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ISSN: 2365-9793

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ABSTRACT

Crime and Prices: Evidence from Thefts of Expensive Precious Metal*

We study whether economic incentives matter for crime in a novel way, through study of expensive precious metal thefts by thieves stealing catalytic converters. We combine sharp, plausibly exogenous variation in the prices of precious metals embedded in converters with newly assembled U.S. data and multiple research designs. We show that phenomenally fast increases in precious metal prices generated a sizeable and rapid rise in auto-part thefts, while subsequent price declines and policy responses quickly reversed this pattern. The resulting boom-and-bust dynamics provide clean evidence that both demand- and supply-side economic forces shape property crime and inform targeted deterrence policies.

JEL Classification: K42

Keywords: expensive precious metals, auto-part theft, catalytic converters

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* This study was funded by the Economic and Social Research Council through the Centre for Economic Performance (CEP), whose financial support is gratefully acknowledged. The authors would like to thank Evan Rose and other participants at the Chicago/CEP Annual Conference 2025 on the Economics of Crime and Justice and the 2025 CEP Annual Conference for their feedback on the previous results. Matteo Sandi also gratefully acknowledges financial support by the "D32-2022 Unpacking Inequalities: Mechanisms and Policies (UNEQUAL)" grant.

1. Introduction

A cornerstone element of research in the economics of crime is the notion that changing incentives affects the economic returns from both legal and illegal activities, and the relativities between them, to spur or deter criminality (Becker, 1968; Ehrlich, 1973, 1996) and generate boom and bust cycles of criminality (Kirchmaier et al, 2020). In this sphere of research, much more is known about the impact of changes in legal opportunities and their drivers (Freeman, 1999; Hjalmarsson et al, 2025; Machin and Sandi, 2025). On the illegal activities side, and associated criminal returns, the evidence base is more limited, reflecting difficulties in measurement and data availability, and in development and implementation of coherent research designs (Draca and Machin, 2015).

Existing evidence on criminal earnings from illegal activities and returns to crime mostly comprises findings from two main sets of research activity (though related questions are sometimes examined in the organised crime area). The first are based around data collection, sometimes in ethnographic research where market participants are asked about their crime involvement and earnings (Freeman, 1999), or from detailed case studies in the field (e.g. Levitt and Venkatesh, 2000; Mastrobuoni and Pinotti, 2015; Melnikov et al, 2020; Sviatschi, 2022; Blattman et al, 2025). The second area is empirical work linking crime to the value of stolen goods. Most of this relates crime to prices of goods stolen by thieves, robbers and burglars, as a growing set of research links higher commodity prices to increased economic returns from theft of copper (Sidebottom et al., 2011, 2014a; Andrews et al., 2014), scrap metal (Lynch and Stretesky, 2011; Draca et al., 2019), electrical equipment (Wellsmith and Burrell, 2005), livestock (Sidebottom, 2013), and other goods (Reilly and Witt, 2008; Draca, 2016; Braakmann et al., 2024).

This paper fits firmly under the second area, offering new evidence on crime responsiveness to sizable price changes. This arises from a recent development where new criminal opportunities with a high return have opened up because of a technological development driven by environmental concerns in the automobile industry. Catalytic converters (also known as "cats") are essential components of vehicle exhaust systems in modern cars, and serve to minimize harmful emissions to promote environmental sustainability and enhance fuel efficiency. They are expensive and have high value because they contain chemically stable precious metals - platinum, palladium, and rhodium.[1] These are among the highest price precious metals in the world. Rhodium is second only to californium

[1] See, e.g., https://sustainability.stanford.edu/news/qa-how-catalytic-converters-cars-go-bad-and-why-it-matters

and is far more widely used in many industrial applications. Palladium is the most expensive and scarcest of the world's four major precious metals – gold, silver, platinum and palladium.[2]

The empirical analysis exploits China's stricter environmental policy in 2019, when the Chinese government mandated the installation of catalytic converters on all vehicles to reduce pollution. By mandating the installation of converters on almost all vehicles, this reform created a surge in global demand for precious metals used in converters.[3] As manufacturers sought to meet China's tighter emissions standards, the international prices of palladium and rhodium spiked up dramatically and almost contemporaneously – and so did the theft of converters in the United States. And, when the commodity prices in world markets subsequently fell, accompanied by policy targeting the thefts, so did cats theft which fell precipitously. Thus, a classic economics of crime boom and bust occurred as criminals first specialised in stealing goods with big valuations driven by huge price increases and then moved away from them as market prices dropped.

The high, and rising, market prices of these precious metals created potentially lucrative opportunities for theft and resale. Thieves monetize stolen converters through unregulated scrap yards, illegal market networks, online sales, or direct metal extraction. Increased metal prices made converters an increasingly attractive target for theft, particularly as their value on secondary markets soared, placing significant economic and security burdens on vehicle owners and insurers across the U.S. and other Western democracies where large numbers of vehicles contain converters. As these swift and steep fluctuations in converter thefts occurred in the context of a stable population of potential offenders, changes in the inherent propensity of potential offenders to abide by the law are unlikely to explain the uptick and downturn in thefts.

Connecting this remarkable boom and bust in cat thefts empirically to the movement of precious metal prices forms the focus of this paper. The paper proceeds by first documenting the huge boom and bust in cat thefts, then moves on to study empirical connections between thefts and the varying prices of the expensive precious metals the devices contain. This enables the garnering of new evidence on crime and economic incentives in a previously unexplored way, and connects to identify a major economic cost concern that has featured in extensive media and policy circles. Media outlets in the U.S. have extensively covered both individual episodes of thefts and policing responses across

[2] See, e.g.: https://www.bullionbypost.co.uk/index/market-commentary/most-expensive-metal/.

[3] Catalytic converters contain the highest concentration of precious metals in modern cars. However, electronics and sensors, airbag systems and spark plugs also contain precious metals.

states, underscoring the virality of converters' thefts and their impact on communities and societal concerns for public safety.[4]

Theft of catalytic converters constitutes a form of property crime with distinct characteristics. First, unlike other stolen goods, converters are valued for their metal content rather than their functionality, making them easier to monetize in secondary markets and ideal to study how property crime responds to financial incentives. Second, the theft of converters is determined by both the demand for stolen metal and the supply of valuable converters, therefore enabling the assessment of the role that both demand-side and supply-side economic drivers of crime may play. Third, thefts often have negative externalities greater than the value of the converter stolen, such as the lasting damage of the vehicles involved, the disruption of victims' daily activities and, in some cases, even the severe violence these thefts might involve.[5] Additional indirect costs generated by converters' thefts, e.g., in the forms of extra-insurance, are also estimated to be in the order of several millions of dollars every year.[6] Fourth, there is a liquid market and public market prices for all the metals contained in converters – and thus for catalytic converters themselves. Fifth, much of the price fluctuations seen in the 2000s and 2010s was driven by the rapid economic development of China that has varied its demand for the metals over time. In all likelihood, the extraordinary increase in the value of catalytic converters in the last decade provided an exogenous economic incentive to potential thieves as converters could be resold more profitably. Developing a comprehensive understanding of the supply and demand factors driving this issue and how these may affect the effectiveness of crime-reducing responses appears critical for research and for policy.

The core results show strong evidence of a positive elasticity of crime to precious metal prices. The empirical analysis is undertaken for 9 years of U.S. data, with three complementary sets of findings that encompass the boom and bust in criminality. First, it examines the evolution of prices and thefts of converters in the U.S. in the last decade. In Becker's (1968) classic framework, individuals make rational decisions to commit crimes when the expected benefits exceed the costs, which include the probability of detection, severity of punishment, and alternative legal earning opportunities. This framework predicts that rising prices of platinum, palladium and rhodium, i.e., the constituent metals of catalytic converters, should increase the attractiveness of converter theft. The analysis shows that, from 2015-2018, the incidence of converters' thefts in the U.S. remained fairly constant, while it spiked

[4] See, e.g., CBS Boston and CBS News.
[5] See, e.g., NYPost.
[6] See, e.g., State Farm data.

up dramatically starting from 2019 and coinciding with China's implementation of stricter environmental policies. The analysis retrieves crime-price elasticities in the range of 0.45-0.89, indicating that a 1% increase in the weighted sum of platinum-group metal prices generates a causal 0.45%-0.89% increase in the auto-parts theft rate. Unlike the settings examined in previous studies, the spike in theft of precious metals examined here arose from environmentally motivated innovation involving a sharp technological change. This finding provides novel evidence of the impact of foreign environmental policy on domestic crime rates.

The paper also investigates the economic reasons underpinning converter theft, quantifying both the role of demand and supply factors and the effectiveness of recent policy reforms aimed at curbing thefts. On the former, the geographic distribution of crime turns out to be important in the way the economics of crime model emphasising monetary returns to crime suggests. Existing research shows that local market structures, infrastructure, and enforcement capacities and practices can influence crime rates (Eck and Weisburd, 1995; Glaeser and Sacerdote, 1999; Gould et al, 2002; Bianchi et al, 2012; Gonzalez-Navarro, 2013; D'Este, 2014).

This study extends this literature in a novel direction by presenting a framework where the roles of both demand- and supply- factors in shaping the spatial distribution of converter theft are quantified, as the presence of both sets of factors may have created a direct avenue for stolen goods to be converted into cash. To measure the local *demand* of stolen metal, the analysis examines the diffusion of recycling establishments, where stolen converters could be easily resold; to measure the local *supply* of valuable converters, the empirical analysis examines the diffusion of hybrid vehicles, which contain particularly valuable converters with a particularly high metal loading. The findings reveal that both the presence of recycling establishments and the greater concentration of hybrid vehicles determined the steep rise in converter thefts in the U.S. since 2019, thus presenting novel evidence that both demand-side and supply-side economic drivers of crime matter for the determination of booms and busts of property crime.

The final part of the analysis considers policy responses. In the last decade, several U.S. states enacted policies aimed at reducing these crimes. Reforms typically focus on recycling facilities and include stricter regulations on the resale of converters, increased penalties for theft and enhanced tracking of transactions involving scrap metal. While these measures are designed to reduce the demand for stolen cats, their effectiveness has not been assessed to date and is likely to depend on local enforcement capacities and the responsiveness of offenders to these increased costs. As reforms were implemented after the cats theft surge in 2019, this lines up well with studies of the way in which crime and crime prevention policy frequently evolve in dynamic cycles of action and reaction.

A set of staggered difference-in-differences specifications show the theft-reducing effects of these reforms were disproportionately concentrated in counties with active recycling establishments, while no disproportionate crime reduction appears in counties with greater shares of hybrid vehicles. As recycling establishments were a direct target of these reforms, this result appears entirely plausible. However, in turn it also suggests that local market conditions can affect both the unintended effects of foreign environmental policy and domestic policy effectiveness, by showing that crime policy has the potential to curb crime surges generated by foreign policy and by underscoring the importance of tailoring interventions to address the specific (demand-side or supply-side) economic drivers of crime.

The findings also contribute to existing literature on the effectiveness of crime prevention policies. A crime-reducing effect originates from police presence (Levitt, 1997; Draca et al, 2011), police staffing (Levitt, 2002; Evans and Owens, 2007; and Lin, 2009), police deployment and tactics (Cohen and Ludwig, 2003; Di Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al, 2011; MacDonald et. al, 2016; Telep and Weisburd, 2016; Mastrobuoni, 2019), and various other programs and practices in policing and the justice system (Skogan and Frydl, 2004; Chalfin and McCrary, 2017; Weisburd et al, 2017). Similarly, targeted policies that address specific crime types, such as anti-metal theft laws, can also reduce theft rates (Sidebottom et al, 2014b; Kirchmaier et al, 2020).

Some related studies focus on the effect of changes in the legislation on auto-part theft. Ayres and Levitt (1998) and Gonzalez-Navarro (2013) show the vehicle theft deterrence effect of Lojack, a brand of stolen vehicle recovery and connected car technology. Morgan et al (2016) and Van Ours and Vollaard (2016) show a crime-reducing impact of electronic engine immobilisers. Mancha (2025) shows that improved supervision of the market for auto-parts reduced auto theft in municipalities with junkyards specialized in auto-parts in São Paulo. This study moves this literature forwards in a novel manner by evaluating the effectiveness of recent policy reforms targeting catalytic converter theft and by providing evidence of whether and how effects of foreign environmental policy may interact with domestic crime policy.

2. Data and Empirical Setting

Crime and Socio-Economic Data

Crime records for the United States originate from the National Incident-Based Reporting System (NIBRS). The Uniform Crime Reporting (UCR) programme previously collected information using both the Summary Reporting System (SRS) and NIBRS, with the former primarily used for the reporting of official crime statistics. However, since January 2021, data are provided exclusively through the NIBRS. As police agencies provide information at the incident-level via NIBRS, this allows us to identify incidents corresponding solely to the theft of motor vehicle parts and accessories (auto-parts-only thefts).

The analysis focuses on police agencies that submitted crime-related data in all 12 months of a given year (i.e., fully reporting) and aggregate the number of incidents at the police-agency level. Each agency was assigned to its dominant county and data were aggregated at the county level.[7] The econometric analysis uses crime data from a balanced panel of counties supplemented with data on time-varying local socio-economic conditions from the US Census Bureau, specifically the American Community Survey (ACS), County Business Patterns (CBP), and the Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics (BLS). Information on local county-level shares of registered light-duty vehicles comes from the US National Renewable Energy Laboratory. Appendices 1-3 report further data details.[8]

Precious Metal Prices

The analysis of precious metal prices uses a weighted sum of the prices of platinum-group metals (PGMs) – platinum, palladium, and rhodium – used in catalytic converters. These metals serve as catalysts enabling the converters to control the exhaust emissions of vehicles with internal combustion engines. An average converter contains about 3-7 grams of platinum, 2-7 grams of palladium, and 1-2 grams of rhodium (Waste Advantage Magazine, 2021). Monthly Engelhard prices of these PGMs were obtained from the US Geological Survey (USGS).[9]

The China VI Vehicle Emission Standards Policy

In 2020, China implemented the "China VI" vehicle emission standards, which are among the world's most stringent regulations aimed at reducing air pollution from automobiles. The policy was announced in 2019, and its standards mandated significant reductions in permissible emissions for light-duty vehicles, including tighter limits on nitrogen oxides, particulate matter, and hydrocarbons. To comply with these stringent requirements, automakers had to enhance vehicle emission control

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[7] A police agency may have jurisdictions that cut across multiple counties or have purview over only part of a county. The dominant county is defined as the most populous county under a police agency.
[8] Figure A1 (Appendix 3) shows crime rates computed for all counties and the county balanced panel crime rates to be strongly correlated.
[9] USGS publishes monthly prices in dollars per troy ounce from the S&P Global Platts Metals Week. Engelhard Corporation is credited with commercializing the first catalytic converter in 1976 (DieselNet, 1998). While the monthly prices were available on USGS from 2015-2022, for 2023 the monthly average was computed using data provided by Badische Anilin- und Sodafabrik (BASF) on https://acrcustomerportal.powerappsportals.com/price-history-graph/.

systems, notably by improving converters and incorporating gasoline particulate filters in addition to three-way converters.

