RESEARCH

Explaining offenders' longitudinal product-specific target selection through changes in disposability, availability, and value: an open-source intelligence web-scraping approach

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Abstract

Objective: To address the gap in the literature and using a novel open-source intelligence web-scraping approach, this paper investigates the longitudinal relationships between availability, value, and disposability, and stealing counts of specific makes and models of gaming consoles.

Methods: Using data from Western Australia (2012–2019) and focusing on specific makes/models of gaming consoles, the relationships between product-specific stealing counts, availability, value, and disposability were examined using time series and cross-sectional analyses.

Results: Support was found for a positive relationship between the changing disposability of specific makes/models of gaming consoles over their lifecycle with corresponding stealing counts, above and beyond changes in availability and value. However, when these attributes were analysed statically, both disposability and value were important.

Conclusions: The results highlight the importance of measuring correlates of 'hot products' longitudinally to better understand offenders' target selection preferences over time—with important implications for theft risk assessment and crime prevention policy and practice. These findings also provide support for the use of similar open-source intelligence web-scraping strategies as a suitable technique for capturing time-specific proxies for product-specific value and disposability.

Keywords: CRAVED, Offender decision making, Partial product life cycles, Stealing, Target selection

Introduction

Stealing offences contribute a significant cost to society in terms of their economic, social, emotional, psychological, and physical harms (Office for National Statistics, 2020; Wickramasekera et al., 2015). Theft of electronic consumer goods, in particular, can also lead to loss of highly valued personal data (Armitage & Pease, 2008). Electronic consumer goods have long comprised the third largest category of goods stolen in domestic burglaries (ONS, 2020; Shaw et al., 2015; Wellsmith & Burrell, 2005), and mobile phones alone have consistently been stolen in over 30% of all 'theft from the person' incidents each year for the past decade (ONS, 2020). As such, the impact of electronic consumer goods on overall property

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crime rates should not be understated and there is a need to understand, predict, and reduce theft of these items.

The central hypothesis tested in this article is that market forces inherent in the life cycle of a good are associated with stealing counts of those goods, and the implication of this is that understanding and predicting these relationships can assist in preventing crime. In addition to being constrained by forces outside of their control like the relative stock of a good in the general population, implicit in this model is the notion that prospective thieves make target selection decisions based on variables such as the changing prices and desirability of goods over time. Work with offenders suggests that they are attuned to stolen goods market dynamics, citing disposability and second-hand value as the most important factors in targeting specific goods (Nee et al., 2019; Schneider, 2005; Stevenson et al., 2001). This is consistent with the finding that the motive for the majority of burglaries is to steal goods to convert to cash, often to fund drug use (Cromwell et al., 1991; Stevenson et al., 2001; Wright & Decker, 1996). The notion that offenders demonstrate target selection preferences attuned to stolen goods market dynamics is also consistent with criminal decision-making models that reflect offender domain expertise. For example, in virtual reality burglary settings, while control groups of non-offenders steal haphazardly and end up with a heavier and less valuable haul, experienced burglars expertly discriminate between valuable and less valuable goods relative to their removability (Nee et al., 2015, 2019). Experienced burglars even distinguished between models of iPads, preferring a newer model iPad over a basic model iPad in the simulation (Nee et al., 2019).

Based on such offender interview research, it appears that a meaningful proportion of thieves are attuned to stolen goods market dynamics through an economic motivation to offend. To close the link between stolen goods market dynamics and aggregate consumer good property crime rates, Felson and Clarke (1998) outlined how they believed the stages of a product's life cycle (Levitt, 1965) are related to the product's vulnerability to theft over time. The broad stages of the product life cycle are introduction of the good to the market (or innovation), growth, mass marketing, and market saturation (Levitt, 1965). Felson and Clarke (1998) suggested that it is during the stages of growth and mass marketing that consumer demand for a product peaks in legitimate and stolen goods markets and that theft rates for the product also peak during these stages.

Although there is clear evidence to demonstrate the relationship between some commodity goods (e.g., copper) and acquisitive crime rates (Brabenec & Montag, 2018; Draca et al., 2019; Kirchmaier et al., 2020; Mares & Blackburn, 2017; Sidebottom et al., 2014), research into the impact of factors inherent in consumer good product life cycles on aggregate crime rates is very limited. A recent systematic review identified only four studies to have investigated the relationship between changing prices and stealing counts of specific consumer goods over time (Quinn et al., 2022).[1] Additionally, only two studies have investigated the role of changing ownership levels on stealing counts of specific consumer goods over time (Shaw et al., 2015; Wellsmith & Burrell, 2005). Across these studies, results are mixed. However, these mixed results are to be expected given that the sales climate for electronic consumer goods has shifted substantially since the initial commentary on product life cycle theory and theft. The rapidity of advances in technology and mass production of electronic consumer goods has meant that newer models of electronic goods are introduced to the market at a rapid rate, leading consumers to invest in these newer models despite the ongoing functionality of existing models (Mailley et al., 2006). This means that for overarching goods categories (e.g., gaming console) prices remain high, and they become locked in the growth and mass marketing stages of the life cycle—effectively prolonging or even preventing market saturation (Mailley et al., 2006).[2] Instead, specific makes and models of electronic consumer goods undergo their own unique life cycles, dubbed 'partial product life cycles' (Mailley et al., 2008; Shaw et al., 2015; Thompson, 2017; Wellsmith & Burrell, 2005). These specific makes and models of electronic consumer goods skip the traditional introduction stage as they enter the market with high consumer desirability and sales. Additionally, their lifespans are also much shorter than earlier electronic products because they become obsolete faster, either functionally or psychologically, due to the rapidity of advances in technology and the subsequent release of newer models (Hsueh, 2011; Lebreton & Tuma, 2006; Mailley et al., 2006).

Some preliminary evidence has emerged in support of the role of partial product life cycles on stealing counts, demonstrating the statistically significant relationship between annual global sales units and annual stealing counts of specific makes and models of gaming consoles (Quinn & Clare, 2021a). Annual sales units were statistically significant predictors of gaming console stealing counts and explained more than 46% of the variance in

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[1] The majority of studies included in the review investigated the relationship between changing prices and stealing counts of commodity goods, like copper.
[2] This essentially means that if you average the prices of all gaming consoles as a single category over time, the prices remain high, and do not show the substantial declines in price that a specific console would. These fluctuations for specific makes and models of goods are likely masked in many police databases due to a lack of recording specificity.

six of the 12 years analysed, and more than 20% of the variation in stealing counts for five of the remaining six years (though these models were not statistically significant). Reasons for the lack of statistical significance for half of the models included a failure to take into account the limited availability of newly released consoles at the start of their lifecycles, and the limitation of using annual global sales units data as a proxy for changing Western Australian consumer desirability for specific consoles (Quinn & Clare, 2021a). The present research addresses each of these gaps and provides the first systematic investigation of the relationships between multiple market forces and stealing counts for specific makes and models of consumer goods.

Candidate market forces to investigate are derived from existing fragmented research on the topic (Felson & Clarke, 1998; Quinn & Clare, 2021a; Shaw et al., 2015; Wellsmith & Burrell, 2005), but also informed by the clear overlaps between market forces inherent in partial product life cycles and CRAVED attributes.[3] The *value* and *disposability* attributes[4] of the CRAVED framework have been recognised as having the greatest impact on which goods are stolen most, in the context of electronic consumer goods (Armitage & Pease, 2008; Clarke, 1999). However, it is important to recognise that if the stock of a good in the population (*availability*) is very low, stealing counts for that good are also likely to remain low, regardless of changes in its *value* or *disposability.* In this way, ownership levels (availability), prices (value), and consumer desirability (disposability) can be seen as *criminogenic* market forces.

