]	[0.20]	[0.08]	[0.01]	[0.01]	[0.01]	[0.03]	[0.14]	[0.01]	[0.01]	[0.01]	[0.01]
F: DOLS models with single leads and lags							1.39*	1.48*	1.45*	1.23*	1.23*	1.12*
							(0.10)	(0.12)	(0.08)	(0.13)	(0.13)	(0.16)
							[0.15]	[0.11]	[0.02]	[0.01]	[0.01]	[0.01]
G: DOLS models with three leads and lags							1.44*	1.52*	1.51*	0.99*	1.00*	1.01*
							(0.10)	(0.10)	(0.12)	(0.28)	(0.30)	(0.30)
							[0.08]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
H: DOLS models with four leads and lags							1.50*	1.57*	1.54*	1.04*	1.29*	1.69*
							(0.11)	(0.10)	(0.11)	(0.40)	(0.46)	(0.43)
							[0.24]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]
I: Log copper replaced by price index[d]	1.59*	1.57*	1.50*	1.18*	1.19*	1.06*	1.67*	1.63*	1.58*	1.17*	1.18*	1.15*
	(0.15)	(0.14)	(0.14)	(0.11)	(0.11)	(0.14)	(0.12)	(0.14)	(0.11)	(0.18)	(0.18)	(0.33)
	[0.03]	[0.06]	[0.10]	[0.01]	[0.01]	[0.01]	[0.04]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]
J: Outcome replaced by log of all metal-related thefts[d]	1.29*	1.24*	1.18*	0.94*	0.94*	0.82*	1.36*	1.29*	1.25*	0.91*	0.93*	0.84*
	(0.13)	(0.11)	(0.11)	(0.10)	(0.09)	(0.11)	(0.10)	(0.11)	(0.11)	(0.17)	(0.17)	(0.19)
	[0.01]	[0.04]	[0.04]	[0.01]	[0.01]	[0.01]	[0.02]	[0.06]	[0.01]	[0.01]	[0.01]	[0.01]
Observations	120	120	119	119	119	119	115	115	114	114	114	114

Note: Table reports alternative estimates of models (1) through (12) from Table 3. 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 the value of stolen material below 5,000 CZK.

[b] The outcome is the logarithm of the number of metal thefts with the total damage below 5,000 CZK.

[c] The outcome is the logarithm of the number of metal thefts, which involved break-in and thus qualified as crimes regardless the damage.

[d] 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.

[e] The outcome is the logarithm of the number of all thefts involving nonferrous metals, that is all thefts where one of the objects was of the theft.

that were the case, these estimates of price elasticity could be interpreted as conservative. Consistent with the predictions, the estimates of the effect of copper prices on metal theft with damage below the threshold in block C are mostly somewhat smaller than our baseline estimates in Table 3. In specification (6) and DOLS specifications (10), (11), and (12), the estimated elasticity is higher than in the corresponding baseline models. 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 the value of stolen goods less than 5,000 CZK, as reported in block D of Table 5. Lastly, in block E we reestimate our baseline models with the outcome defined as the log of 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 5,000 CZK threshold is irrelevant. The estimates of the elasticity of break-in involving thefts are slightly smaller from the baseline models, but these differences are not statistically significant. To summarize, these results are inconsistent with the interpretation 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 a crime.

3.4 Robustness Checks

The remainder of Table 5 offers additional specification checks. Blocks F, G, and H report results of DOLS models from Table 3 with alternative number of leads and lags (one, three, and four) of differenced explanatory variables. The results are similar to baseline DOLS estimates and the differences in coefficients are not statistically significant. To check the sensitivity of our results to the choice of price index, we have replaced the log copper price by log of composite price consisting of LME price of aluminum and copper with weights of 1/3 and 2/3, respectively. This choice was motivated by results in Table 1, which suggest that these two metals constitute the bulk of metal thefts. The estimates of elasticity, reported in block I, are about 5 to 30 log points higher across the 12 specifications, but the differences are mostly not statistically significant. Lastly, in block J 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 with primary object other than metal. The estimates of price elasticity of such defined metal thefts with respect to copper price are about 20 log points smaller and five out of 12 estimates are smaller than unity, but the distance is not statistically significant.