Catalytic converters reduce harmful emissions by converting pollutants into less harmful gases. The enhanced emission standards necessitated the use of more advanced catalytic converters containing increased amounts of PGMs, which serve as catalysts in the emission reduction process. This requirement led to a surge in demand for these metals, as manufacturers sought to meet the new regulatory standards. The reform also reflects the country's commitment to improving air quality and public health by lowering vehicular emissions, a significant source of urban pollution. Announced in 2019 with a phased implementation schedule, standards were initially set to be applied in two stages. First, "China VIa", originally scheduled for July 2020 but implemented earlier in some regions. Second, "China VIb", planned for July 2023 with stricter limits on nitrogen oxides and particulate matter. Advance notice gave automakers time to comply with the new requirements, but the enforcement of "China VIa" in 2020 drove immediate changes in vehicle production and increased demand for converters.

Descriptive Analysis

Figure 1 shows trends in PGM prices, and thefts of auto-parts and motor vehicle thefts from January 2015 to December 2023. Following almost four years of relatively stable prices on average, from late-2018 when the Chinese reform was announced onwards till mid-2021, Figure 1(a) shows very sharp spikes in the prices of palladium and rhodium, respectively doubling and quadrupling between the start of 2019 and 2021. Subsequently the prices pulled right back, perhaps due to the gradual shift towards electric vehicles that do not have converters installed as they are auto-catalysts for emissions control (Devitt & Shivaprasad, 2024; The Northern Miner Group, 2025). PGM prices started to fall from around mid-2021 until they returned to their pre-"China VI" shock values in 2023.

Figure 1(b) shows all motor vehicle thefts and thefts of auto-parts in particular as shares of property offences. While thefts of auto-parts remained stable (i.e., as a share of total property crime) from 2015-2018, they rose markedly from 2019 to early-2022 following the upsurge in the prices of palladium and rhodium. Thereafter, the share of auto-parts-only thefts tapered till the end of 2023, closely following the dynamics of the boom and bust seen in PGM prices.[10]

[10] Figure A2 (Appendix 3) shows these statistics are strongly correlated between all counties and the balanced panel of counties. Figure A3 (Appendix 3) uses administrative records from the Metropolitan Police Service (MPS) of London (UK) to show a very similar boom and bust of cat theft in London from 2015-2023.

The NIBRS data does not separately categorize the specific auto-parts that the aggregate category measures. It is clear, however, that the vast majority of vehicle-part thefts since 2019, and the lion's share of the overall rise over time, are due to thefts of converters. Industry, market, insurance claim and media reports all confirm this. Appendix 4 offers a detailed cataloguing of this, based upon different sources in the US (i.e., claims data; local news and local police reports; industry and governmental agencies) to show that catalytic converter thefts constitute the vast majority of auto-parts theft and the rise over time that is measured in the NIBRS data. Converters' thefts entirely dominate the auto-parts thefts category and its increase and decline since 2019.

3. Results

Macro and County Analysis: Time Series and Panel Estimates

Crime-price elasticities are estimates from macro and county level empirical specifications. The macro estimates come from aggregate time series specifications that relate catalytic converter thefts to platinum-group metal (PGM) prices, for an array of versions of the following general dynamic specification:

$$Theft_t = \alpha + \sum_{k=0}^{2} \beta_k Price_{t-k} + \sum_{k=1}^{2} \gamma_k Theft_{t-k} + \sum_{j=1}^{11} M_{j,t} + \tau_t + \epsilon_t \qquad (1)$$

where $Theft_t$ is the monthly auto-parts-only theft rate,[11] $Price_t$ is the monthly weighted sum of the Engelhard's PGM's prices in period t,[12] and time and seasonality effects are modelled through a linear time trend τ and, for each month j in the calendar year, through month-fixed effects $M_{j,t}$.

When no lags are included, Newey-West standard errors with serial correlation of order two (i.e., two months) are computed for the autocorrelation structure. With inclusion of lagged variables, Newey-West standard errors of order zero (i.e., heteroskedastic with no autocorrelation) are used since the lags model these dynamics. The choice of two lags is based on the Schwarz Information Criterion (SIC), and a cointegrating relationship exists between *Theft* and *Price* together with the inclusion of lagged variables and month dummy variables.[13]

[11] County-level monthly theft rates are aggregated as an average weighted by the county-level population size. The county-level theft rate is calculated by summing the number of auto-parts-only thefts across fully-reporting police agencies deflated by the population under their jurisdiction in the dominant county, and expressing the number of thefts per 100,000 people.

[12] The weighted sum proxies the value of an average catalytic converter, with the weights based on the minimum metal loading of an average catalytic converter (i.e., 3 grams of platinum, 2 grams of palladium, 1 gram of rhodium). The weighted sum is computed as $3\ X\ Price_{Platinum} + 2\ X\ Price_{Palladium} + 1\ X\ Price_{Rhodium}$. Figure A4 (Appendix 5) shows IMF's and Engelhard's prices are strongly correlated.

[13] Appendix 5 reports additional information on the time series analysis. Figure A5 shows the correlation between the weighted sums of PGM prices and county-specific population-weighted averages of autoparts-only theft rates. Tables A1, A2 and A3

The second set of estimates come from considering spatial variation and estimating the contemporaneous and long-run effects using a balanced panel of counties and their monthly autoparts-only theft rates. The following equation was estimated:

$$Theft_{c,t} = \alpha + \sum_{k=0}^{2} \beta_k Price_{t-k} + \sum_{k=1}^{2} \gamma_k Theft_{c,t-k} + \delta' X_{c,t} + \epsilon_{c,t} \tag{2}$$

where $Theft_{c,t}$ is the monthly auto-parts-only theft rate of county *c* and $Price_t$ indicates the monthly weighted sum of the Engelhard's PGM prices in period *t*. Month-, year- and county-fixed effects, and socio-economic variables including the annual local unemployment rate and annual local population share of youths aged 16-24 years old were included in the vector of controls $X_{c,t}$. As in the time series analysis, equation (2) was estimated with and without the lags of the *Theft* and *Price* variables. In both the time series and panel analyses, long-run effects are computed as $\beta_0 + \beta_1 + \beta_2$ when only the lags of prices are included, and as $\frac{\beta_0+\beta_1+\beta_2}{1-\gamma_1-\gamma_2}$ when lags of both prices and thefts are included. Elasticities are computed by making use of the relevant averages of the *Theft* and *Price* variables.[14]

Table 1 shows the time-series and county-level panel estimates of the auto-parts crime-price elasticities in columns (1)-(6) and (7)-(12) respectively. Evidence of strong, positive and significant crime-price elasticities appears.[15] The dynamics of auto-parts' theft appear significantly affected by the dynamics of precious metal prices. In the time-series analysis, the statistical significance of the contemporaneous and lagged effects of prices on thefts is unaffected by the inclusion of a linear time trend in columns (4)-(6). The long-run estimated effects in columns (1)-(6) are statistically significant, and the effect becomes stronger as more dynamics are considered. The implied crime-price elasticities are in the range of 0.45-0.89, indicating that a 1% increase in the weighted sum of PGM prices causes a 0.45%-0.89% increase in the auto-parts theft rate.

The county-level panel analysis in columns (7)-(12) displays positive and statistically significant estimates also when considering spatial variation in thefts and controlling for socio-economic controls across localities. Here the estimates indicate that a 1% increase in the weighted sum of PGM prices causes a 0.22%-0.73% increase in the auto-parts theft rate. Interestingly, the comparison of the estimates

show results of the Augmented Dickey-Fuller test in Levels and First Differences, Log-Likelihood and SIC analysis and Johansen Trace test statistic.

[14] Long-run elasticities were calculated as the long-run effect multiplied by the relevant average price divided by the relevant average theft rate.

[15] Tables A4-A5 (Appendix 5) show consistent results using the maximum metal loading instead, i.e., 7 grams of platinum, 7 grams of palladium, 2 grams of rhodium.

in columns (1) and (4) with those in columns (7) and (10), with the latter including county fixed effects and displaying an estimate of roughly half the size of the estimate in column (1), reveals that approximately half of the variation in the impact of PGM prices on auto-part thefts was *between* counties and half was *within* counties.[16] The inclusions of lags reduces this gap between time-series and panel estimates. Akin to a placebo test, Table A8 in Appendix 7 shows that the dynamics of PGM prices did not affect other crime categories during this period.

China VI Policy: Demand for vs. Supply of Precious Metals

What factors caused the boom and bust in auto-part thefts? Understanding whether and to which extent demand-side and supply-side economic drivers of crime played a role is important for research and policy. This part of the analysis investigates the role of both sets of economic drivers, by exploring the geographic distribution of cat theft spikes in the U.S. following the announcement of the China VI Policy in 2019.

Considering whether *demand* for stolen precious metals drove the boom, the analysis investigated whether the presence of material recyclers may have attracted potential converter thieves, as scrap metal and used automobile parts dealers are a natural place to sell stolen converters and profit off the stolen converters. Counties with and without the presence of material recycler establishments were identified from County Business Patterns (CBP) data.[17] Since crime is typically local in nature as offenders tend not to travel to commit a crime (Kirchmaier et al, 2024), close availability of material recyclers should have made it easier for thieves to profit following the rise in PGM prices. Therefore, counties with material recyclers may have witnessed a disproportionate increase in autoparts-only theft rates following the China VI Policy.

To understand whether *supply* of converters may have driven the boom, the analysis considered whether the presence of hybrid vehicles may have attracted potential thieves. The share of light-duty vehicles registered in 2016 that were hybrid vehicles was measured using data from the United States National Renewable Energy Lab. Converters in hybrid vehicles are more valuable because they have higher metal loading compared with non-hybrid vehicles (Collinson, 2020; Stevens, 2024; Yantakosol, 2025). The share of hybrid light-duty vehicles was calculated for each county, with a focus on whether the county's hybrid share was above or below the median in the county balanced panel.

[16] Tables A6-A7 (Appendix 6) show robustness of results using the Blundell-Bond (1998) estimator given the possible Nickell (1981) bias with dynamic panel estimation with fixed effects in large N and small T panels.

[17] This corresponds to the North American Industry Classification System (NAICS) code 423930, which identifies the wholesale distribution of recyclable materials including scrap metal and used automobile parts.

A set of difference-in-differences specifications was defined and an event study analysis was conducted where treated and untreated groups were defined by identifying counties with and without the presence of material recycler establishments in 2010 and with differential shares of hybrid vehicles in 2016. Since the price shock did not originate in the U.S. and it was plausibly exogenous to the pre-existing socio-economic and crime dynamics in the U.S., the treatment status appears plausibly exogenous. Formally, the difference-in-differences specification for both cases can be expressed as:

$$Theft_{c,t} = \alpha + \beta Post_t \; X \; Estab_c + \delta_1 Post_t + \delta_2 Estab_c + \eta' X_{c,t} + \epsilon_{c,t} \tag{3}$$

$$Theft_{c,t} = \alpha + \beta Post_t \; X \; Hybrid_c + \delta_1 Post_t + \delta_2 Hybrid_c + \eta' X_{c,t} + \epsilon_{c,t} \tag{4}$$

with $Theft_{c,t}$ indicating the monthly autoparts-only theft rates of county *c* in period *t*, $Post_t$ taking value 1 for periods in years 2019 or later (and 0 otherwise), $Estab_c$ taking value 1 for counties with at least one material recycler establishment in 2010 (and 0 otherwise), $Hybrid_c$ taking value 1 for counties whose share of hybrid vehicles was above (or equal to) the median in 2016 (and 0 otherwise), and $X_{c,t}$ including the annual local unemployment rate and annual local population share of youths aged 16-24 years old. In both equations, the parameter of interest is β.

Figure 2 displays both unconditional descriptive trends in counties with and without material recyclers, and above- and below-median hybrid shares (Figures 2(a) and 2(c) respectively) and event study OLS estimates when time-varying local socio-economic characteristics and fixed effects for county and year are controlled for (Figures 2(b) and 2(d) respectively).[18] In both cases, similar trends in auto-parts-only theft rates appear between treated and untreated localities before 2019. Consistently, the pre-trends appear individually and jointly insignificant in Figures 2(b) and 2(d), indicating that the distribution of material recycler establishments and differing share of hybrid vehicles across counties did not predict the trends of auto-parts-only thefts before the China VI Policy. Following the policy, crime rates in counties with material recyclers and above-median share of hybrid vehicles increased dramatically, while remaining nearly unaffected in other counties. The downward movement in crime following the boom is also much steeper in treated counties, and indeed one that follows the boom-and-bust dynamics of PGM prices quite closely. This is shown by the descriptive trends in Figures 2(a) and 2(c) and by the lags being jointly significant in Figures 2(b) and 2(d).

These results show the importance of both material recyclers and hybrid vehicles as conduits to cat thefts, in turn indicating that both demand-side and supply-side economic drivers of crime

[18] Table A9 (Appendix 8) shows point estimates for the average pre-post difference-in-differences.

played a key role. The ease of access to recycling hubs evidently incentivised these thefts, by allowing thieves to discard of the goods quickly, reducing the risk of apprehension and enabling them to take profit from their stolen goods. This is akin to the "demand" side of the picture, with the material recyclers providing the "demand" for converters. Similarly, the ease of access to more precious converters, proxied by hybrid vehicles, also incentivised cat thieves who were evidently more responsive to price dynamics in these localities. Hybrid vehicles and their more valuable converters provided a particularly profitable source of loot for thieves, and thus their greater supply increased the incentive for potential thieves to perpetrate more lucrative thefts.