As we have seen through the discussion of offender interview research, burglars appear to be attuned to stolen goods market dynamics. In the present article, we investigate the link between legitimate market forces and stolen goods market dynamics by analysing the relationships between availability, value, and disposability, and aggregated stealing counts (from residential burglaries) of specific makes and models of gaming consoles (with relatively consistent size (concealability) and weight (removability) measures). This analysis, which tests the capacity of relevant CRAVED attributes to explain consumer good target selection preferences over time, is the first time these connected, dynamic factors have been tested in this way. The present article also introduces a novel approach to web-scraping relevant data for crime science analyses of this kind. Several hypotheses guide this investigation.

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[3] The CRAVED framework outlines the attributes of goods which make them more susceptible to theft according to an analysis of consistent hot products: concealable, removable, available, valuable, enjoyable, and disposable (Clarke, 1999).

[4] Where *value* incorporates the monetary value of a good, and *disposability* reflects the capacity for offenders to convert stolen goods to cash (Clarke, 1999).

1. More recently released models of gaming consoles (models that are still mass produced for sale in retail outlets) will exhibit a large correlation between availability and stealing counts due to the constraining factor of limited availability at this stage of the partial product life cycle, despite high value and disposability.
2. Older models of gaming consoles (models that are no longer mass produced for sale in retail outlets) will exhibit a large correlation between decreasing disposability and decreasing stealing counts due to the waning demand for stolen versions of the good in stolen goods markets.
3. Older models of gaming consoles (models that are no longer mass produced for sale in retail outlets) will exhibit a large correlation between decreasing value and decreasing stealing counts due to the decreasing value of stolen versions of the good in stolen goods markets.
4. An interaction between availability, disposability, and value will explain the majority of variance in stealing counts of specific makes and models of gaming consoles over time.
5. Gaming consoles with the highest value and the greatest disposability will have the highest corresponding stealing counts, controlling for availability during respective starts of lifecycles.

Methods

Domestic burglary stealing counts data
The Western Australian Police Force (WAPF) provided anonymised data on all incidents where items were flagged as stolen between January 2007 and December 2019, inclusive. For the purpose of this analysis, a subsection of this database was used. Specifically, the number of incidents in which *PlayStation 2, PlayStation 3, PlayStation 4, PlayStation Portable, Xbox 360, Xbox One, Nintendo Wii,* and *Nintendo DS* consoles were stolen from domestic dwellings between January 2012 and December 2019 were calculated separately for each console and aggregated at the monthly level for inclusion in the analysis using *R* (R, 2020).[5]

Value: Second-hand prices data
Web scraping is the process of extracting data from websites using a scripting language (php coding in this instance) by targeting a specific webpage, extracting

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[5] Throughout this article we use "stealing counts" to refer to the number of incidents in which a specific good was stolen from a domestic dwelling in a given time period.

the underlying HTML code, parsing the relevant data, and replicating it elsewhere. Web scraping is an emerging open-source intelligence tool for investigating illicit markets (see Maybir & Chapman, 2021, for an example with an online ecstasy user forum).[6] In the present study, a web scraping approach developed on the open-source text and source code editor software, *Atom*, was used to collect publicly accessible time series data on second-hand prices for gaming console adverts on legitimate online market platforms.[7]

All identifiable captures for webpages containing gaming console adverts on Gumtree—United Kingdom (UK) and eBay—UK between January 2012 and December 2019 were scraped and product title and price data were parsed.[8] These data included adverts for gaming console accessories, video games, and faulty gaming consoles. To remove these irrelevant records, code was written in *R* (R, 2020) to parse out adverts containing related terms as well as those from a lower price range (equivalent to video game prices for that console) and upper price range (outliers in the dataframe, attributable to rare models or large gaming packages). The retained advert prices were then aggregated (by averaging) at the monthly level for each console and rebased to 2019 prices, using the UK Consumer Price Index (Office for National Statistics, 2021). Figure 1 shows the relationships between second-hand market prices and stealing counts for *PlayStation 4* (a), *Xbox One* (b), *PlayStation 3* (c), *Xbox 360* (d), *PlayStation Portable* (e), *Nintendo Wii* (f), *PlayStation 2* (g), and *Nintendo DS* (h) consoles between 2012 and 2019, presented in reverse chronological order for product release date.

Availability: Cumulative faulty adjusted global lifetime sales data

Annual global unit sales (millions) data were obtained from the market research company *Statista* for the same time period as the stealing counts data.[9] An initial monthly time series dataset was constructed from the

annual global unit sales data by inserting intermediary data points with equal weights between two consecutive annual cumulative sales data points. This smoothed the data for the period in which gaming consoles were sold through retail outlets consistent with the upward trend during this time. When sales through retail outlets ceased, the peak cumulative sales data point was held constant over the remainder of the time period of the analysis. To account for the impact of faulty or damaged consoles being thrown out by the public and not resold (and therefore being unavailable for theft), the monthly count of specific gaming console adverts that contained the terms 'faulty', 'broken', or 'damaged' were divided by the corresponding total monthly count of specific gaming console adverts. The average proportions of faulty adverts for each console were then subtracted from the cumulative global sales units data points used previously.[10] Specifically, to obtain the first faulty-adjusted availability proxy value for a given console, this formula was used: (present month's unadjusted sales) − (average % of faulty consoles * present month's unadjusted sales), and then to obtain each respective value after that for a given console, this formula was used: (previous month's faulty-adjusted availability proxy value + present month's unadjusted sales)—((average % of faulty consoles) * (previous month's faulty-adjusted availability proxy value + present month's unadjusted sales)). Figure 2 shows the relationships between cumulative faulty adjusted global lifetime sales and stealing counts for *PlayStation 4* (a), *Xbox One* (b), *PlayStation 3* (c), *Xbox 360* (d), *PlayStation Portable* (e), *Nintendo Wii* (f), *PlayStation 2* (g), and *Nintendo DS* (h) consoles between 2012 and 2019.

Disposability: Google trends search interest data

The proxy for disposability comprised monthly Google Trends search interest data for each gaming console in Western Australia (WA) between January 2012 and

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[6] Open-source intelligence refers to the use of publicly available information for the purpose of addressing a specific intelligence problem.

[7] https://web.archive.org/—which is a digital library containing historical captures of web pages.

[8] The decision was made to scrape UK data as there were significantly more archived pages for this region than a region more local to that of the stealing counts dataset (an increase in data volume by approximately 344%), and prices between the two Western market-based countries should be equivalent. Consoles were also released at similar times in the two regions: five consoles were released on the exact same day in Australia and the UK, and the remaining three consoles were released one day, 6 days, and 16 days apart, respectively.

[9] Statista is a global business data platform that captures and shares market and consumer trends (Statista, 2021). All of the gaming consoles sales data were retrieved from Statista with the exception of *PlayStation 2* sales which were retrieved from a Wikipedia page with reputable sources (Wikipedia, 2021).