4 Conclusion

The paper tests the economic model of criminal behavior using data on metal thefts in the Czech Republic over a ten-year period from 2003 until 2012. During this period prices varied widely. We argue, that this variation on metal prices constitutes a natural experiment faced by metal thieves. This is because metal prices are set at the world market in which stolen metal in the Czech Republics is unlikely to play an important role. However, one may still contest that there is an endogenous element in world copper prices. If this were the case, relationship between metal prices and thefts in the data would be weaker then the true causal effect of change in prices on thefts. The expected direction of endogeneity bias in our estimates is thus toward zero, making our results conservative. Our results are thus consistent with the economic model of crime, wherein the criminal behavior is modeled as a rational agent's decision driven by the cost-benefit ratio of undertaking criminal activities. We must conclude that opportunity makes a thief.

References

Aruga, Kentaka and Shunsuke Managi. 2011. "Price Linkages in the Copper Futures, Primary, and Scrap Markets." *Resources, Conservation and Recycling* 56:43–47.

Beccaria, Cesare. 1995 [1764]. *On crimes and punishments and other writings*. Cambridge and New York: Cambridge University Press.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76:169–217.

Bennett, Luke. 2008. "Assets under attack: metal theft, the built environment and the dark side of the global recycling market." *Environmental Law and Management* 20:176–183.

Bennett, Oliver. 2012a. "Scrap Metal Dealers Bill." Research Paper no. 12/39, House of Commons Library, London.

———. 2012b. "Scrap Metal Dealers Bill: Committee Stage Report." Research Paper no. 12/66, House of Commons Library, London.

Bentham, Jeremy. 1823. *An Introduction to the Principles of Morals and Legislation*, vol. II. London: Printed for W. Pickering.

———. 2008 [1830]. *The rationale of punishment*. Amherst, NY: Prometheus.

Chisholm, John and Chongwoo Choe. 2005. "Income variables and the measures of gains from crime." *Oxford Economic Papers* 57:112–119.

Davidson, Russell and James G. MacKinnon. 2003. *Econometric Theory and Methods*. Oxford University Press, USA.

Di Tella, Rafael and Ernesto Schargrodsky. 2004. "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack." *American Economic Review* 94:115–133.

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81:521–65.

———. 1996. “Crime, Punishment, and the Market for Offenses.” *Journal of Economic Perspectives* 10:43–67.

Engle, Robert F. and C. W. J. Granger. 1987. “Co-Integration and Error Correction: Representation, Estimation, and Testing.” *Econometrica* 55:251.

Klick, Jonathan and Alexander Tabarrok. 2005. “Using Terror Alert Levels to Estimate the Effect of Police on Crime.” *Journal of Law and Economics* 48:267–279.

Kooi, Brandon R. 2010. “Theft of Scrap Metal.” Problem-oriented Guides for Police Series no. 58, U.S. Department of Justice, Washington, DC.

Labys, W. C., H. J. B. Rees, and C. M. Elliott. 1971. “Copper Price Behaviour and the London Metal Exchange.” *Applied Economics* 3:99–113.

Levitt, Steven D. 1997. “Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime.” *American Economic Review* 87:270–290.

———. 2002. “Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply.” *American Economic Review* 92:1244–1250.

Lipscombe, Sally and Oliver Bennett. 2012. “Metal theft.” Standard Note no. SN/SHA/6150, House of Commons Library, London.

McGill, Robert, John W. Tukey, and Wayne A. Larsen. 1978. “Variations of Box Plots.” *American Statistician* 32:12–16.

Montag, Josef. Forthcoming. “A Radical Change in Traffic Law: Effects on Fatalities in the Czech Republic.” *Journal of Public Health*.

Murray, Michael P. 1994. “A Drunk and Her Dog: An Illustration of Cointegration and Error Correction.” *American Statistician* 48:37–39.

Newey, Whitney K. and Kenneth D. West. 1987. “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica* 55:703–708.