To test whether demand or supply of precious metals played a greater role in the boom and bust of cat theft, the following general specification nesting equations (3) and (4) was also estimated:

$$\begin{aligned} Theft_{c,t} = \alpha + \beta_e Post_t \; X \; Estab_c + \beta_h Post_t \; X \; Hybrid_c + \delta_1 Post_t + \delta_2 Estab_c \\ + \delta_3 Hybrid_c + \eta' X_{c,t} + \epsilon_{c,t} \end{aligned} \tag{5}$$

Figure 3 shows that when both the $Estab$ and $Hybrid$ variables are included, the estimates of β_e and β_h are positive and statistically significant. Pre-trends appear statistically insignificant with the leads being jointly insignificant. More interestingly, β_e and β_h appear statistically indistinguishable from each other. The estimates of the leads and lags of both $Estab$ and $Hybrid$ and the dynamics appear quite similar, suggesting that both factors played similarly important roles. Both Figure 3 and Table A9 (Appendix 8) show that adding time and county fixed effects leaves conclusions unchanged. The most restrictive specification shows that auto-part theft rates increased by 1.64 in areas with recycling establishments, i.e., 25.8% of the pre-2019 average in treated areas, and by 1.73 in areas with greater shares of hybrid vehicles, i.e., 26.8% of the pre-2019 average in treated areas.

U.S. Policy Reforms: Presence of Material Recyclers and Hybrid Vehicles

How did crime policy in the U.S. respond to this boom? In response to the rampant theft of catalytic converters, several U.S. states enacted reforms involving converters at some point between 2021 and 2023. These reforms mostly applied to recycling establishments as they entailed prohibition of material recyclers from purchasing converters unless acquired from industrial accounts or other commercial entities; limitations on the mode of purchase and payment (e.g., prohibiting cash transactions above a certain value when the transaction involved converters); or imposition of certain record-keeping and documentation (e.g., recording identification information of the seller). The final part of the analysis empirically studies these responses and their interaction with the distribution of material recyclers and registered light-duty hybrid vehicles, i.e., the demand-side and supply-side economic drivers of theft documented above. A balanced panel of counties was defined across 35 different states. Since three of them – Michigan, Nebraska, and Ohio – did not enact any reforms from 2021-23, counties in these states were classified as "never-treated" and used as control group.[19]

This analysis exploits the staggered implementation of these reforms. Callaway and Sant'Anna (2021) difference-in-differences estimates were produced, and time was centred around the reforms. Akin to a triple-differencing, Figure 4(a) shows coefficient estimates for counties with material recyclers vis-à-vis those without. Before the reforms, the joint tests of the differences in the leads appear statistically insignificant, suggesting that counties with and without material recyclers were on similar trends. Upon the law reform, thefts trended downwards especially in counties with material recyclers. As these reforms focused on recycling facilities and regulated in a much stricter way the legal requirements around sales of converters to recycling facilities, they increased the risk for thieves to get caught when selling to recycling facilities and made it harder for thieves to profit from their stolen goods via these facilities.[20] Taking the difference of the Average Treatment Effects on the Treated (ATT) for counties with and without material recyclers yields the triple-differences estimate, which is negative and statistically significant, showing that auto-part theft rates decreased by an extra 1.62 units in areas with recycling establishments, i.e., 25.5% of the pre-2019 average in treated areas.[21]

Figure 4(b) compares counties with above-median shares of hybrid vehicles with other counties, and no statistically significant pre-trends appear again. However, while a decline in thefts following the law reform appears evident, no statistically significant difference appears between counties with above-median shares of hybrid vehicles and other counties. The difference of the ATT for counties with above-median hybrid shares and the ATT of counties with below-median hybrid shares is close to 0 and statistically insignificant.

These results show that regulations targeting material recyclers were an effective means of combatting such crimes in areas characterised by the presence of these establishments. Since these requirements were imposed on these businesses, the fact that disproportionate effects of the reforms appear in these counties seems entirely plausible. However, the results also highlight that local economic drivers of crime can affect domestic policy effectiveness: by showing that the reforms did not exert a disproportionate effect in localities with disproportionate shares of hybrid vehicles, this evidence underscores the importance of tailoring interventions to address the specific demand-side or

[19] Table A10 (Appendix 9) reports the full list of reforms and corresponding dates.
[20] Figure A6 (Appendix 9) shows coherent results when restricting the analysis to urban counties.
[21] Consistent evidence appears from Brazil in Mancha (2025).

supply-side economic drivers of crime. This is especially important given that growing environmental concerns would likely shift more consumers towards hybrid vehicles.[22]

4. Conclusion

This paper documents a dramatic boom and bust in catalytic-converter thefts and links it to a large, exogenous change in the value of the constituent metals contained in them. When China announced and implemented stricter vehicle-emission standards, global demand for platinum, palladium and rhodium surged, raising converter prices and spurring converter thefts globally. When metal prices fell and U.S. states regulated converter resale, theft rates declined. The results provide very strong evidence on the relationship between market prices and property crime, newly showing the applicability of Becker's (1968) framework to property crimes tied to precious metals and highlighting the role of global market dynamics in shaping booms and busts of criminality.

The paper also shows the importance of both demand-side and supply-side economic drivers of crime, emphasizing the role of local market structures in enabling theft, and how these generate differential incentives for criminals across space. It also highlights the importance of understanding what economic factors drive crime dynamics by showing that recent U.S. reforms aimed at curbing converter theft were particularly effective in counties with active recycling establishments unlike in localities with relatively high shares of hybrid vehicles. This highlights the importance of understanding the economic drivers of crime to be able to tailor policy interventions to localized economic incentives, an insight that is not only relevant for addressing this specific crime but also offers a broader framework for analysing crimes influenced by economic incentives. Put together, by showing strong crime-price connections and understanding how they come about among opportunistic criminals, the findings provide new, valuable insights for combating similar crimes and new ones that may emerge as criminals exploit economic opportunities. Overall, the findings are highly supportive of the core economics of crime prediction that market incentives offered by price and value changes of commodities act as strong determinants of criminality, especially in the property crime domain, and in doing so generate a boom and bust cycle of criminality.

[22] Or electric vehicles too, albeit the latter do not have catalytic converters.

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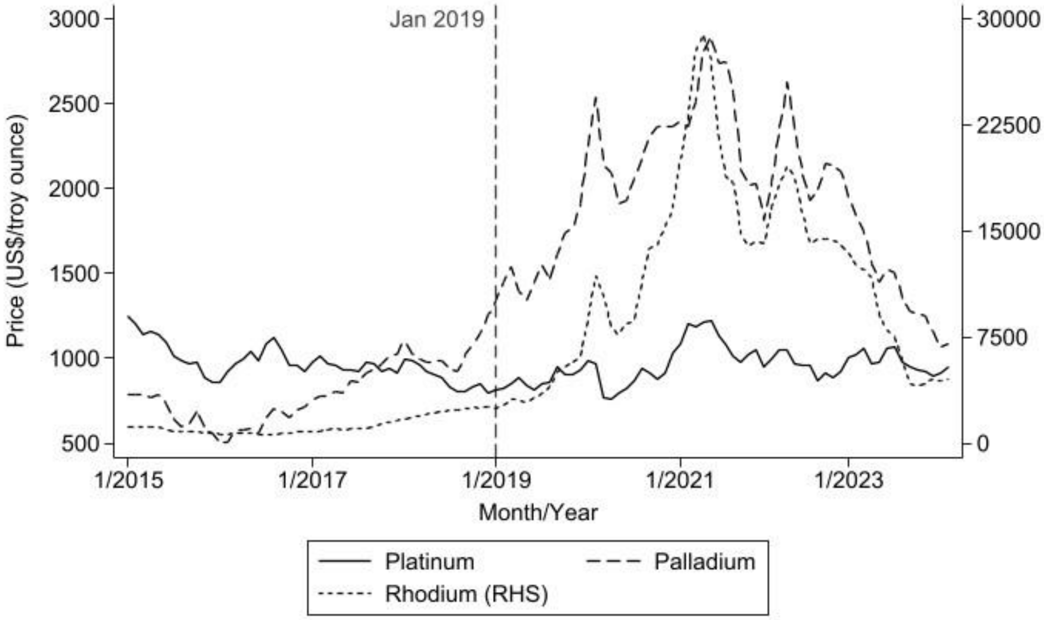
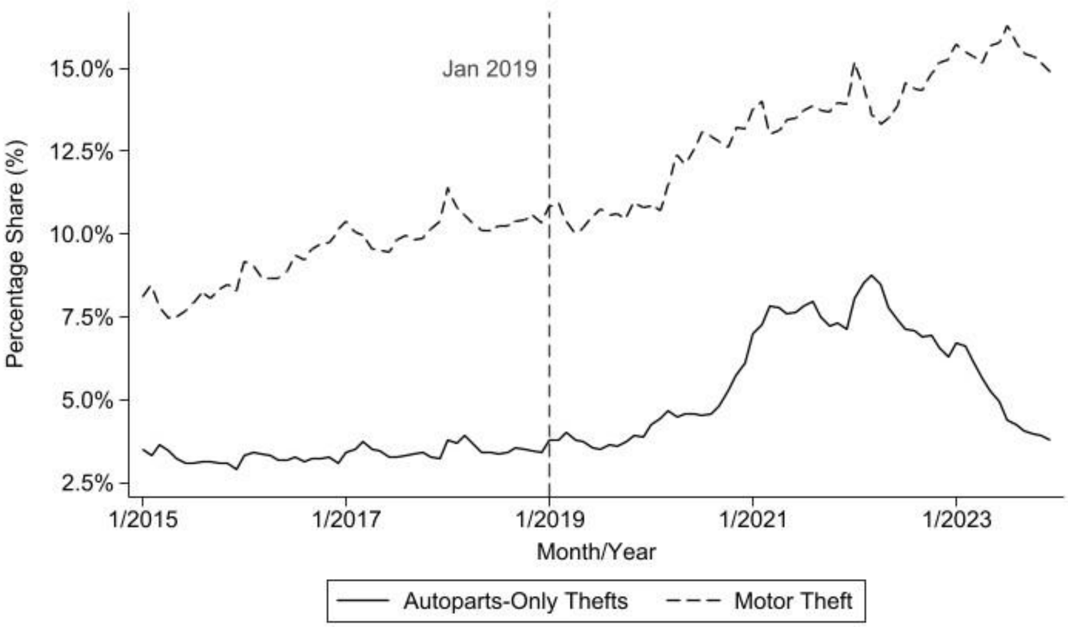
Figure 1. Trends in Prices of Precious Metals and Auto-Part Thefts, 2015-2023

(a) Prices of Platinum-Group Metals



(b) Share of Property Crime



Notes: Figure 1 shows trends in Platinum-Group Metals (PGM) prices, and thefts of auto-parts and motor vehicle thefts from January 2015 to December 2023. In particular, Figure 1(a) shows trends in the prices of platinum, palladium and rhodium, while Figure 1(b) shows trends of all motor vehicle thefts and thefts of auto-parts in particular as shares of property offences. The property crime share was calculated by using fully-reporting police agencies in the National Incident-Based Reporting System (NIBRS) dataset, and applying the Hierarchy Rule. More details are reported in Appendix 1. Property crime includes burglary, larceny-theft, and motor vehicle theft as per the crime data methodology noted on the FBI's Crime Data Explorer https://cde.ucr.cjis.gov/.

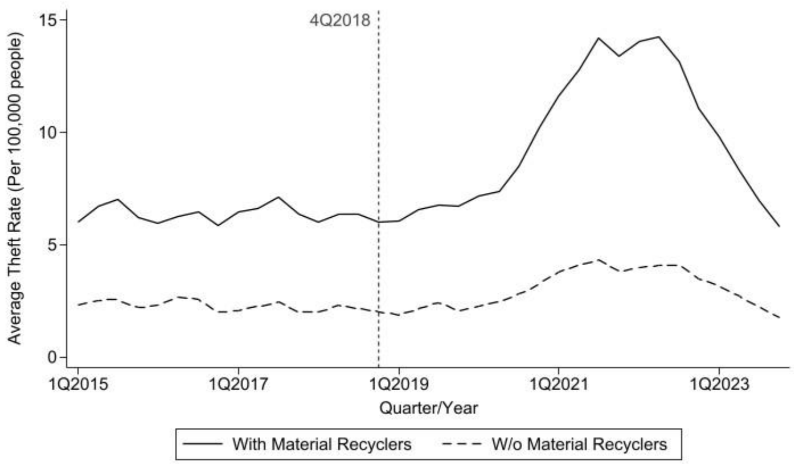
Table 1. Time-Series and Panel Estimates of Crime-Price Elasticities, 2015-2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Price_t$	0.277	0.137	0.123	0.276	0.145	0.127	0.135	0.108	0.119	0.135	0.108	0.119
	(0.033)	(0.122)	(0.029)	(0.045)	(0.125)	(0.025)	(0.017)	(0.023)	(0.031)	(0.017)	(0.023)	(0.031)
$Price_{t-1}$		-0.188	-0.125		-0.211	-0.124		-0.145	-0.093		-0.145	-0.093
		(0.221)	(0.060)		(0.227)	(0.050)		(0.031)	(0.040)		(0.031)	(0.040)
$Price_{t-2}$		0.343	0.041		0.376	0.057		0.254	0.064		0.254	0.064
		(0.123)	(0.047)		(0.130)	(0.040)		(0.029)	(0.021)		(0.029)	(0.021)
$Theft_{t-1}$			0.957			0.818			0.463			0.462
			(0.100)			(0.100)			(0.023)			(0.023)
$Theft_{t-2}$			-0.070			0.066			0.332			0.331
			(0.097)			(0.090)			(0.013)			(0.013)
Linear Time Trend	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic Controls	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Number of Observations	108	96	96	108	96	96	140,292	137,694	137,694	140,292	137,694	137,694
Number of Counties	-	-	-	-	-	-	1,299	1,299	1,299	1,299	1,299	1,299
Long-Run Effect	0.277	0.293	0.351	0.276	0.311	0.517	0.135	0.217	0.441	0.135	0.217	0.437
	(0.033)	(0.017)	(0.055)	(0.045)	(0.023)	(0.095)	(0.017)	(0.024)	(0.099)	(0.017)	(0.024)	(0.096)
Long-Run Elasticity	0.454	0.502	0.603	0.454	0.533	0.887	0.224	0.360	0.731	0.224	0.360	0.725

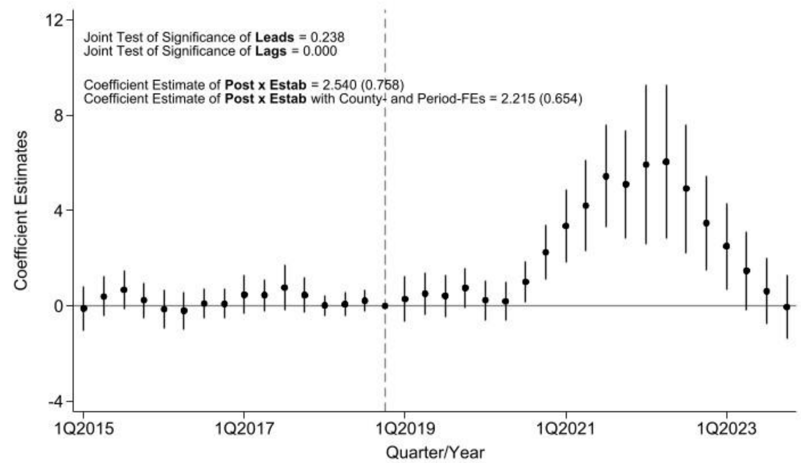
Notes: Table 1 shows the time-series and county-level panel estimates of the auto-parts crime-price elasticities. In particular, time-series estimates are presented in columns (1)-(6) and county-level panel estimates are presented in columns (7)-(12) respectively. Dependent variable multiplied by 1,000 for easier readability of estimated coefficients. In columns (1)-(6), Newey-West standard errors with serial correlation of order 2 are reported in parentheses when lagged variables are excluded, while Newey-West standard errors of order 0 are reported in parentheses when lagged variables are included. In columns (7)-(12), estimates were weighted by the total population of the county, and standard errors clustered at the county level are reported in parentheses.