[10] The assumption here was that the average proportion of a console's adverts that were marked as faulty, broken, or damaged in the online second-hand markets would be a reasonable indication of the relative overall proportion of faulty versions of that console in the wider population (due to it reflecting the overall durability of that console). However, given the fact that a large proportion of faulty consoles would still be resold (albeit at a reduced price) rather than thrown out, it is expected that the proportion of consoles actually thrown out due to them no longer working would be a fraction of our proxy. As such, our proxy likely grossly over-estimates the true decrease in consoles available to burglars as a function of faulty consoles being thrown out. Nevertheless, the objective of this proxy was to test whether stealing counts decrease as a function of value and disposability of goods above and beyond decreases in availability. So, if decreasing prices or consumer desirability are still shown to be significantly associated with decreasing stealing counts when controlling for our availability proxy which overestimates the decrease in available consoles once retail sales cease, then it further supports the hypothesis. It is also worth pointing out another possibility that many more faulty/older consoles are thrown out than assumed in our proxy. In this instance, our proxy would likely under-estimate the decrease in available older consoles.

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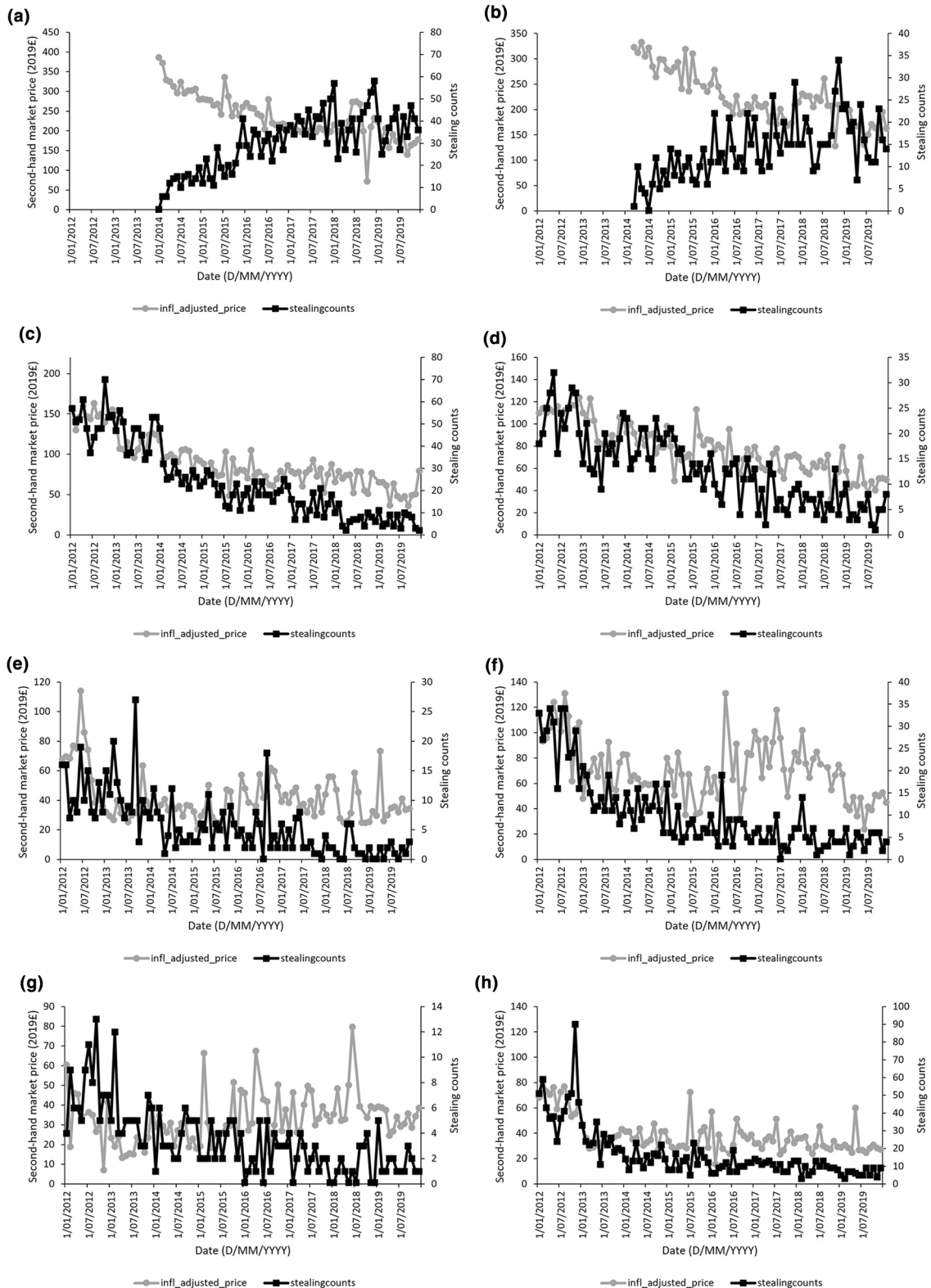
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Fig. 1 Inflation-adjusted second-hand market (eBayUK and GumtreeUK) prices and WA stealing counts for *PlayStation 4* (**a**), *Xbox One* (**b**), *PlayStation 3* (**c**), *Xbox 360* (**d**), *PlayStation Portable* (**e**), *Nintendo Wii* (**f**), *PlayStation 2* (**g**), and *Nintendo DS* (**h**) consoles between 2012 and 2019

December 2019, reflecting the changing consumer desirability of each console over the timeframe. Specifically, the Google Trends data were obtained for each console for the maximum time period they extended retrospectively (January 2004 for all consoles), and up until December 2019, to capture the peak popularity of older consoles during this window. This was important because the Google Trends numbers reflect search interest relative to the highest data point for a given region and time, such that 100 is the peak popularity for the term and other numbers are relative to this. Figure 3 shows the relationships between Google Trends search interest scores and stealing counts for *PlayStation 4* (a), *Xbox One* (b), *PlayStation 3* (c), *Xbox 360* (d), *PlayStation Portable* (e), *Nintendo Wii* (f), *PlayStation 2* (g), and *Nintendo DS* (h) consoles between 2012 and 2019.

Results

Given the hypothesised constraining role of limited availability on gaming consoles at the beginning stages of their lifecycle (defined here as goods still being mass produced for sale in retail outlets), it was important to establish which consoles this affected. Table 1 shows the release dates and discontinued dates of each of the consoles included in the analysis. The *PlayStation 4* and *Xbox One* consoles were both released during the time period of the analysis and continued to be mass produced for sale in retail outlets throughout the analysis period. As such, interpretation of the results will need to take into account the constrained availability of these two consoles at the outset of the analysis period.

Correlational analyses of the relationship between market force proxies and console stealing counts

To initially test the relationships between the proxies for the availability, value, and disposability of each gaming console with their respective stealing counts over time (and begin to test hypotheses 1, 2, and 3), a series of correlational analyses on the raw data were performed. Table 2 presents a correlation matrix depicting the coefficients for the relationships between stealing counts, cumulative faulty adjusted lifetime sales, Google Trends search interest scores, and mean second-hand prices for each of the consoles between 2012 and 2019.

