One Flew Over the Cuckoo's Clock

Selling Exclusivity Through Conspicuous Goods on Evolution

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Abstract Despite the increase of specialised law enforcement and commercial art crime databases concerning the registration of luxury products, it remains an often-overlooked category in art crime research. This chapter analyses the market for luxury products, focusing specifically on watches, jewellery, and designer clothing, on defunct anonymous marketplace *Evolution*, which was active between January 2014 and March 2015. We argue that this marketplace works as a way to buy exclusivity through the purchase of both original and counterfeited luxury goods, here called 'conspicuous goods'. The goods we focus on in our analysis endow cultural value, and their possession allows consumers to display a higher level of distinction. However, rather than looking at consumers who desire to differentiate themselves by purchasing these objects, we were more interested in how the market is structured to best sell these products. Therefore, we have implemented a series of statistical analyses on the market supply, focusing on the type of traded object, their brand, and the average prices in Bitcoin, finding that a brand effect on price is at work both in counterfeited and original conspicuous goods. This signals that the market is aware of the dynamics of conspicuous goods and its sellers behave accordingly.

1 Introduction

On 6 November 2014, law enforcement agencies around the world, in a cooperative effort of Europol and the FBI, took part in *Operation Onymous*. During this operation, over 200 online anonymous marketplaces (commonly known as 'dark

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markets', 'dark nets', or 'cryptomarkets') were closed down (Afilipoaie & Shortis, 2015). In the operation, over 1 million USD worth of Bitcoin was confiscated, 17 arrests were made, and gold, silver, weapons, computers, and cash were seized. This included high-profile marketplace Silk Road 2.0. Not all marketplaces were closed down. The dark market *Evolution*, which in 2014 was "(. . .) considered to be the market leader, with commentators putting this down to its sleek interface, quick loading times and security features such as multi-signature escrow", saw a 26 percent increase of sales when Silk Road 2.0 went defunct (ibid, pp. 2–3).

There is no systematic or uniform definition for what constitutes a dark market. Overall, the common denominator between different dark marketplaces is that they offer a platform for risk management for participants who wish to make anonymous transactions (Soska & Christin, 2015). They are not, in contradiction to popular belief, in themselves platforms that sell illicit products. Apart from mitigating risk, these online markets can, for example, function as "virtual brokers" that connect multiple vendors, and can even link "online wholesalers with offline retail-level distributors" (Aldridge & Décary-Hétu, 2016, pp. 12–13). What separates the online anonymous marketplace from other online marketplaces such as eBay is the fact that the first ensures complete anonymity, shielding all your personal information (such as IP address), which the latter cannot.

Despite drugs being one of the predominant products sold on online anonymous marketplaces (Aldridge & Décary-Hétu, 2016; Červený & van Ours, 2019; Soska & Christin, 2015), a substantial amount of both original and counterfeit luxury products (such as watches, jewellery, and designer clothes) are offered for sale. These goods can be categorised as so-called 'Veblen goods' or 'conspicuous goods'. These goods, first discussed by Thorstein Veblen in 1899, concern those goods that people with high wealth often consume to great extent to showcase their prosperity to achieve greater social status. In online anonymous marketplaces the supply for these goods indicates a certain demand for objects that can increase the "cultivation of the aesthetic faculty" (Veblen, 1899, p. 75) and indicates a possible driver for distinction that can only be achieved by owning a Veblen good (Bourdieu, 1984; Trigg, 2001). In a certain way, by displaying a form of distinction through material and cultural wealth, "members of higher classes voluntarily incur costs to differentiate themselves from members of lower classes [. . .], knowing that these costs must be large enough to discourage imitation" (Bagwell & Bernheim, 1996, p. 350). These goods however are an often-overlooked category in art crime research, despite the increasing focus of both specialised law enforcement and commercial databases for these objects. The anonymous marketplace positions itself as an ideal location to supply these products as they can be acquired anonymously, and with little risk to the individual seller and buyer.

In this research, we have analysed this category of conspicuous goods by studying the online anonymous market for these objects, specifically focusing on their price and branding mechanisms. We did this by analysing the supply dynamics of both counterfeit and authentic conspicuous goods sold on Evolution. Rather than looking however at the ways in which consumers themselves display patterns of conspicuous consumption, we look at the way the market for these goods is

structured. As such, rather than viewing objects as a passive entity, we argue that these objects themselves display an agency of 'desire' and that sellers on this market are aware of the desires these goods provoke. We argue therefore that these goods have criminogenic qualities: in addition to being objects that allow for the idea of upwards social mobility, they also 'invite' acts of criminal behaviour, such as counterfeiting. We argue that this particular illicit market is aware of this, by increasing prices for these goods and framing them as 'desirable' objects by specifying brands and relying on brand effects.