Figure 2. Unconditional Trends and Event Study OLS Estimates of the Impact of the China VI Policy on Auto-Parts Theft Rates by Presence of Material Recyclers or Hybrid Vehicles Share, 2015-2023

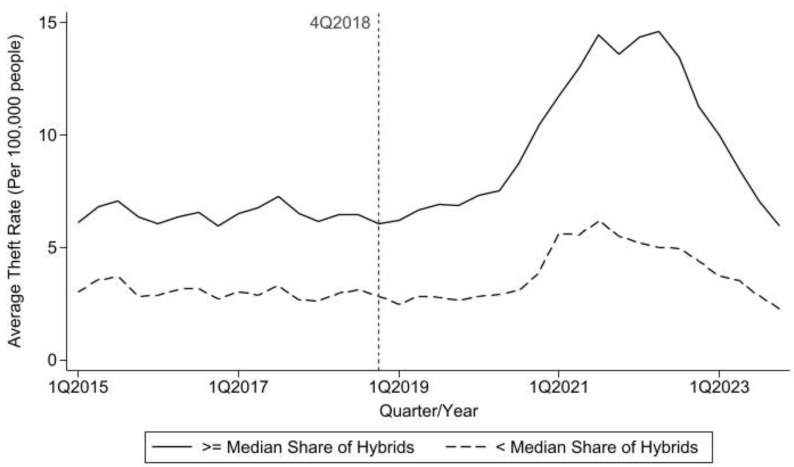
(a) Material Recyclers: Autoparts-only Thefts



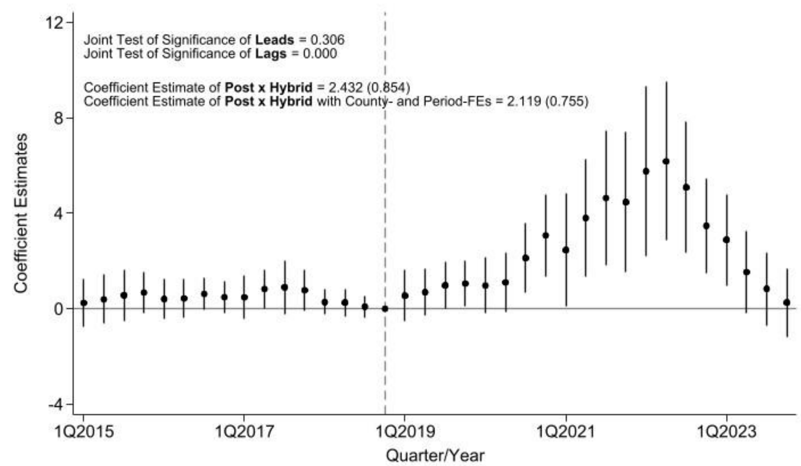
(b) Material Recyclers: Coefficient Estimates



(c) Hybrid Vehicles: Autoparts-only Thefts

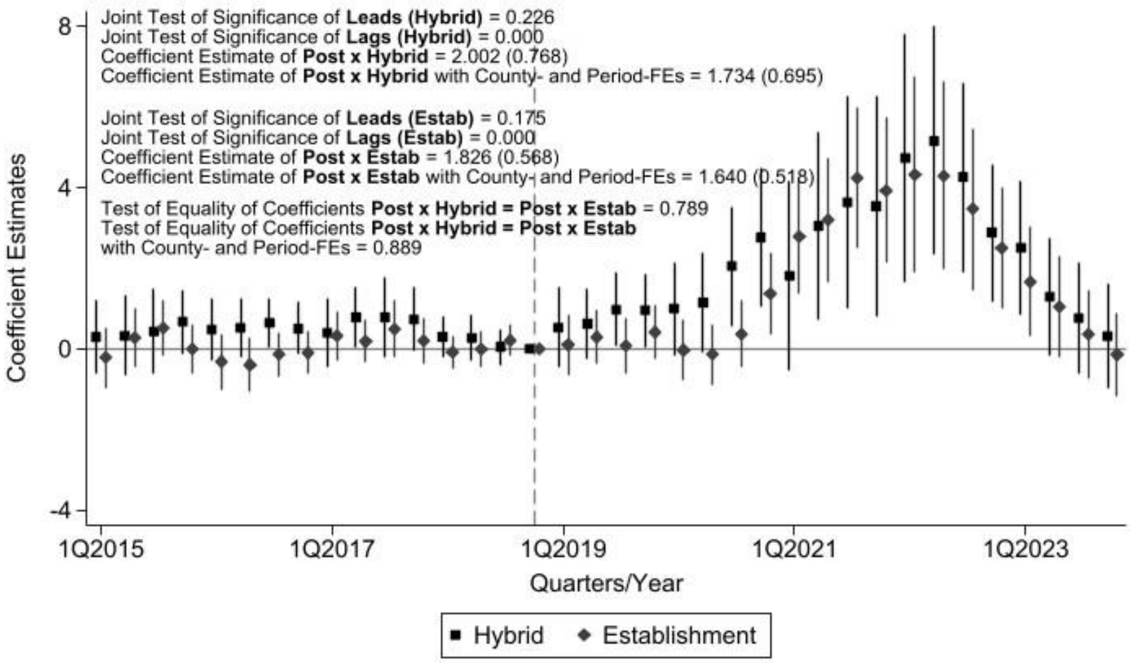


(d) Hybrid Vehicles: Coefficient Estimates



Notes: Figures 2(a) and 2(c) plot the county-population-weighted unconditional average of auto-parts theft rates obtained for counties with and without material recyclers, and above- and below-median hybrid shares respectively, with an average taken across the respective months for each quarter (e.g., the crime rate for 1Q2015 is the average of Jan 2015 to Mar 2015). Figures 2(b) and 2(d) plot the event study OLS estimates from the difference-in-differences specification in equations (3) and (4) where time-varying local socio-economic characteristics (i.e., the annual local unemployment rate and annual local population share of youths aged 16-24 years old) and fixed effects for county and year are controlled for. The regressions are weighted by the total population of each county, and standard errors clustered at the county level are found in parentheses. The full set of point estimates underlying the charts are reported in Appendix Table A9 in Appendix 8.

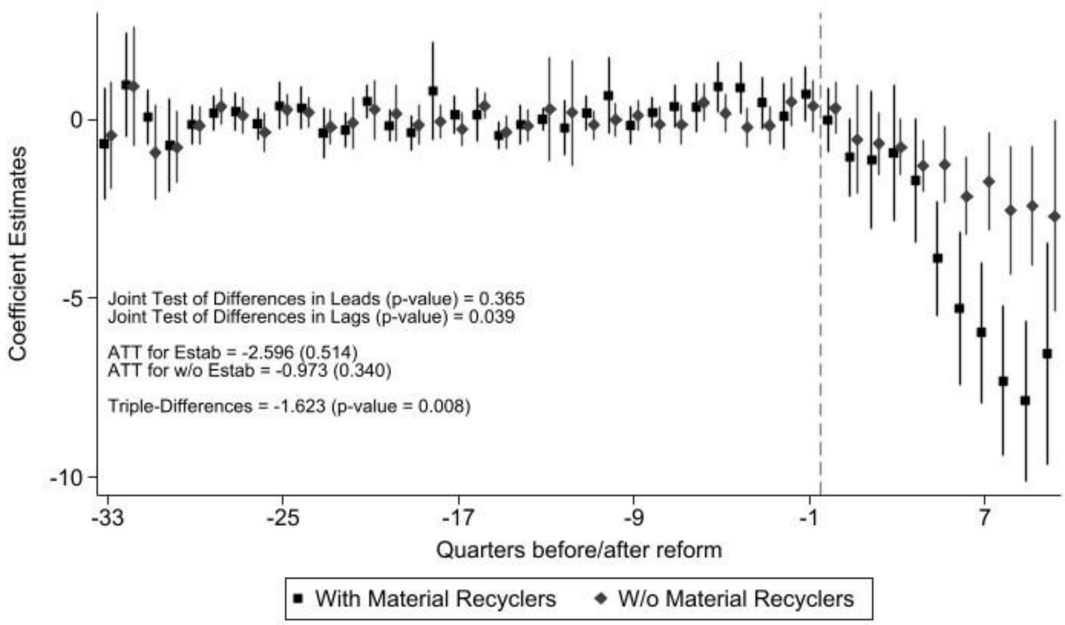
Figure 3. Event Study OLS Estimates of the Impact of the China VI Policy on Auto-Parts Theft Rates by Presence of Material Recyclers and Hybrid Vehicles Share, 2015-2023



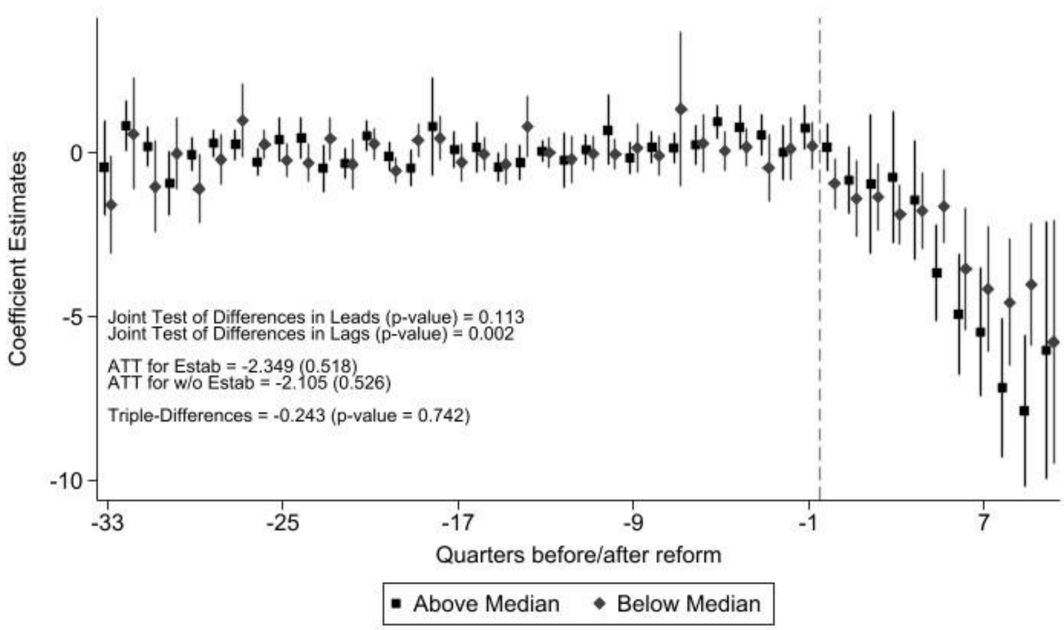
Notes: Figure 3 plots the event study OLS estimates from the difference-in-differences specification in equation (5) where time-varying local socio-economic characteristics (i.e., the annual local unemployment rate and annual local population share of youths aged 16-24 years old) and fixed effects for county and year are controlled for. The regressions are weighted by the total population of each county, and standard errors clustered at the county level are found in parentheses. The full set of point estimates underlying the chart are reported in Appendix Table A9 in Appendix 8.

Figure 4. Callaway and Sant'Anna (2021) Estimates of Law Reforms on Auto-Parts Theft Rates by Presence of Material Recyclers or Hybrid Vehicles Share, 2015-2023

(a) Presence of Material Recyclers



(b) Share of Hybrid Vehicles



Notes: Figure 4 shows Callaway and Sant'Anna (2021) estimates of the impact of crime policy in the US from 2021-23 on auto-part theft rates. Akin to a triple-differencing, Figure 4(a) shows coefficient estimates for counties with material recyclers vis-à-vis those without. Figure 4(b) compares counties with above-median shares of hybrid vehicles with other counties. In both charts, time was centred around the reforms. Estimates are weighted by the total population of each county, and standard errors clustered at the county level are found in parentheses. As in Callaway and Sant'Anna (2021), pre-reforms coefficients are "short" differences, i.e., on a one-period basis. E.g., the coefficient associated with -33 compares period -34 with period -33. All the post-reforms coefficients should be interpreted with respect to period -1.

Supplemental Appendix

Appendix 1 - Data for the United States

Crime Data: National Incident-Based Reporting System (NIBRS). The NIBRS data for the years 2015–2023 were downloaded from the Crime Data Explorer (CDE) of the Federal Bureau of Investigation (2025) as found on https://cde.ucr.cjis.gov/. The data are provided at the incident-level with each incident tagged to the originating reporting police agency.

As mentioned in the main text, the focus is on police agencies that submitted crime-related data in all 12 months of a given year (i.e., fully-reporting). This is because the FBI estimates and imputes missing data for agencies that supply less than 12 months of data in a given year using their own estimation procedures as highlighted by the FBI regarding its crime data methodology found on the CDE.

We also require that the police agencies be tagged to their Federal Information Processing Standard (FIPS) county code where relevant as the socio-economic control variables are available by the FIPS county codes and not the UCR county codes, and we exploit the cross-county variations for the panel estimates. In the data extracted from the CDE, the FIPS county codes were provided for the years 2017–2023 so earlier years were supplemented with the information obtained from the datasets distributed by the Inter-university Consortium for Political and Social Research (ICPSR) for 2015–2016.

Following this, in instances where the police agency has its FIPS county code missing in some year(s) but has it recorded in other year(s), we assigned the latter as its FIPS code for the missing year(s). We also leveraged the FIPS codes found under United States Bureau of Justice Statistics (2018) to supplement the dataset.