As depicted in Fig. 2 and the correlational analyses presented in Table 2, there was a positive association between monthly cumulative faulty adjusted lifetime sales and monthly stealing counts for the two consoles which continued to be mass produced for sale in retail outlets throughout the time period of the analysis (*PlayStation 4* and *Xbox One* consoles, Fig. 2(a) and (b)), as well as for all other consoles except the *Nintendo Wii* console (Fig. 2(f)) which reached peak cumulative sales

much later than the other discontinued consoles involved in the analysis. The plotted raw time series data and correlational analyses also suggest a positive association between Google Trends search interest and stealing counts for all consoles included in the analysis, with the exception of *Xbox One* consoles. The relationship between mean second-hand prices of consoles with their respective stealing counts appears to be more nuanced. For the two consoles which continued to be mass-produced throughout the analysis the association is negative, as the initial limited availability of the console to prospective burglars appears to constrain their capacity to exploit the high (albeit decreasing) prices of these consoles. For consoles further along in their lifecycle, falling second-hand prices appear to be positively associated with falling stealing counts until the consoles reach a lower threshold (around £50) at which the prices stabilise somewhat while stealing counts continue to fall. This likely explains the statistically significant correlations between second-hand prices and stealing counts for some consoles, but not others, as depicted in Table 2. In sum, over the entire life cycle of a console, Google Trends search interest appears to be the best linear predictor of the console's respective stealing counts. However, correlational analyses can be spurious due to issues such as deterministic trends and omitted variable bias. As such, it is necessary to perform more rigorous statistical testing to account for these issues.

Multivariate autoregressive time series models of the relationship between market force proxies and console stealing counts

Due to the way in which the cumulative faulty adjusted lifetime sales measure was calculated, and its subsequent lack of temporal volatility, the faulty adjusted lifetime sales measure was dropped from this part of the analysis.[11] An additional variable—the monthly stealing count of other electronic goods from domestic dwellings[12]—was included in the analyses to control for omitted variables which might conceivably explain variations in stealing counts of *any* given electronic good, such as changes in household security or law enforcement

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[11] Time series analyses essentially work by detrending a time series (in addition to meeting other assumptions) and testing the association between short-term (e.g., monthly) fluctuations for each time series variable included in the analysis. However, because we artificially created the intermediary points (smoothed the data) to convert the faulty adjusted lifetime sales data from an annual dataset to a monthly one, this meant that the time series was simply an upward or downward trend for each console. This means that if the faulty adjusted lifetime sales time series is de-trended, it essentially becomes meaningless in an analytic context.

[12] This was calculated by counting the number of incidents in the WAPF database in which an electronic good (except for the specific console involved in a given analytic model) was stolen from a domestic dwelling between January 2012 and December 2019, aggregated at the monthly level.

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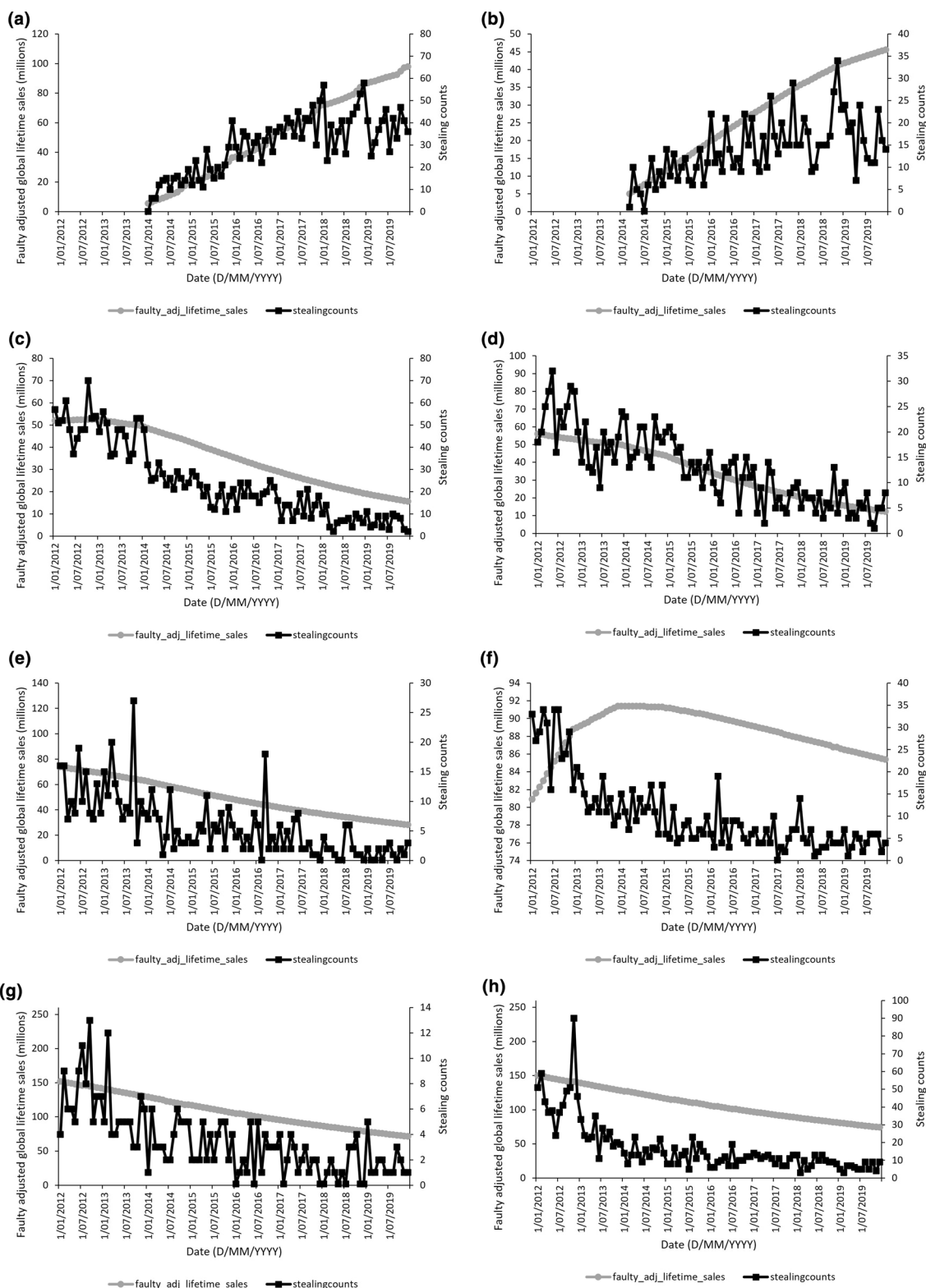
Fig. 2 Cumulative faulty adjusted global lifetime sales (millions) and WA stealing counts for *PlayStation 4* (**a**), *Xbox One* (**b**), *PlayStation 3* (**c**), *Xbox 360* (**d**), *PlayStation Portable* (**e**), *Nintendo Wii* (**f**), *PlayStation 2* (**g**), and *Nintendo DS* (**h**) consoles between 2012 and 2019