Posick, Chad, Michael Rocque, Kevin Whiteacre, and David Mazeika. 2012. "Examining Metal Theft in Context: An Opportunity Theory Approach." *Justice Research and Policy* 14:79–102.

Posner, Richard A. 1985. "An Economic Theory of the Criminal Law." *Columbia Law Review* 85:1193–1231.

Saikkonen, Pentti. 1991. "Asymptotically Efficient Estimation of Cointegration Regressions." *Econometric Theory* 7:1–21.

Sidebottom, Aiden, Matt Ashby, and Shane D. Johnson. Forthcoming. "Copper Cable Theft: Revisiting the Price–Theft Hypothesis." *Journal of Research in Crime and Delinquency*.

Sidebottom, Aiden, Jyoti Belur, Kate Bowers, Lisa Tompson, and Shane D. Johnson. 2011. "Theft in Price-Volatile Markets: On the Relationship between Copper Price and Copper Theft." *Journal of Research in Crime and Delinquency* 48:396–418.

Stock, James H. and Mark W. Watson. 1993. "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems." *Econometrica* 61:783–820.

Tsebelis, George. 1989. "The Abuse of Probability in Political Analysis: The Robinson Crusoe Fallacy." *American Political Science Review* 83:77–91.

Watkins, Clinton and Michael McAleer. 2004. "Econometric Modelling of Non-ferrous Metal Prices." *Journal of Economic Surveys* 18:651–701.

Appendix

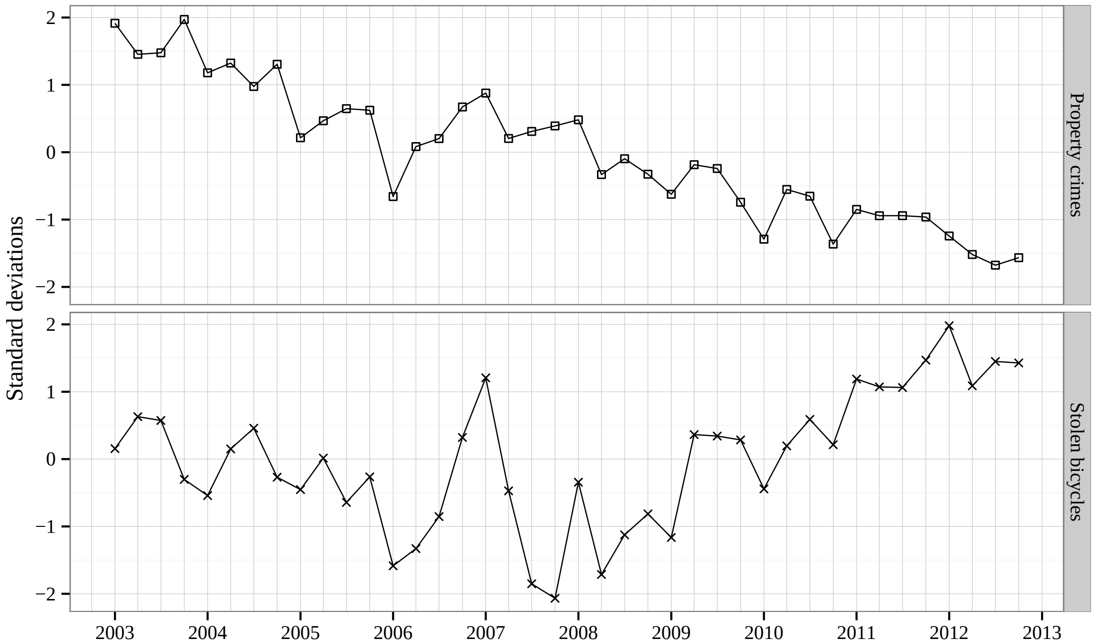

Figure A1: Copper prices and the number of criminal cases involving nonferrous metals reported to the Czech Police (quarterly averages, thefts are lagged by one month). Data are deseazoned, demeaned, and divided by respective standard deviations.

Table A1: The world market and metal prices at a Czech scrap yard

	Scrap yard prices (logs)					
	Copper		Aluminium		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)				
Aluminium			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

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