For the period of study, two county codes had changes made as highlighted by Dorn (2021). We updated the county codes where necessary.[23] Additionally, more substantial changes were made in Connecticut as it shifted to using its nine planning regions as its county-equivalent geographical units from 2022/2023 onwards as detailed in Census Bureau, Commerce (2022). More details on this, together with the updates made to the dataset to reflect this change, are provided in Appendix 2.

We obtain the balanced panel of counties by first assigning each agency's crime to its dominant county which is defined as the county where it has most policing jurisdiction, measured by the population size (relative to all other counties over which it has purview). We then constructed the balanced panel by focusing on counties that featured throughout the entire period from January 2015 to December 2023. While we initially obtained 1,370 counties in the balanced panel, 71 of them had zero population attributed to them due to the associated police agencies being zero-population agencies. Hence, the balanced panel of counties ended up consisting of 1,299 counties. Zero-population agencies could arise due to overlapping policing jurisdiction, so these agencies are recorded as having zero population and the population is assigned to the most local agency with primary law enforcement responsibility for that population. These zero-population agencies are typically State police, Transit police, or University police, etc. (Maltz and Targonski, 1999, 2002; Banks et al., 2016).

US Census Bureau: American Community Survey (ACS). We use the ACS 5-year estimates from 2015–2023 to ensure that we obtain the relevant data for all counties in the balanced panel given that the 1-year estimates provide data only for a limited subset of counties. Using the ACS data obtained for the population by age and sex, we calculated the local population share of youths (aged 16-24 years old) and

[23] The two changes arise from the merging of the independent city of Bedford (FIPS 51515) into Bedford County (FIPS 51019), and the renaming of Shannon County (FIPS 46113) to Oglala Lakota County (FIPS 46102).

also obtained the total county population. The youth share was used as a control variable in the panel regressions while the total county population was used as weights in the regressions.

US Census Bureau: County Business Patterns (CBP). Prior to 2017, the CBP contains information on the number of establishments under the 6-digit North American Industry Classification System (NAICS) code across all counties in the US each county. Hence, we use this to obtain the number of material recycler establishments (NAICS: 423930) in 2010. This information was used to identify which counties display the presence of material recyclers.

US Bureau of Labour Statistics (BLS). The BLS Local Area Unemployment Statistics (LAUS) provides the county-level annual unemployment rate. We use these data from 2015–2023 to serve as a control variable in the regression analysis.

US National Renewable Energy Laboratory. The National Renewable Energy Laboratory, which is under the US Department of Energy (DOE), has made information on the county-level light-duty vehicle inventory publicly available.[24] This dataset provides information on vehicle registration as of the year 2016 by vehicle type, fuel type, and model year. This information was used to identify the 2016 share of hybrid vehicles amongst all light-duty vehicles for each county.

Appendix 2 - Change to County-Equivalents in the State of Connecticut

As obtained and reproduced from Census Bureau, Commerce (2022), Table 2 in the Federal Register Notices (reproduced below) shows the Counties-to-Planning Regions Approximation.

TABLE 2—COUNTIES-TO-PLANNING REGIONS APPROXIMATION

County	2020 Census population count	Planning region	2020 Census population count
		Greater Bridgeport	325,778
Fairfield	957,419	Western Connecticut	620,549
Hartford	899,498		
Tolland	149,788	Capitol	976,248
Litchfield	185,186	Northwest Hills	112,503

TABLE 2—COUNTIES-TO-PLANNING REGIONS APPROXIMATION—Continued

County	2020 Census population count	Planning region	2020 Census population count
Middlesex	164,245	Lower Connecticut River Valley	174,225
		Naugatuck Valley	450,376
New Haven	864,835	South Central Connecticut	570,487
New London	268,555	Southeastern Connecticut	280,430
Windham	116,418	Northeastern Connecticut	95,348

We used the above in mapping the data provided under the old counties to the new county-equivalents, in the manner detailed below. In most cases, unless otherwise specified, we approximated the values as follows.

Firstly, in instances where the old county is approximated by two new county-equivalents, we approximate it as $New_{before} = Old_{before} \times \frac{New_{2020Population}}{Old_{2020Population}}$. For example, with Fairfield (FF) being split into Greater Bridgeport (GB) and Western Connecticut (WC), the value for Greater Bridgeport in Year 2015 was approximated as:

$$GB_{2015} = FF_{2015} \times \frac{GB_{2020Population}}{FF_{2020Population}} = FF_{2015} \times \frac{325{,}778}{957{,}419}$$

[24] This can be accessed via Data.Gov at https://catalog.data.gov/dataset/city-and-county-vehicle-inventories-f07a0/resource/809eba7d-8857-4431-9c5f-e88fe4506d27.

and $WC_{2015} = FF_{2015} \times \frac{WC_{2020Population}}{FF_{2020Population}} = FF_{2015} \times \frac{620{,}549}{957{,}419}$.

Secondly, where the new county-equivalent is approximated by two old counties, we estimate as $New_{before} = \left(Old^1_{before} + Old^2_{before}\right) \times \frac{New_{2020Population}}{Old^1_{2020Population} + Old^2_{2020Population}}$. For example, with Hartford (HF) and Tolland (TL) being combined to Capitol (CP), the value for Capitol in Year 2015 was estimated as:

$$CP_{2015} = (HF_{2015} + TL_{2015}) \times \frac{CP_{2020Population}}{HF_{2020Population} + TL_{2020Population}}$$
$$= (HF_{2015} + TL_{2015}) \times \frac{976{,}248}{(899{,}498 + 149{,}788)}.$$

Lastly, where the new county-equivalent is approximated by only one old county, we approximate it as $New_{before} = Old_{before} \times \frac{New_{2020Population}}{Old_{2020Population}}$. For example, with Northwest Hills (NH) being approximated by Litchfield (LF), the value for Northwest Hills in Year 2015 was approximated as: $NH_{2015} = LF_{2015} \times \frac{NH_{2020Population}}{LF_{2020Population}} = LF_{2015} \times \frac{112{,}503}{185{,}186}$.

Crime Data: National Incident-Based Reporting System (NIBRS). In cases where the police agencies in Connecticut had entries in the 2023 dataset with the updated FIPS code, we backfilled the old FIPS code with the updated FIPS code. For the remaining cases where this was not possible, we apportioned and scaled the crime data by making use of the approximations as detailed above. We also note that Tolland and Middlesex counties were not featured in the dataset after the relevant cleaning procedure. Hence, any further approximation for Capitol came solely from Hartford and there was no additional further approximation for Lower Connecticut River Valley.

US Census Bureau: American Community Survey (ACS). The total population and the youth population were approximated as above. The youth share was then computed with the youth population divided by the total population.

US Census Bureau: County Business Patterns (CBP). Given that we have defined the presence of material recyclers as having a non-zero number of establishments, this approximation would not be overly meaningful.

US Bureau of Labour Statistics (BLS). The Local Area Unemployment Statistics (LAUS) were already updated by the US BLS to reflect the new county-equivalent geographical units, so no approximation was necessary.

US National Renewable Energy Laboratory. For instances where the old county is mapped directly to one new county-equivalent unit, or where a single old county is split into two new county-equivalent units, the same 2016 share of hybrid vehicles was used since any factor would be cancelled out when taking shares.

However, when two old counties were combined into a single new county-equivalent unit, we used the 2020 Census Population to weight it accordingly. Specifically, this applies to Hartford (HF) and Tolland (TL) being combined to Capitol (CP), where:

$$CP_{2016Share} = HF_{2016Share} \times \frac{HF_{2020Population}}{HF_{2020Population} + TL_{2020Population}}$$
$$+ TL_{2016Share} \times \frac{TL_{2020Population}}{HF_{2020Population} + TL_{2020Population}}$$
$$= HF_{2016Share} \times \frac{899{,}498}{899{,}498 + 149{,}788} + TL_{2016Share} \times \frac{149{,}788}{899{,}498 + 149{,}788}.$$

Appendix 3 - United States Aggregate Crime Statistics

The official crime statistics published by the FBI Uniform Crime Reporting (UCR) programme follows the Hierarchy Rule. Under this Rule, only the most serious offence is recorded for incidents with multiple crimes. The offense types in descending order of hierarchy (seriousness) are murder and non-negligent manslaughter, rape, robbery, aggravated assault, burglary, larceny-theft, and motor vehicle theft. Motor vehicle theft is an exception to the Hierarchy Rule when reporting crime statistics (Federal Bureau of Investigation, 2004). Per the crime data methodology found on the FBI Crime Data Explorer (CDE) accessed via https://cde.ucr.cjis.gov/ from which we obtained the official crime rates, violent crime includes murder and non-negligent manslaughter, rape, robbery, and aggravated assault while property crime includes burglary, larceny-theft, and motor vehicle theft.

NIBRS data were converted to be consistent with the Summary Reporting System (SRS) by following the offense codes as highlighted by Federal Bureau of Investigation (2012).[25] For comparison with the official statistics, we applied the rule and used the total population under the jurisdiction of the police agencies to calculate aggregate statistics.

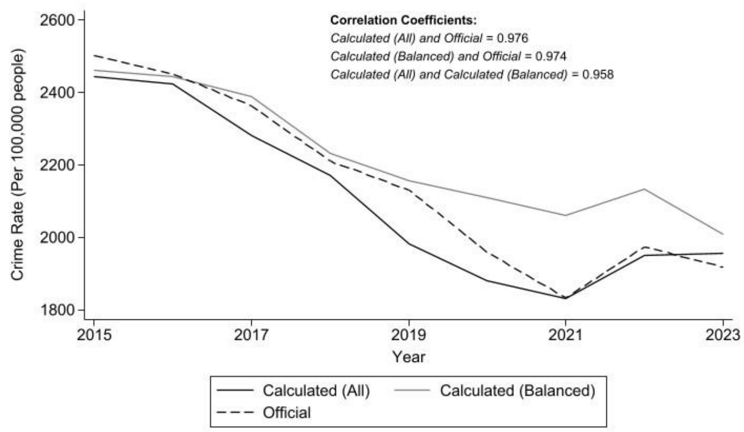
Figure A1 presents crime rates as computed by either using all fully-reporting police agencies for the US or using the balanced panel of counties, together with the official statistics. The crime rates as computed for the US (i.e., "all") and the balanced panel of counties (i.e., "balanced") are almost perfectly correlated. Importantly, the calculated crimes rates are very similar to the official statistics with strong correlation and similar overall trends especially for property crime and larceny-theft, the latter being the category under which the theft of motor vehicle parts and accessories is contained.

As the official statistics are available only for index crimes, we use the dataset to delve more into the aggregate statistics for the theft of motor vehicle parts in Figure A2. Figure A2(a) plots autoparts-only and motor thefts as a proportion of property crime in the US, calculated using all fully-reporting police agencies (this is featured in the main paper under Figure 1) and using the balanced panel of counties. Figure A2(b) also shows that autoparts-only thefts as a share of larceny-thefts was largely stable from 2015 until seeing a much sharper growth from 2019 onwards. It peaked sometime in mid-2021/2022 before trending back down, following the price dynamics. Figure A2 shows "all" and "balanced" statistics to be almost perfectly correlated.

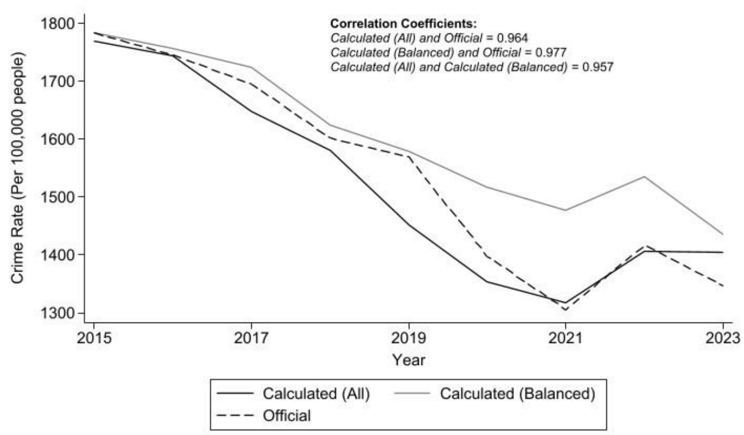
[25] There are some instances in which the reporting agency has multiple entries of a given incident number (which is meant to uniquely identify an incident) with different incident dates. In such instances, the initial/earliest incident date is treated as the actual incident data while using the relevant information such as the offense codes as updated in the latest date.

Figure A1. Calculated Statistics vs. Official Statistics (2015–2023)

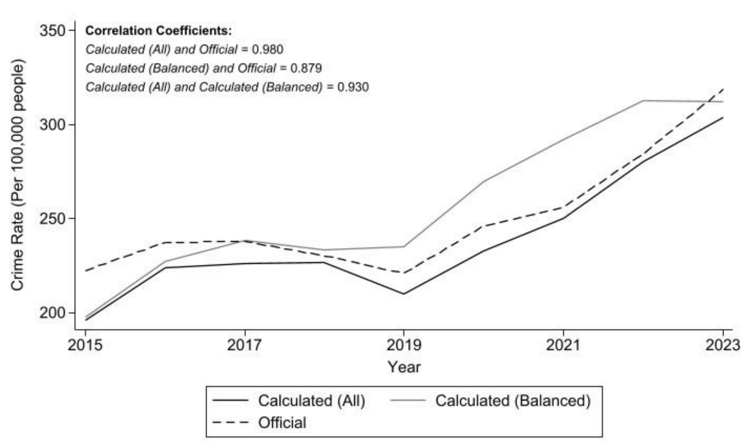
(a) Property Crime



(b) Larceny-theft



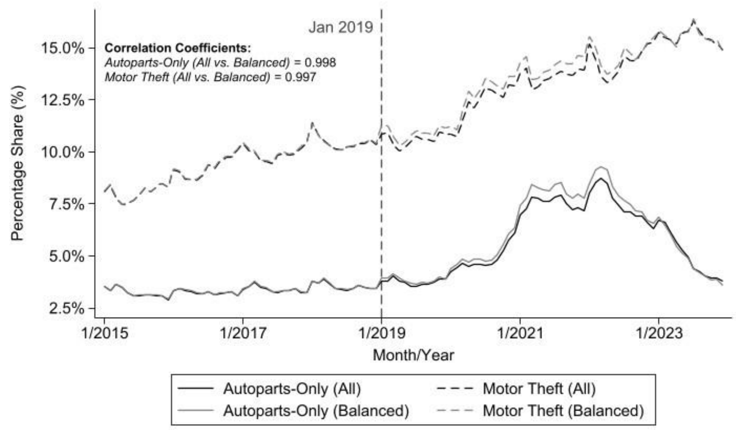
(c) Motor Vehicle Theft



Source: Authors' calculations. Official statistics were obtained from the FBI's CDE at https://cde. ucr.cjis.gov/ (Federal Bureau of Investigation, 2024)).