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Fig. 3 WA Google Trends search interest and WA stealing counts for *PlayStation 4* (**a**), *Xbox One* (**b**), *PlayStation 3* (**c**), *Xbox 360* (**d**), *PlayStation Portable* (**e**), *Nintendo Wii* (**f**), *PlayStation 2* (**g**), and *Nintendo DS* (**h**) consoles between 2012 and 2019
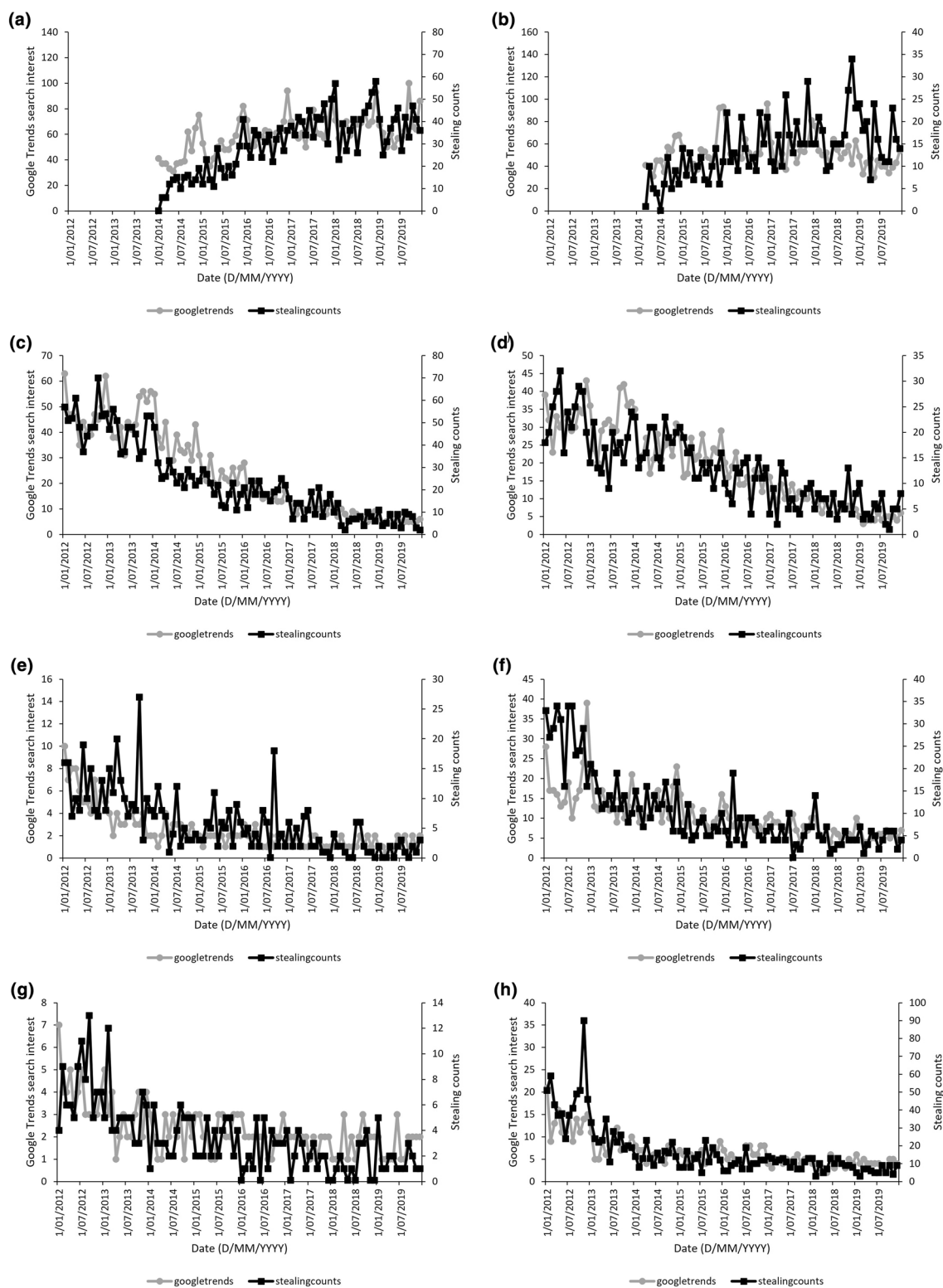
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Table 1 Release dates and discontinued dates of gaming consoles involved in the analyses

Console name	Release date	Discontinued date
PlayStation 4	2013	Ongoing
Xbox One	2013	Ongoing
PlayStation 3	2007	2017
Nintendo Wii	2006	2016
Xbox 360	2005	2017
PlayStation Portable	2005	2014
Nintendo DS	2004	2014
PlayStation 2	2000	2013

practices. First, all variables included in these analyses (monthly gaming console stealing counts, monthly Google Trends scores, monthly mean prices, and monthly stealing counts of other electronic goods) were log transformed. Next, several diagnostic tests were performed to check for stationarity and autocorrelation of the data and to specify the most appropriate analytical model. Stationarity refers to time series data where the mean and variance are constant over time. We opted for the Augmented Dickey-Fuller procedure for determining whether the time series data were stationary or nonstationary. The results suggested that one or more of the

Table 2 Correlation matrix depicting correlation coefficients for stealing counts and market forces (faulty adjusted sales = availability, Google trends = disposability, and mean price = value) of each console—2012–19

	Stealing counts	Faulty adjusted sales	Google trends
PlayStation 4			
Faulty adjusted sales	0.78***		
Google trends	0.65***	0.60***	
Mean price	− 0.72***	− 0.82***	− 0.54***
Xbox One	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.60***		
Google trends	0.06	− 0.05	
Mean price	− 0.53***	− 0.84***	0.00
PlayStation 3	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.89***		
Google trends	0.89***	0.93***	
Mean price	0.86***	0.83***	0.84***
Xbox 360	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.83***		
Google trends	0.78***	0.92***	
Mean price	0.73***	0.83***	0.77***
PlayStation Portable	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.69***		
Google trends	0.53***	0.75***	
Mean price	0.29**	0.30**	0.45***
Nintendo Wii	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	− 0.32**		
Google trends	0.61***	0.03	
Mean price	0.50***	− 0.25*	0.36***
PlayStation 2	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.70***		
Google trends	0.47***	0.62***	
Mean price	− 0.28**	− 0.28**	0.09
Nintendo DS	Stealing counts	Faulty adjusted sales	Google trends
Faulty adjusted sales	0.73***		
Google trends	0.74***	0.74***	
Mean price	0.63***	0.58***	0.68***

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

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log-transformed variables for each of the consoles were nonstationary. A widely practiced method of dealing with nonstationary data is to transform the data using first differencing. First differencing was applied to all variables included in the models, consistent with procedures used in other work (Greenberg, 2001; Sidebottom et al., 2014). As shown in Additional file 1: Appendix S1, this transformation meant that all log-transformed, first-differenced variables were now stationary.

Autocorrelation refers to serial dependency of the residual errors of time series data which leads to biased standard errors of the regression coefficients. To check for possible autocorrelation, a Durbin-Watson test statistic was computed for each of the console models. The Durbin-Watson test statistic was statistically significant for all console models except for the *PlayStation 4* model, indicating these models exhibited autocorrelation. Given the evidence of serial dependency in the data, it was necessary to account for this in the respective analyses. Partial autocorrelation function (pacf) plots were generated for the stealing counts dependent variable in each model and visually inspected to examine the nature of the autocorrelation. The pacf plots suggested that the strongest autocorrelation for the stealing counts dependent variable in the *PlayStation 3, PlayStation Portable, Xbox 360, Xbox One, Nintendo Wii,* and *Nintendo DS* models were for observations separate by a single (one month) lag, indicating first-order autocorrelation, while for the *PlayStation 2* model it was for observations separated by three lags (three months), indicating third-order autocorrelation. This suggested that a lagged dependent variable for the *PlayStation 3, PlayStation Portable, Xbox 360, Xbox One, Nintendo Wii,* and *Nintendo DS* stealing counts, and a third-order lagged dependent variable for the *PlayStation 2* stealing counts should be included in the relevant multivariate time series model to correct for autocorrelation. The subsequent Durbin-Watson test statistics calculated for each of the models with the relevant lagged dependent variables were non-significant, indicating that autocorrelation was now corrected for in all of the console models. Due to the theoretical likelihood that changing value and disposability exhibit a delayed impact on stealing counts (through a stolen goods market disposal feedback mechanism), models were also estimated using lagged mean second-hand prices and Google Trends search interest variables. Table 3 presents the results of the multivariate autoregressive time series analyses for models with statistically significant coefficients.[13]

The results of the multivariate autoregressive time series analyses yielded statistically significant log–log coefficients for one-month lagged *Xbox One* Google Trends search interest on *Xbox One* monthly stealing counts, 1-month lagged *PlayStation 3* Google Trends search interest on *PlayStation 3* monthly stealing counts, and monthly *Xbox 360* Google Trends search interest on *Xbox 360* monthly stealing counts. In contrast, there were no statistically significant coefficients for mean second-hand prices on stealing counts for any of the consoles. While it is noteworthy that only three of the eight consoles analysed yielded statistically significant coefficients for the association between Google Trends search interest and stealing counts, this is not unexpected given some of the statistical properties of the data involved. For example, while inclusion of a lagged dependent variable to control for autocorrelation is effective, it can also exert a downward force on the model coefficients (Achen, 2000). Additionally, given the stationarity of many of the log-transformed Google Trends time series for different consoles prior to first-differencing, it is possible these variables were over-differenced after this secondary transformation was applied. Indeed, the three consoles which exhibited statistically significant Google Trends search interest coefficients were comparatively newer consoles with greater variability in Google Trends scores throughout the period of the analysis. In contrast, older consoles exhibited comparatively little variability in Google Trends scores as they were less searched throughout the entire period of the analysis.

So far we have considered consoles independently of one another in the analyses. Next, we estimate fixed effects panel regression models which incorporate the time series data for market forces and stealing counts of all consoles.

Fixed effects panel regression models of the relationship between market force proxies and console stealing counts

To prepare the panel data, only observations between January 2014 and December 2019 were used to ensure the data for all consoles were balanced.[14] Using the log-transformed panel data for the stealing counts and Google Trends search interest scores of all gaming consoles, the following baseline model was estimated:

$$Log\left(C_{gt}\right) = \alpha_g + \beta Log\left(G_{gt}\right) + \tau_t + \varepsilon_{gt}$$

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[13] The non-significant results were excluded due to space limitations and are available on request.

[14] This was because the *PlayStation 4* and *Xbox One* consoles were released towards the end of 2013 and therefore data were not available prior to this date for these consoles.

Table 3 Estimates of stealing counts-Google Trends search interest and stealing counts-mean price elasticities—2012–2019

	Log (Stealing counts) β	Standard Error	*p* value
Xbox One			
Log (Google trends) lag1	0.846	0.384	< 0.05
Log (Mean price) lag1	0.067	0.671	n.s
Log (Other electronic stealing counts)	1.386	0.744	n.s
Lagged dependent variable	− 0.441	0.113	< 0.001
PlayStation 3	Log (Stealing counts) β	Standard Error	*p* value
Log (Google trends) lag1	0.389	0.181	< 0.05
Log (Mean price) lag1	− 0.226	0.191	n.s
Log (Other electronic stealing counts)	0.788	0.337	< 0.05
Lagged dependent variable	− 0.472	0.090	< 0.001
Xbox 360	Log (Stealing counts) β	Standard Error	*p* value
Log (Google trends)	0.528	0.193	< 0.01
Log (Mean price)	0.150	0.237	n.s
Log (Other electronic stealing counts)	0.282	0.410	n.s
Lagged dependent variable	− 0.447	0.089	< 0.001

The variance inflation factor (vif)—a measure of multicollinearity between model variables—was calculated for all model variables and values ranged between 1.00 and 1.12, where a vif above 10 indicates high correlation and is a cause of concern). Variables with the term 'lag1' indicate a time series variable where the values are lagged by one month. *B* coefficients can be interpreted as a 1% change in the independent variable being associated with a *B*% change in stealing counts. For example, a 1% change in Google trends values for the *Xbox One* console was associated with a 0.85% change in stealing counts of that console

where, *C* is the count of gaming consoles stolen, *G* is the Google Trends search interest score, α_g is a gaming console-specific fixed effect, τ_t is a year*month dummy to control for time effects, and ε_{gt} is an error term. The inclusion of the gaming console-specific and time fixed effects ensures the estimated elasticity β is a within-product elasticity identified from changes in stealing counts and Google Trends search interest scores. Given the pre-established autocorrelation of the stealing counts data, the model is also estimated with a lagged dependent variable included. The results of the baseline fixed effects panel regression model are presented in Table 4.

Model specifications (1) and (2) produce a robust, statistically significant elasticity of gaming console monthly stealing counts with respect to monthly Google Trends search interest. The estimate is similar across the two specifications which differ based on the inclusion of time fixed effects. Moreover, inclusion of the lagged dependent variable in specification (3) to control for autocorrelation still yields a statistically significant coefficient which does not reduce much in size. This suggests the estimates are robust to temporally persistent stealing counts dynamics (Draca et al., 2019). To determine the possible bias that may still exist in the above elasticities due to time-varying omitted variables that change both stealing counts and Google Trends search interest over and above the time fixed effects already included in the model, the lag structure of the Google Trends search interest effects can be examined. Additionally, other market force variables can be included in the model to account for the possible influence of these

variables on stealing counts. To this end, the following model was estimated:

$$
\begin{aligned}
Log\big(C_{gt}\big) = {} & \alpha_g + \beta Log\big(G_{gt}\big) + \beta Log\Big(G_{g\,(t-1)}\Big) \\
& + \beta Log\Big(G_{g\,(t-2)}\Big) + \beta Log\Big(G_{g\,(t-3)}\Big) \\
& + \beta Log\big(P_{gt}\big) + \beta Log\big(F_{gt}\big) + \tau_t + \varepsilon_{gt}
\end{aligned}
$$

where, the additional term (*t—n*) reflects the lagged variable of *n* months, *P* is the mean price of gaming consoles,

Table 4 Baseline estimates of stealing counts-Google Trends search interest elasticities—2014–2019

	Log (Stealing counts) β		
	(1)	(2)	(3)
Log (Google trends)	0.842***	0.886**	0.698***
	(0.082)	(0.279)	(0.167)
Lagged dependent variable			0.277***
			(0.076)
Console fixed effects	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes
Number of consoles	8	8	8
Number of observations	576	576	576

*** $p < 0.001$ ** $p < 0.01$. Standard errors clustered by console code in parentheses. *B* coefficients can be interpreted as a 1% change in the independent variable being associated with a *B*% change in stealing counts. For example, in specification (1), a 1% change in Google trends values was associated with a 0.84% change in stealing counts

Table 5 Estimates of stealing counts-Google Trends search interest elasticities allowing for disposability dynamics and the influence of other market forces

	Log (Stealing counts) β						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (Google trends)	0.886**	0.626**	0.575**	0.578**	0.591**	− 0.080	− 0.005
	(0.279)	(0.212)	(0.215)	(0.215)	(0.187)	(0.067)	(0.039)
Log (Google trends) lag1		0.447***	0.327***	0.351**	0.348**	0.097	0.179*
		(0.089)	(0.093)	(0.112)	(0.109)	(0.093)	(0.090)
Log (Google trends) lag2			0.221***	0.258***	0.284***	0.199*	0.314***
			(0.059)	(0.062)	(0.067)	(0.096)	(0.058)
Log (Google trends) lag3				− 0.072	− 0.074	− 0.105	− 0.172
				(0.016)	(0.169)	(0.132)	(0.184)
Log (Mean price)					− 0.669**	− 0.178	− 0.138
					(0.233)	(0.149)	(0.120)
Log (FA sales)						1.096***	0.291
						(0.133)	(0.204)
Console fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of consoles	8	8	8	8	8	8	6
Number of observations	576	576	576	576	576	576	432

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard errors clustered by console code in parentheses. FA = faulty adjusted cumulative lifetime sales. Variables with the term 'lagx' indicate a time series variable where the values are lagged by x months. *B* coefficients can be interpreted as a 1% change in the independent variable being associated with a *B*% change in stealing counts. For example, in specification (1), a 1% change in Google trends values was associated with a 0.89% change in stealing counts

and *F* is the (cumulative) faulty adjusted global lifetime sales of gaming consoles. The results of this fixed effects panel regression model are presented in Table 5.