Figure A2. Autoparts-only Thefts' Share of Crime (2015–2023)

(a) Share of Property Crime



(b) Share of Larceny-thefts

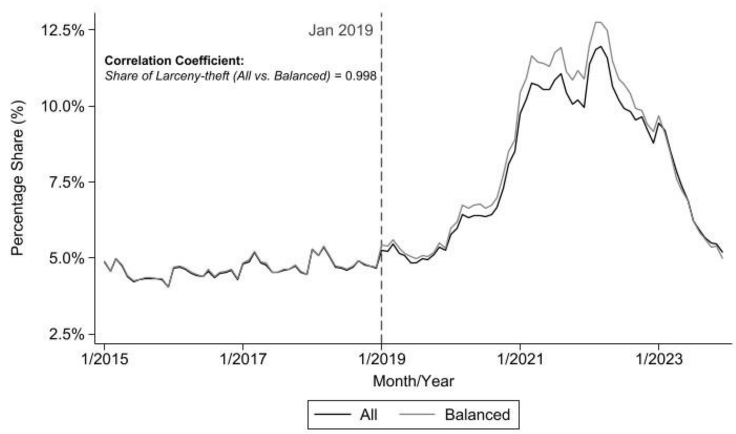
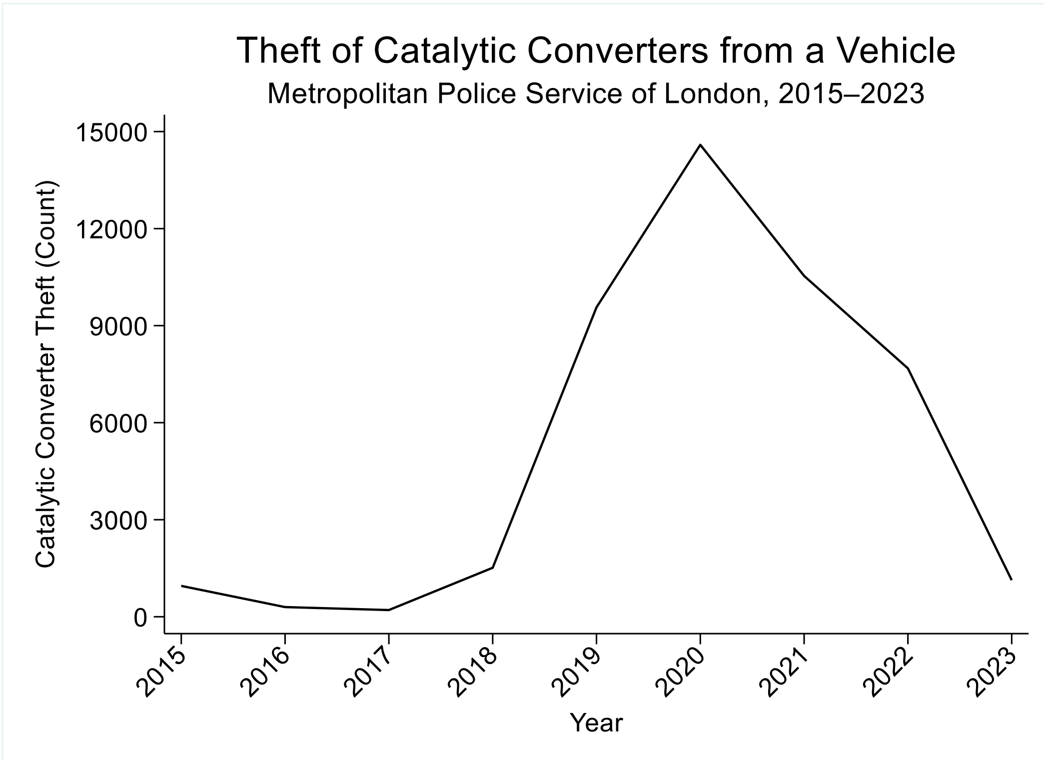


Figure A3. Theft of Catalytic Converters from a Vehicle in London, UK (2015–2023)



Source: Authors' calculations. Official records of catalytic converter thefts from vehicles in London for the 2015-2023 period were obtained from the Metropolitan Police Service of London via a Freedom-Of-Information (FOI) Request.

Appendix 4 - Share of Auto-Part Thefts that are Catalytic Converter Thefts

This Appendix gathers evidence from insurance data, local reports and government statements to show that catalytic converter thefts constitute the overwhelming majority of auto-part thefts during our study period and that catalytic converter thefts generated the boom and bust in auto-part thefts that are studied in this paper.

National insurance and industry data

A surge in catalytic converter theft claims is seen in insurance data. Insurance companies track catalytic converter theft claims separately because converters are especially costly to replace. The National Insurance Crime Bureau (NICB) and several insurers provide national claim counts:

Year	Catalytic-converter theft claims (NICB/State Farm)	Evidence
2019	**2,500–3,389 claims**	State Farm received approximately 2,500 catalytic-converter theft claims in 2019 (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts). NICB data reported 3,389 thefts nationwide (see online: Catalytic Converter Thefts Skyrocket Across the Nation | National Insurance Crime Bureau).
2020	**10,000–16,660 claims**	State Farm recorded about 10,000 claims (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts). NICB recorded 16,660 claims (see online: NICB: Catalytic Converter Thefts Surge Nationwide) and identified catalytic converters as the most frequently stolen auto part.
2021	**≈32,000–52,206 claims**	State Farm's claims tripled to ≈32,000 (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts). NICB compiled 52,206 catalytic-converter thefts nationwide, i.e., a 1,215% increase since 2019 (see online: Auto-part thefts continue to spike in first half of 2022)
2022	**≈45,000–64,701 claims**	State Farm recorded ≈45,000 claims (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts). NICB's May 2023 report counted 64,701 catalytic-converter thefts (see online: NICB: Catalytic Converter Thefts Surge Nationwide).

Other sources corroborate these numbers. Carfax (an auto-history database) analysed millions of repair records and estimated that up to 153,000 catalytic converters were stolen in 2022 (see online: CARFAX: UP TO 153,000 CATALYTIC CONVERTERS STOLEN IN 2022). NICB noted that California alone accounted for 37 % of all catalytic-converter thefts in 2021 (see online: Auto-part thefts continue to spike in first half of 2022).

The data above reveal a steep increase in catalytic-converter thefts. Claims grew from just a few thousand in 2019 to tens of thousands by 2021–2022. Insurers also reported steep increases: *Allstate* said converter replacements surged 1,155% between 2019 and 2022, with Oregon and Washington experiencing increases over 7,000% (see online: NICB: Catalytic Converter Thefts Surge Nationwide). State Farm also observed that average claim amounts rose from $1,900 in 2019 to $2,500 in 2022 (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts).

At the same time, there are comparatively low claims for other auto-parts. NICB's only publicly broken-out auto-part category besides converters is truck tailgates. A 2018 NICB study found 1,877 insured tailgate theft claims in 2016 and 1,788 in 2017 (see online: NICB: Truck tailgates; and Insured Tailgate Thefts Post Slight Decline | National Insurance Crime Bureau). By contrast, catalytic-converter theft claims numbered more than 64,000 by 2022 (see online: NICB: Catalytic Converter Thefts Surge Nationwide) — two orders of magnitude higher.

Insurers seldom report national totals for wheels, tires or stereo thefts, but available data suggest they are small. For example, tailgate theft claims were under 2 thousand per year (see online: NICB: Truck tailgates), and no other part showed anywhere near the growth seen for converters. This disparity strongly suggests that most motor-vehicle-parts theft claims relate to catalytic converters.

Local and state evidence

Pennsylvania

The Pennsylvania Auto Theft Prevention Authority together with the Lehigh Valley Regional Intelligence and Investigation Center published a report providing information on 2020 auto-related thefts at a local, regional, and national level. It noted as "increase in the number of catalytic converter thefts in 2020, a trend that was also reflected across both the U.S. and internationally" and that "catalytic converters were reported to be the most stolen part from motor vehicles in 2020". In their survey, respondents reported the increase in catalytic converter thefts as one of the key challenges (see online: Auto Theft and Vehicle Crimes)

Santa Monica, California

The Santa Monica Police Department compiled detailed statistics on auto-part thefts. In the first quarter of 2023, the department recorded 180 incidents of auto-parts theft, and catalytic converters accounted for 81% of those reports (see online: Santa Monica Daily Press). Calls for catalytic-converter theft skyrocketed from 27 calls in 2019 to 229 in 2020, 302 in 2021, 312 in 2022, and 151 calls in early 2023 (see online: Santa Monica Daily Press). These local data show that converter thefts overwhelmingly dominate auto-part theft reports in a major California city.

Los Angeles, California

A 2022 article by Crosstown Los Angeles analysed publicly available LAPD data on auto-part thefts. From January–June 2022 there were 2,778 reports of car-part thefts, i.e., up 182% from 2019 (see online: Auto-part thefts continue to spike in first half of 2022). Although the LAPD dataset does not specify which parts were stolen, the article notes that "the most frequent target are catalytic converters" (see online: Auto-part thefts continue to spike in first half of 2022), citing NICB's figure of 52,206 catalytic-converter thefts nationwide in 2021 and remarking that California accounted for 37% of these thefts (see online: Auto-part thefts continue to spike in first half of 2022).

It was also reported that around 1,600 catalytic converters were stolen per month in a report published 2023 (see online: Californians plead guilty in $600 million nationwide catalytic converter theft scheme). Based on the data available on the FBI Crime Data Explorer, there were 42,433 incidents of motor vehicle parts or accessories thefts in 2023, with 38,941 of them being exclusively thefts and are not linked to other forms of offenses. This implies that around 45% to 49% of such thefts were catalytic converter thefts.

San Diego, California

The San Diego Association of Governments (SANDAG) published their annual crime report in 2022, which highlighted that the theft of motor vehicle parts increased by 71% in 2021, with catalytic converters being stolen most often (see online: New SANDAG Report Finds an Increase in Violent Crime in the San Diego Region)

Berkeley, California

In its annual report, the Berkeley Police Department recorded 312 thefts of catalytic converters in 2024 (see online: 2024 Berkeley Police Department Annual Report). Based on the data from the FBI Crime Data Explorer, the Berkeley Police Department recorded 472 thefts of motor vehicle parts or accessories, with 442 of them being unrelated to any other types of offenses, implying that around 66% to 71% of the thefts were of catalytic converters.

New York City and suburbs

An October 2022 press release from New York's governor reported a dramatic rise in catalytic converter thefts: the New York Police Department recorded 5,548 catalytic-converter thefts in New York City by August 14, 2022, compared with 1,505 during the same period in 2021 (see online: Governor Hochul Announces New Actions to Crack Down on Catalytic Converter and Auto Theft | Governor Kathy Hochul). Nassau County saw converter thefts rise from 445 in 2021 to 1,549 in 2022, while Suffolk County went from 289 to 819. The announcement also noted that NICB recorded an increase from roughly 1,300 catalytic-converter thefts in 2018 to more than 52,000 in 2021 (see online: Governor Hochul Announces New Actions to Crack Down on Catalytic Converter and Auto Theft | Governor Kathy Hochul).

These state and local statistics reinforce the insurance data, as they show that converter thefts increased exponentially from 2019 to 2022 and constituted the overwhelming majority of auto-part theft reports during this period.

Henrico County, Hanover County and Richmond City, Virginia

Based on a report by NICB, Henrico County Police Department, Hanover County Sheriff's Office, and Richmond City Police Department registered 683, 60, and 566 respective catalytic converter thefts during the period of January – September 2022. For Henrico County Police Department, it was further reported that it registered 504 catalytic converter thefts during the period of January – September 2021. For Richmond City Police Department, it was further reported that it registered 559 catalytic converter thefts for the whole of 2021 (see online: Partnership launches to combat catalytic converter theft as law enforcement brings deterrent to residents).

Based on the data available on the FBI Crime Data Explorer, for January – September 2022, Henrico County Police Department recorded 671 thefts of motor vehicle parts or accessories, with 652 of them being unrelated to any other types of offenses, Hanover County Sheriff's Office recorded 86 and 70 thefts respectively, and Richmond City Police Department recorded 685 and 665 thefts respectively. This implies that around 70% to 100% of the thefts were of catalytic converters.

Furthermore, Henrico County Police Department recorded 608 thefts of motor vehicle parts or accessories, of which 583 of them were unrelated to any other types of offenses, in January – September 2021. This means that between 83% and 86% of such thefts were of catalytic converters. Additionally, Richmond City Police Department recorded 798 thefts of motor vehicle parts or accessories, with 776 of them being unrelated to any other types of offenses, for the full year of 2021. This implies that between 70% and 72% of such thefts were of catalytic converters.

Fairfax County, Virginia

By early-2022, a steep increase in auto-related thefts and thefts from vehicles was already registered. The prevalence of the theft of motor vehicle parts rose over the years, with "numbers for theft of motor vehicle parts… 135 in 2020, 123 in 2021, and now 416 in 2022". Catalytic converters were highlighted as among the items stolen, and given the uptick in motor vehicle crimes throughout Virginia, this prompted "lawmakers to create new legislation surrounding the theft of catalytic converters…" (see online: Theft of catalytic converters and other car parts has skyrocketed this year)

Cambridge, Massachusetts

The Cambridge Police Department highlighted that larcenies from motor vehicles increased 27% in 2021 relative to 2020, mostly driven by the thefts of catalytic converters across the city (see online: 2021 Annual Crime Report Cambridge Police Department).

Government and industry commentary

Federal and state officials consistently describe catalytic converter theft as the main auto-part theft. For example:

- NICB officials emphasised that converter thefts are "skyrocketing," with claims rising from 16,660 in 2020 to 64,701 in 2022. NICB president David Glawe described converter theft as an underreported crime that affects communities nationwide (see online: NICB: Catalytic Converter Thefts Surge Nationwide).
- California law enforcement identified catalytic converters as the most stolen part from vehicles and noted that thieves can earn $50–$250 per converter, or up to $800 for hybrid vehicles (see online: NICB: Catalytic Converter Thefts Surge Nationwide).
- State Farm pointed out that converter theft claims jumped from 2,500 in 2019 to 32,000 in 2021 and 45,000 in 2022, while average claim values also rose (see online: State Farm® data reveals 74 percent drop in catalytic converter thefts).
- Allstate reported that converter replacement claims for its customers increased 1,155% from 2019 to 2022, with some states experiencing increases over 7,000% (see online: NICB: Catalytic Converter Thefts Surge Nationwide).
- Carfax estimated about 153,000 converters were stolen nationwide in 2022, indicating that official insurance claims understate the true scale (see online: CARFAX: UP TO 153,000 CATALYTIC CONVERTERS STOLEN IN 2022).