Specifications (1), (2), (3), and (4) demonstrate that the relationship between changing Google Trends search interest and stealing counts of gaming consoles persists with a two-month delay. That is, Google Trends search interest for a given gaming console two months prior is still significantly related to stealing counts of that console in the present month. This suggests that any confounding time-varying omitted variable would need to follow a similarly short-run relationship with changing stealing counts. Specification (5) shows that inclusion of the mean second-hand price variable does not significantly change the stealing counts-Google Trends search interest elasticity, and that mean second-hand price actually exhibits a significant negative relationship with stealing counts. This is likely driven by the two most valuable (and still mass-produced) consoles involved in the analysis, which as previously described, can be explained by the fact that the availability of these consoles to prospective burglars appears to constrain their capacity to exploit the high (albeit decreasing) prices of the consoles. Specification (6) shows that the stealing counts-Google Trends search interest elasticity at the two-month lag persists even with the inclusion of the grossly over-estimated decreasing availability of consoles reflected in the cumulative faulty

adjusted global lifetime sales measure. Moreover, when the two newest consoles are removed from the model as in specification (7), the stealing counts-Google Trends search interest elasticity at the two-month lag increases, and the availability proxy loses significance. As such, ignoring the last two specifications, a conservative estimate emerging from these results is that a 10% increase (decrease) in the Google Trends search interest of a gaming console is associated with a 5% increase (decrease) in stealing counts of that gaming console that same month.

Up to now we have only considered within-console variance in stealing counts and market forces. Next, we test the availability, value, and disposability of consoles in

Table 6 Cross-sectional estimates of stealing counts-market force relationships between consoles in 2014

	(Stealing counts) β	Standard Error	p value
Google trends	− 1.907	2.570	n.s
FA sales	− 0.594	1.081	n.s
Google trends*FA sales	0.197	0.052	< 0.05

FA = faulty adjusted cumulative lifetime sales. The variance inflation factor (vif)—a measure of multicollinearity between model variables—was calculated for all model variables and values ranged between 1.43 and 5.12, where a vif above 10 indicates high correlation and is a cause of concern). Mean price was not included in the reported results because neither mean price alone, nor an interaction between mean price and faulty adjusted sales, significantly predicted stealing counts in 2014

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Table 7 Cross-sectional estimates of stealing counts-market force relationships between consoles in 2016, 2017, 2018, and 2019

	Stealing counts β							
	2016	2016	2017	2017	2018	2018	2019	2019
Google trends	3.430*		5.134**		5.277**		5.705***	
	(1.326)		(1.221)		(0.902)		(0.696)	
Mean price		0.985		1.798*		1.722*		1.925**
		(0.424)		(0.544)		(0.450)		(0.424)
FA sales	− 0.253	− 0.388	0.523	0.653	0.668	1.003	0.277	1.070
	(1.029)	(1.077)	(1.021)	(1.224)	(0.785)	(1.098)	(0.505)	(0.795)

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard errors clustered by console code in parentheses. FA = faulty adjusted cumulative lifetime sales. The variance inflation factor (vif)—a measure of multicollinearity between model variables—was calculated for all model variables and values ranged between 1.01 and 1.25, where a vif above 10 indicates high correlation and is a cause of concern). Google trends and mean price variables were tested in separate models due to multicollinearity

explaining the variance in stealing counts *between* consoles. These analyses were conducted to test hypotheses 4 and 5.

Between-console cross-sectional regression models

Given the cross-sectional nature of these analyses, data were aggregated at the annual level and the relationship between gaming console stealing counts with the availability, value, and disposability of gaming consoles were analysed separately for each year in which data were available (2014–2019, inclusive). Table 6 presents the results of the 2014 cross-sectional regression model that yielded a statistically significant coefficient.[15]

These results suggest that an interaction between the cumulative faulty adjusted global lifetime sales of a console and the Google Trends search interest was a statistically significant predictor of which consoles were most stolen in 2014 (the year when *PlayStation 4* and *Xbox One* consoles entered the market), and explains the majority of variance in stealing counts, though the model did not quite reach statistical significance (Adjusted $R^2 = 0.66$, $p = 0.06$). While a similar interaction variable was expected to significantly predict stealing counts in 2015, no variables reached statistical significance for that year.[16] Table 7 presents the results of the 2016–2019 (inclusive) regression models that yielded statistically significant coefficients.

For each year between 2016 and 2019 (inclusive), Google Trends search interest was a statistically significant predictor of which consoles were stolen most, controlling for cumulative faulty adjusted global lifetime sales. Moreover, in 2017, 2018, and 2019, Google Trends search interest explained the majority of variance in stealing counts of gaming consoles, and the models

were statistically significant (Adjusted $R^2 = 0.69$, $p < 0.05$, Adjusted $R^2 = 0.84$, $p < 0.01$, and Adjusted $R^2 = 0.93$, $p < 0.001$, respectively). Mean second-hand price was also a statistically significant predictor of which consoles were stolen most in 2017, 2018, and 2019, controlling for cumulative faulty adjusted global lifetime sales.

Discussion and conclusions

Support was found for a positive relationship between the changing disposability of specific makes and models of gaming consoles over their life cycle with corresponding stealing counts, controlling for availability of the console to prospective burglars. Consistent with hypotheses 1 and 2, the limited availability of a specific electronic good at the outset of its life cycle appears to exert a constraining influence on a prospective burglar's capacity to steal these goods, but once goods are sufficiently available, the changing disposability best explains their relative stealing counts. A conservative pooled estimate for the impact of our proxy for changing disposability (Google Trends search interest—reflecting legitimate consumer desirability) on stealing counts is that a 10% increase (decrease) in local Google Trends search interest of a console is associated with a 5% increase (decrease) in local stealing counts of that gaming console that same month. This is consistent with the notion that offenders are attuned to stolen goods market dynamics (Nee et al., 2019; Schneider, 2005; Stevenson et al., 2001) and that legitimate market forces inherent in partial product life cycles are predictive of theft trajectories of those products. Evidence was also found for a significant positive relationship between lagged Google Trends search interest scores and stealing counts at the one-month and two-month lag, consistent with the notion that burglars become attuned to changing disposability of goods through a stolen goods market

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[15] Regression models with non-significant coefficients were excluded due to space limitations and are available on request.

[16] Results of the 2015 regression models are available on request.

disposal feedback mechanism. This can be understood in terms of offender crime scripts (Cornish, 1994; Cornish & Clarke, 2017), whereby a burglar's difficulty in disposing of a particular good may lead to the target selection (at the goods level) step of their overarching internal behavioural model of a criminal event to be revised, such that in future burglaries that good is less prioritised over other goods. Indeed, this is consistent with the finding that burglars have an ever-changing hierarchy of goods that they prefer to steal (Sutton, 2010).