In contrast, there is little evidence of significant growth in other auto-part theft categories. NICB's tailgate theft report shows claims were steady at 1,877 in 2016 and 1,788 in 2017 (see online: NICB: Truck tailgates; and Insured Tailgate Thefts Post Slight Decline | National Insurance Crime Bureau). There are few public sources for wheel or stereo theft counts, but they are not singled out by insurers or law-enforcement agencies. The disproportionate focus of government and industry on catalytic converters underscores the conclusion that they dominate auto-part theft.

Conclusion

Because NIBRS data do not separate catalytic-converter thefts from other motor-vehicle-parts offenses, the available data do not enable us to calculate an exact share. However, the evidence assembled in this Appendix strongly supports the claim that most auto-part thefts since 2019 have been thefts of catalytic converters:

1. Insurance claims for catalytic-converter thefts surged from about 3 thousand in 2019 to roughly 50–65 thousand by 2022, while claims for other parts (e.g., tailgates) remained in the low thousands. This implies converters accounted for a large majority of auto-parts claims.

2. Local and state crime data confirm that catalytic converters dominate auto-parts theft reports, with Santa Monica police attributing 81 % of auto-part theft reports to converters and the LAPD noting that converters are the most frequent target.

3. Government and industry commentary consistently highlight catalytic-converter thefts, and new legislation targets converters specifically (see online: Governor Hochul Announces New Actions

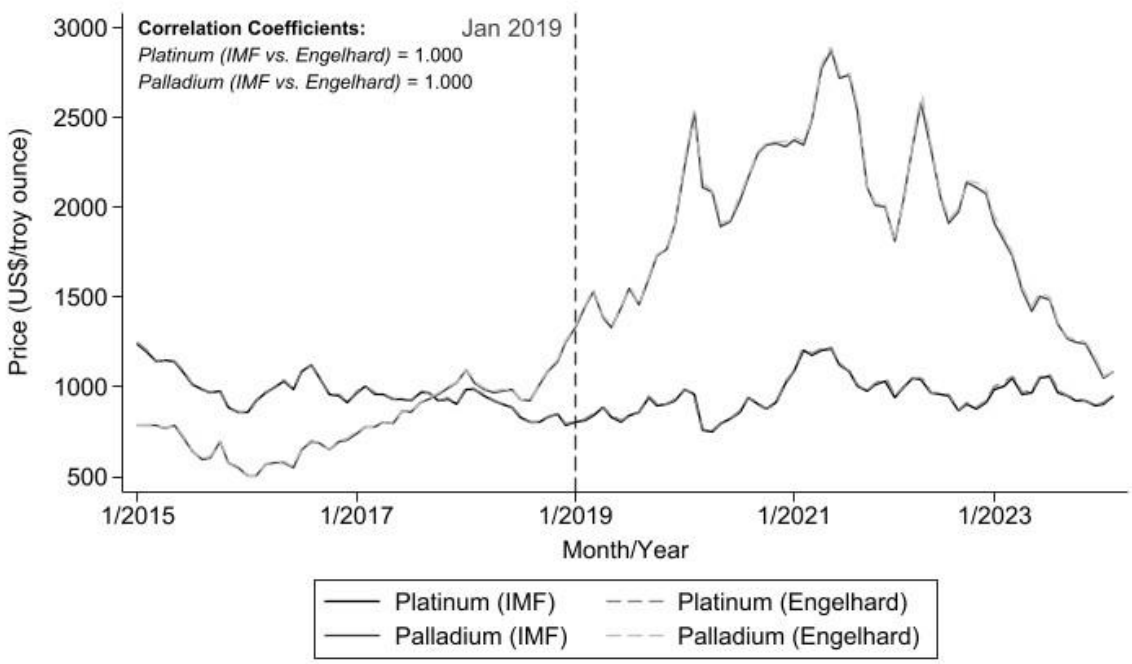
to Crack Down on Catalytic Converter and Auto Theft | Governor Kathy Hochul). There is no comparable public concern or evidence about other parts.

While precise nationwide percentages cannot be computed because they are not contained in our detailed NIBRS data, the convergence of insurance claims, local crime statistics, and expert commentary demonstrates that catalytic converters constituted the overwhelming majority of auto-part thefts in the United States since 2019.

Appendix 5 - Supplement on Time Series Analysis

Since an average catalytic converter contains the three platinum-group metals (PGMs) – namely platinum, palladium, and rhodium – we used the Engelhard prices instead of the International Monetary Fund (IMF) Primary Commodity Price System (PCPS) as the latter does not feature rhodium. As seen in Figure A4, the IMF and Engelhard prices are almost-perfectly correlated.

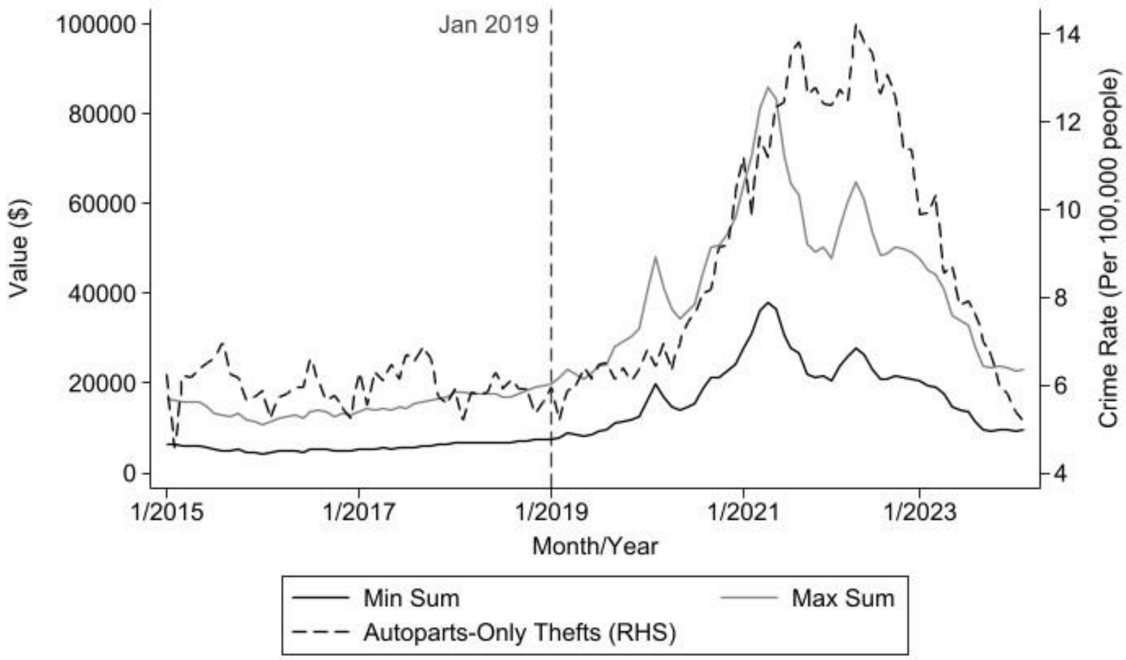
Figure A4. IMF vs. Engelhard Prices (2015–2023)



The value of a catalytic converter is measured as a weighted sum of the prices of these PGMs given that an average converter contains about 3-7 grams of platinum, 2-7 grams of palladium, and 1-2 grams of rhodium (Waste Advantage Magazine, 2021). The main analysis assigned weights based on the minimum metal loading (i.e., 3 grams of platinum, 2 grams of palladium, and 1 gram of rhodium). Here, we also feature the results when assigning weights based on the maximum metal loading (i.e., 7 grams of platinum, 7 grams of palladium, 2 grams of rhodium). We term the former as the minimum sum (denoted by $Price_{min}$) and the latter as the maximum sum (denoted by $Price_{max}$), where $Price_{min} = 3 \times Price_{Pt} + 2 \times Price_{Pd} + 1 \times Price_{Rh}$ and $Price_{max} = 7 \times Price_{Pt} + 7 \times Price_{Pd} + 2 \times Price_{Rh}$.

Figure A5 shows co-movements between the weighted sums and county-population-weighted average of autoparts-only theft rates.

Figure A5. Weighted Sum of Prices of PGMs and Thefts (2015–2023)



With the Augmented Dickey-Fuller (ADF) test, we could not reject the null hypothesis of a unit root for the relevant variables. Upon taking a first difference, denoted Δ_1, we reject the null hypothesis at the 1% significance level. Thus, we conclude that the variables are integrated of order 1, i.e., I(1).

Table A1. Augmented Dickey-Fuller test in Levels and First Differences, 2015 to 2023

	$Price_{min}$	$Price_{max}$	*Theft*
Test Statistic	-1.030	-1.023	-1.120
Number of Months	107	107	107
	$\Delta_1 Price_{min}$	$\Delta_1 Price_{max}$	$\Delta_1 Theft$
Test Statistic	-5.443***	-5.598***	-14.378***
Number of Months	106	106	106

Notes: * Significant at 10%; ** significant at 5%; *** significant at 1%.

To determine the number of lagged variables to include in a system with *Price* and *Theft*, we used the Schwarz Information Criterion (SIC) and identified that having two lags results in the lowest SIC. This is irrespective of the inclusion of the centred month dummy variables (see Table A2.)

We opt to include month dummies to account for the monthly seasonality. The Johansen test identifies the existence of 1 cointegrating relationship in a system with *Price* and *Theft* (including two lags of these variables and month dummy variables). *Price* and *Theft* are cointegrated irrespective of whether we use the minimum or maximum (weighted) sum price.

Table A3 shows the Johansen Trace test statistic and the long-run effect which corresponds to the β coefficient in the following cointegrating relationship:

$$Theft_t = a + \beta Price_t + \epsilon_t \tag{A1}$$

As the main analysis uses $Price_{min}$, we estimate the crime-price elasticities with respect to $Price_{max}$ for robustness (see Tables A4 and A5). In this case, the estimated elasticities are very similar to the use of $Price_{min}$.

Table A2. Log-Likelihood and Schwarz Information Criterion (SIC), 2015 to 2023

With $Price_{min}$ and *Theft*

Lag Length	Log-Likelihood	SIC	Log-Likelihood	SIC
0	-1170.657	24.484	-1164.288	25.397
1	-924.781	19.552	-873.706	19.533
2	-899.868	19.223	-856.303	19.361
3	-895.658	19.325	-852.029	19.462
4	-890.927	19.417	-847.583	19.560
Month Fixed Effects	No	No	Yes	Yes
Number of Months	96	96	96	96

With $Price_{max}$ and *Theft*

Lag Length	Log-Likelihood	SIC	Log-Likelihood	SIC
0	-1248.794	26.112	-1242.945	27.036
1	-1000.361	21.126	-949.296	21.108
2	-977.608	20.842	-934.042	20.981
3	-973.324	20.943	-929.712	21.081
4	-968.550	21.034	-925.474	21.183
Month Fixed Effects	No	No	Yes	Yes
Number of Months	96	96	96	96

Table A3. Johansen Trace Test and Long-Run Effect, 2015 to 2023

With $Price_{min}$ and *Theft*		
Max Rank	Log-Likelihood	Trace Statistic
0	-949.310	17.078
1	-941.769	1.997#
2	-940.771	
Number of Months	106	106
Long-Run Effect	0.348	
(β)	(0.040)	

With $Price_{max}$ and *Theft*		
Max Rank	Log-Likelihood	Trace Statistic
0	-1034.702	15.657
1	-1027.925	2.103#
2	-1026.874	
Number of Months	106	106
Long-Run Effect	0.157	
(β)	(0.020)	

Notes: # denotes the selected rank based on the trace statistic with 5% critical value.

Table A4. Time Series Estimates of Crime-Price Elasticities with *Pricemax*, 2015 to 2023

	(1)	(2)	(3)	(4)	(5)	(6)
$Price_{max,t}$	0.123	0.051	0.054	0.124	0.054	0.055
	(0.014)	(0.057)	(0.013)	(0.019)	(0.059)	(0.012)
$Price_{max,t-1}$		-0.069	-0.049		-0.079	-0.048
		(0.105)	(0.026)		(0.107)	(0.022)
$Price_{max,t-2}$		0.148	0.012		0.164	0.019
		(0.059)	(0.021)		(0.063)	(0.018)
$Theft_{t-1}$			0.952			0.807
			(0.100)			(0.099)
$Theft_{t-2}$			-0.057			0.085
			(0.099)			(0.091)
Linear Time Trend	No	No	No	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Months	108	96	96	108	96	96
Long-Run Effect	0.123	0.131	0.161	0.124	0.139	0.242
	(0.014)	(0.007)	(0.027)	(0.019)	(0.010)	(0.048)
Long-Run Elasticity	0.489	0.539	0.662	0.490	0.575	1.000

Notes: Table A4 shows the time-series estimates of the auto-parts crime-price elasticities when using $Price_{max}$ to measure Platinum-Group-Metal (PGM) prices, i.e., the maximum loading of metals in a catalytic converter. Dependent variable multiplied by 1,000 for easier readability of estimated coefficients. Newey-West standard errors with serial correlation of order 2 are reported in parentheses when lagged variables are excluded, while Newey-West standard errors of order 0 are reported in parentheses when lagged variables are included.