Given that we controlled for longitudinal availability of different consoles when analysing the impact of changing disposability on stealing counts, our interpretation of these findings is that when more experienced burglars are inside a dwelling, their offence-specific domain expertise would lead them to leave behind consoles that are in low demand. Instead, these burglars would target only those goods they know to be in high demand (whether that be a different gaming console—if available, or other goods entirely). This fits with experienced burglars optimising the value of their stolen goods haul while taking into account physical limitations (the size and weight of the haul) when removing it from the dwelling (Nee et al., 2015, 2019). More specifically, it fits with the finding that experienced burglars were more interested in stealing a newer model iPad than an older model iPad during a virtual reality burglary simulation, when compared to a non-burglar sample (Nee et al., 2019). Another possibility is that when experienced burglars are faced with a lack of rewarding targets, they choose to cut their losses rather than steal goods they know they will have to use more time and effort to dispose of (and for a lower return). This fits with a recent study to highlight the association between the decreasing reward of property crimes during the property crime drop (due to the decreasing value of electronic consumer goods) with the increasing proportion of burglaries in which nothing was stolen (Quinn & Clare, 2021b).

Unlike investigations of price-theft relationships for specific commodity goods like copper, steel, and oil (see Quinn et al., 2022) where statistically significant positive relationships have consistently been found, the relationship between mean second-hand prices of electronic consumer goods with their respective stealing counts appears to be more nuanced. The correlational evidence presented here, although inconclusive for this variable, shows an initial inverted relationship between second-hand prices and stealing counts of gaming consoles as the initial limited availability of the console to prospective burglars appears to constrain their capacity to exploit the high (albeit decreasing) prices. As a console progresses further along the life cycle and retail sales cease, decreasing second-hand prices appear to be positively associated with decreasing stealing counts until the consoles reach a lower price threshold (around £50 in this instance), at which point prices stabilise but stealing counts continue to decrease. Future research should attempt to identify with greater precision this lower threshold at which goods become unworthy of stealing and model the non-linear relationship between second-hand prices and stealing counts. Another possible explanation for the lack of significant linear relationship between prices and stealing counts in this paper is that the adverts scraped from the online second-hand markets incorporated sales of original packaged goods sold through non-traditional "retail" outlets. As such, the stabilisation of mean second-hand prices in the years in which a console was discontinued from traditional retail outlet sales may reflect the absorption of this market by the non-traditional "retail" outlets online.

Consistent with hypothesis 4, support was found for an interaction between the availability and disposability of any given console significantly predicting stealing counts in the first year in which the two newest consoles involved in the analysis began their lifecycle. Support was also found for the most valuable and disposable consoles in 2017, 2018, and 2019 significantly predicting stealing counts, controlling for availability, and also explaining the majority of variance in stealing counts over these years. This finding, which is consistent with hypothesis 5, is more aligned with existing cross-sectional analyses of the association between CRAVED attributes and stealing counts (for example, see Smith, 2018). This finding also fits with criminal decision-making models that reflect offender domain expertise (Nee & Meenaghan, 2006; Nee et al., 2015, 2019). Specifically, it appears to reflect at an aggregate level, the 'expert' target selection of burglars towards goods that are the most valuable and easily disposable in stolen goods markets given the time and removability constraints that exist during the crime event.

There were a number of data limitations for this study worth mentioning. While the open-source intelligence web-scraping approach proved tenable and yielded a usable dataset, the haphazard archival nature of the price data source placed constraints on the amount and periodicity of price data that could be collected. Future research should employ a similar web-scraping approach but utilise it in a prospective sense to periodically scrape localised, live webpages for intel. Another limitation was the proxy used for the longitudinal availability of each console. As mentioned throughout, this proxy likely

grossly over-estimated the proportion of consoles that become unavailable to prospective burglars once they are discontinued and eventually thrown-out due to being irreparable or deemed not worth the effort of re-selling. The calculation of this time series from an annual dataset also precluded more rigorous examination of this proxy with the multivariate autoregressive time series modelling. Future research should identify and investigate more suitable proxies for availability of specific makes and models of electronic consumer goods to burglars. Finally, given the nature of the police-recorded stealing counts data, there is the possibility of reporting bias affecting results. Specifically, victims may have differentially reported consoles as stolen depending on their personal value to them, which may encompass market force measures of price and demand, thus obscuring these relationships with actual stealing counts. However, it is worth noting that a recent study examining the potential impact of changes in prices of specific consumer goods on victim reporting found that this influence is very limited (Draca et al., 2019). This provides some reason to believe that any influence of victim reporting bias on the findings presented in this study are also very limited.

Despite these data limitations, the present article presents robust evidence for the role of changing legitimate consumer desirability (disposability) on stealing counts. It also suggests that when the CRAVED framework is tested on consumer goods in a dynamic sense, disposability is the best predictor of offenders' target selection at the goods level, even when controlling for changing availability of these goods. Moreover, it shows that while burglars are highly responsive to changes in disposability of specific makes and models of goods over time, they appear less responsive to changes in value, seemingly due to second-hand prices stabilising at a lower threshold while stealing counts continue to fall. Additionally, the present article provides evidence that legitimate market forces (including data retrieved from open-source intelligence web-scraping practices) can be used as suitable proxies for stolen goods market dynamics and predict theft risk over an electronic consumer good's life cycle.

The results presented in this article have important implications for theft risk assessment, policy, and crime prevention practices. Broadly, the results support continued efforts to reduce the disposability of stolen versions of a good (Armitage & Pease, 2008; Kirchmaier et al., 2020; Mares & Blackburn, 2017). Indeed, recent work has presented a case for the reduced reward of property crime partially explaining the property crime drop phenomenon across Western market-based countries (Quinn & Clare, 2021b). More specifically, the results provide the basis for the development of theft indices (see Laycock, 2004; Mailley et al., 2008) for electronic consumer goods identifying the specific makes and models with the greatest theft risk over time, controlling for availability and other market forces. This would serve to instil a culture where manufacturers are encouraged to improve reward-reduction technology to have a less risky product (for example, see Laycock, 2004) or otherwise suffer reputational brand damage. This same effect can also be achieved through government policy targeted towards the manufacturers of electronic consumer goods, advocating an industry responsibility to design out crime. Additionally, mapping the longitudinal theft risk of specific electronic consumer goods would enable identification of the time periods that consumers should be on highest alert for theft of specific consumer goods (particularly for theft from the person offences). This would serve to increase consumer vigilance for theft of specific goods in a targeted way, through opportunity reduction in the first instance, and market disruption in the second. For example, consistent with the market reduction approach (Sutton, 1998), second-hand online market actors could be encouraged to be on the lookout for suspicious adverts of goods with a high theft-risk using an advert banner alert. Additionally, second-hand market platforms could be required to exercise greater responsibility in ensuring the legitimate ownership of products sold through the platforms. From a policy evaluation perspective, taking into account the influence of criminogenic market forces on stealing counts of specific goods would yield a more reliable outcome measure for the evaluation of situational crime prevention initiatives aimed at target hardening or reward-reduction (Guerette & Clarke, 2003).

Abbreviations
CRAVED: Concealable, removable, available, valuable, enjoyable, disposable; FA: Faulty adjusted cumulative lifetime sales; ONS: Office for National Statistics; UK: United Kingdom; VIF: Variance inflation factor; WA: Western Australia; WAPF: Western Australian Police Force.

Supplementary Information
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Additional file 1: Appendix S1. Augmented Dickey-Fuller Test for Unit Root using log-transformed and log-transformed, first-differenced variables.

Availability of data and materials
Data and code can be made available upon request.

Declarations

Competing interests
The authors declare that they have no conflicts of interest.

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