Table A5. County-level Panel Estimates of Crime-Price Elasticities, 2015 to 2023

	$Price_{min}$						*$Price_{max}$*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Price_t$	0.135	0.108	0.119	0.135	0.108	0.119	0.063	0.044	0.051	0.063	0.044	0.051
	(0.017)	(0.023)	(0.031)	(0.017)	(0.023)	(0.031)	(0.008)	(0.010)	(0.013)	(0.008)	(0.010)	(0.013)
$Price_{t-1}$		-0.145	-0.093		-0.145	-0.093		-0.053	-0.034		-0.053	-0.034
		(0.031)	(0.040)		(0.031)	(0.040)		(0.013)	(0.017)		(0.013)	(0.017)
$Price_{t-2}$		0.254	0.064		0.254	0.064		0.108	0.023		0.108	0.023
		(0.029)	(0.021)		(0.029)	(0.021)		(0.012)	(0.009)		(0.012)	(0.009)
$Theft_{t-1}$			0.463			0.462			0.463			0.462
			(0.023)			(0.023)			(0.023)			(0.023)
$Theft_{t-2}$			0.332			0.331			0.332			0.331
			(0.013)			(0.013)			(0.013)			(0.013)
Unemployment Rate				0.901	0.872	0.224				0.901	0.872	0.224
				(0.371)	(0.359)	(0.068)				(0.371)	(0.359)	(0.068)
Youth Share				11.050	17.707	3.330				11.050	17.707	3.330
				(40.669)	(41.293)	(7.918)				(40.669)	(41.293)	(7.918)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	140,292	137,694	137,694	140,292	137,694	137,694	140,292	137,694	137,694	140,292	137,694	137,694
Number Of Counties	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299
Long-Run Effect	0.135	0.217	0.441	0.135	0.217	0.437	0.063	0.099	0.198	0.063	0.099	0.196
	(0.017)	(0.024)	(0.099)	(0.017)	(0.024)	(0.096)	(0.008)	(0.011)	(0.044)	(0.008)	(0.011)	(0.042)
Long-Run Elasticity	0.224	0.360	0.731	0.224	0.360	0.725	0.249	0.397	0.790	0.249	0.397	0.783

Notes: Table A5 shows the county-level panel estimates of the auto-parts crime-price elasticities. In particular, $Price_{min}$ was used in columns (1) to (6) as in the main paper to measure Platinum-Group-Metal (PGM) prices, i.e., the minimum loading of metals in a catalytic converter, while $Price_{max}$ was used in columns (7) to (12) to measure PGM prices, i.e., the maximum loading of metals in a catalytic converter. Dependent variable multiplied by 1,000 for easier readability of estimated coefficients. Estimates were weighted by the total population of the county, and standard errors clustered at the county level are reported in parentheses.

Appendix 6 – Supplement to County-level Analysis and DiD Estimates of the China VI Policy

With lags of the dependent variable included in the estimation, coupled with the balanced county panel dataset having a large N (1,299) and small T (108), one may worry about the Nickell (1981) bias and estimates being downward-biased. To address this concern, the Blundell-Bond (1998) estimator was used.

In particular, we used the 5th to 16th lags as instruments for the Blundell-Bond (1998) estimator, i.e., a total of 12 lags (a year's worth) to attempt reducing the number of instruments. This corresponds to Column (2) in Table A6. We started from the 5th lag to accommodate the presence of AR(4) in the residuals (in first differences). We also collapsed (aggregated) the instruments to circumvent the problem of having too many instruments (Roodman, 2009). This corresponds to Column (3) in Table A6.

Table A6 shows that the Blundell-Bond estimates yield higher long-run elasticities, which is within-expectation since the Nickell-bias is downward-biased. However, the relevant statistics shown in Table A7 raise concerns regarding the instruments used as the test statistics do not fully support the exogeneity of these instruments.

Table A6. OLS and Blundell-Bond Estimates, 2015-2023

	(1)	(2)	(3)
$Price_t$	0.119	0.126	0.130
	(0.031)	(0.037)	(0.039)
$Price_{t-1}$	-0.093	-0.088	-0.073
	(0.040)	(0.049)	(0.050)
$Price_{t-2}$	0.064	0.029	0.008
	(0.021)	(0.023)	(0.033)
$Theft_{t-1}$	0.463	0.624	0.509
	(0.023)	(0.036)	(0.185)
$Theft_{t-2}$	0.332	0.345	0.480
	(0.013)	(0.032)	(0.170)
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	No	No
Estimation Method	OLS	Blundell-Bond	Blundell-Bond
Number of Observations	137,694	137,694	137,694
Number of Counties	1,299	1,299	1,299
Long-Run Effect	0.441	2.183	6.197
	(0.099)	(0.643)	(2.883)
Long-Run Elasticity	0.731	3.619	10.271

Notes: The OLS and Blundell-Bond estimation was weighted by the total population of the county, and standard errors were clustered at the county level.

Table A7. Statistics from the Blundell-Bond Estimation, 2015-2023

	Non-Collapsed Specification (1)	Collapsed Specification (2)
AR Test for Residuals in First Differences (p-value)		
AR(1)	0.000	0.047
AR(2)	0.003	0.237
AR(3)	0.000	0.086
AR(4)	0.005	0.024
AR(5)	0.420	0.188
Hansen Test of Overidentifying Restrictions (p-value)	0.644	0.062
Difference-in-Hansen Tests of Exogeneity of Instrument Subsets (p-value)		
Instrument Subset: Lags of Dependent Variable		
Hansen Test excluding subset	0.282	N.A.
Difference	1.000	N.A.
Instrument Subset: All Other Variables		
Hansen Test excluding subset	0.445	0.047
Difference	1.000	0.508

Notes: The Hansen Test of Overidentifying Restrictions is weakened by the presence of many instruments. Hence, as suggested by Roodman (2009), collapsing the instruments is a valid alternative. The results do not fully support the exogeneity of the instruments used.

Appendix 7 – Hierarchy crime-price elasticities

We checked for the response of the hierarchy crimes to prices, by including the full set of lagged variables (i.e., two lags of crime and two lags of prices) and report the long-run effects and elasticities below. Table A8 shows that the long-run effects are all statistically insignificant, akin to a placebo test.

Table A8. Time-Series Estimates of Crime-Price Elasticities for Other Crimes, 2015-2023

	Violent Crime	Property Crime	Burglary	Larceny-Thefts	Larceny-Thefts (excludes auto-parts only)	Motor Vehicle Thefts
Long-Run Effect	0.015	0.005	0.008	0.006	0.004	0.012
	(0.014)	(0.006)	(0.012)	(0.008)	(0.006)	(0.014)
Long-Run Elasticity	0.259	0.073	0.145	0.096	0.063	0.203
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	137,694	137,694	137,694	137,694	137,694	137,694
Number Of Counties	1,299	1,299	1,299	1,299	1,299	1,299

Notes: Table A8 shows the time-series estimates of the crime-price elasticities for other crimes, i.e., not auto-parts theft. Dependent variable multiplied by 1,000 for easier readability of estimated coefficients. The estimation was weighted by the total population of the county, and standard errors were clustered at the county level. Results in Table A8 were estimated without the inclusion of the socio-economic controls, but results are unaffected by the inclusion of these controls.

Appendix 8 - Difference-in-Difference Estimates of the China VI Policy Shock

Table A9. OLS Estimates of the Impact of the China VI Policy on Auto-Parts Theft Rates by Presence of Material Recyclers and Hybrid Vehicles Share, 2015-2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post x Establishment	2.540	2.423	2.215				1.826	1.735	1.640
	(0.758)	(0.711)	(0.654)				(0.568)	(0.543)	(0.518)
Establishment	4.196	4.282					3.194	3.203	
	(0.604)	(0.625)					(0.461)	(0.466)	
Post x Hybrid Vehicles				2.432	2.206	2.119	2.002	1.807	1.734
				(0.854)	(0.802)	(0.755)	(0.768)	(0.731)	(0.695)
Hybrid Vehicles				3.858	4.193		3.079	3.398	
				(0.793)	(0.887)		(0.721)	(0.813)	
Post	0.783			0.933			-0.361		
	(0.159)			(0.388)			(0.450)		
Period Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre average in Establishment areas	6.355	6.355	6.355	6.355	6.355	6.355	6.355	6.355	6.355
Pre average in Hybrid Vehicles areas	6.460	6.460	6.460	6.460	6.460	6.460	6.460	6.460	6.460
Number of Observations	140,292	140,292	140,292	140,292	140,292	140,292	140,292	140,292	140,292
Number of Counties	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299	1,299

Notes: Table A9 shows the event study OLS estimates from the difference-in-differences specification in equation (5) where time-varying local socio-economic characteristics include the annual local unemployment rate and annual local population share of youths aged 16-24 years old. The regressions are weighted by the total population of each county, and standard errors clustered at the county level are found in parentheses.

Appendix 9 - State Regulations

We refer to https://law.justia.com/ to access the full set of respective state laws as well as https://legiscan.com/ to search through the bills. We search for the explicit mention of "catalytic converters" to identify if the state implemented any relevant law reforms.

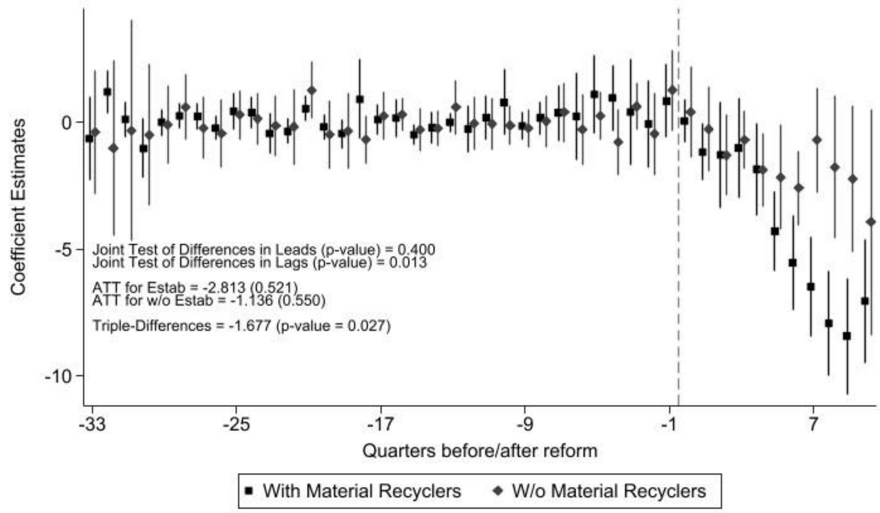
Table A10 contains the 35 states that comprise the balanced panel dataset of counties, and it shows the number of counties in the dataset for each state, the effective date of the reforms and the quarter corresponding to the reforms.

Table A10. List of States and Dates of Reforms

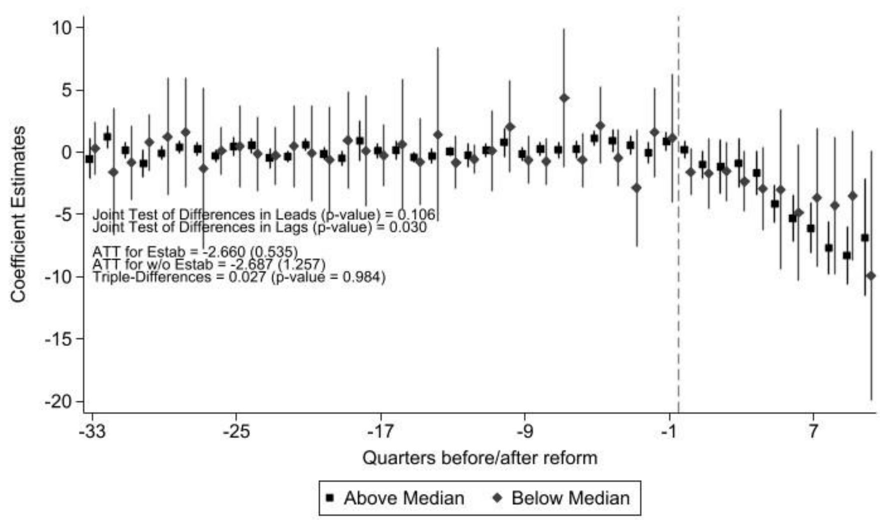
State	Number of Counties	Effective Date	Reform Quarter
Alabama	1	01 Jun 2022	2Q2022
Arizona	3	09 May 2022	2Q2022
Arkansas	70	30 Apr 2021	2Q2021
Colorado	48	07 Jun 2022	2Q2022
Connecticut	9	01 Jul 2022	3Q2022
Delaware	3	28 Apr 2022	2Q2022
Idaho	40	01 Jul 2023	3Q2023
Illinois	1	27 May 2022	2Q2022
Iowa	74	01 Jul 2022	3Q2022
Kansas	64	01 Jul 2023	3Q2023
Kentucky	118	14 Jul 2022	3Q2022
Louisiana	16	01 Aug 2022	3Q2022
Maine	6	08 Aug 2022	3Q2022
Massachusetts	14	05 Jan 2023	1Q2023
Michigan	78	None	None
Mississippi	1	01 Jul 2022	3Q2022
Missouri	7	28 Aug 2021	3Q2021
Montana	38	04 May 2023	2Q2023
Nebraska	32	None	None
New Hampshire	10	04 Aug 2023	3Q2023
North Dakota	45	01 Aug 2023	3Q2023
Ohio	77	None	None
Oklahoma	75	01 Nov 2022	4Q2022
Oregon	20	01 Jan 2022	1Q2022
Pennsylvania	5	02 Jan 2023	1Q2023
Rhode Island	5	30 Jun 2022	2Q2022
South Carolina	44	01 Jun 2021	2Q2021
South Dakota	23	01 Jul 2022	3Q2022
Tennessee	93	01 Jul 2021	3Q2021
Texas	35	01 Sep 2021	3Q2021
Utah	14	04 May 2022	2Q2022
Virginia	128	01 Jul 2022	3Q2022
Washington	36	30 Mar 2022	1Q2022
West Virginia	29	07 Jul 2021	3Q2021
Wisconsin	37	17 Mar 2022	1Q2022

Figure A6. Callaway and Sant'Anna (2021) Estimates of Law Reforms on Auto-Parts Theft Rates by Presence of Material Recyclers or Hybrid Vehicles Share in Urban Counties, 2015-2023[26]

(a) Presence of Material Recyclers



(b) Share of Hybrid Vehicles



Notes: Figure A6 shows Callaway and Sant'Anna (2021) estimates of the impact of crime policy in the US from 2021-23 on auto-part theft rates in urban counties. Akin to a triple-differencing, Figure A6(a) shows coefficient estimates for counties with material recyclers vis-à-vis those without. Figure A6(b) compares counties with above-median shares of hybrid vehicles with other counties. In both charts, time was centred around the reforms. Estimates are weighted by the total population of each county, and standard errors clustered at the county level are found in parentheses. As in Callaway and Sant'Anna (2021), pre-reforms coefficients are "short" differences, i.e., on a one-period basis. E.g., the coefficient associated with -33 compares period -34 with period -33. All the post-reforms coefficients should be interpreted with respect to period -1.

[26] We used the National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties, which categorises counties as metropolitan (urban) or non-metropolitan (rural). The 2013 classification was used as it would be the most recent classification without crossing into the time period of the dataset (2015-2023).