2 The Market for Conspicuous Goods: A New Avenue for Art Crime Research

Studies on crimes in the art world often focus on cultural commodities, and concern, amongst other topics, the theft of cultural artefacts (Kerr, 2015), the policing of art and heritage crime (Oosterman, 2019; Oosterman & Yates, 2020), the illicit trafficking and looting of cultural objects (Mackenzie et al., 2019; Yates, 2015), legislation (Roodt & Carey-Miller, 2013), financial regulation and fraud on the art market (Hufnagel & King, 2020) and the looting of antiquities (Brodie, 2003). An often-overlooked category in art crime research however is that of luxury goods, here called conspicuous goods, such as watches, jewellery, and designer clothes. Despite the lack of academic scrutiny concerning these objects, specialised law enforcement agencies (e.g., Interpol) and commercial databases such as the Art Loss Register (ALR) have recently started including these goods in designated categories within their databases to great extent. At the time of writing, Interpol's *Stolen Works of Art Database* contains over 1000 items in the "Watch/Clock" category, over 2600 items in the "Jewellery" category, and over 180 items in the "Clothing/Textile" category, making up roughly 8 percent of Interpol's entire database. In 2015, the ALR even introduced *The Watch Register*: an online database of stolen wristwatches totalling over 70,000 watches, signalling the significant scale of these goods as distinct categories in both public and commercial databases.[1] Indeed, as mentioned previously, most studies analysing online anonymous marketplaces focus on drugs or arms, but tend to leave out other types of goods that perhaps make up for a small percentage of what the marketplace has on offer, but nevertheless tend to accumulate to tens of thousands of items. Which is quite similar to the distribution of these categories in law enforcement and commercial databases: they make up a small sub-section of a much larger database, but nevertheless encompass as significant number of items. The discussion of the appeal of this market, and the analyses thereof, must therefore consider three things: (1) these overlooked categories need to be included as they make up a significant sub-section of cultural and artistic goods, (2) conspicuous goods, like artistic and cultural objects, can be

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[1] At the time of writing, May 2021.

considered as objects of desire that facilitate an aesthetic experience, and (3) that these goods have a symbolic function that operates in an extensive network of social and cultural relations (Albrecht, 1968). These social and cultural relations can turn these desirable goods into so-called criminogenic objects.

Discussing the automobile industry as a criminogenic market structure, Farberman (1975) argues that inequality have "[...] elites play [a powerful role] in controlling society's central master institutions by establishing political and economic policies which set the structural conditions that cause other (lower level) people to commit crime" (p. 438). We understand how these central master institutions create asymmetries in society (Passas, 1999), however little is known about the effect that objects have on people's willingness to commit crime, here art-related crimes. Additionally, different levels of authority correspond to different classes. One can argue that, within the art world, there are dominant and dominated classes, and those who strive for symbolic capital are those in the dominant classes (Bourdieu, 1984). Those without significant knowledge of the field (also dubbed *cultural capital*), economic wealth (*economic capital*), or network (*social capital*) are not able to participate fully in this world and thus become outsiders (ibid). This in turn makes the desire to become a member of this world, even stronger. As we will discuss in our analysis, possibly increasing the desire to own these specific types of goods. Bourdieu (1983, 1984) further emphasises that arts and culture only exist in a social and cultural context and function not only as markers for cultural taste, but also markers of distinction and *place* for individuals. More specifically, they signal one's position within the class society. Discussing luxury products in our analysis, we can connect the theories of Bourdieu to conspicuous goods. As aptly discussed by Trigg (2001), where Veblen (1899) focuses mostly on the 'trickle-down' phenomenon of Veblen goods, where the higher social classes are more inclined to distinguish themselves from the lower classes, Bourdieu also considers the tastes and values of lower classes. A lower (or working) class that actively resists the cultural tastes of those in the higher classes (p. 105). These discussions of the higher classes and the ways in which they position themselves by, amongst other things, the consumption of conspicuous goods to elevate their distinction is not new, but how this relates to the market structures of online anonymous marketplaces, is an under-researched avenue.

The desire of the higher classes to distinguish themselves from the lower classes have also been the subject of conservation within economic discussions of so-called "brand effects" (e.g., Dodds et al., 1991; Erdem & Swait, 2004; Schroeder, 2005). The presence of a brand has an additional influence on the *perceived value* of a good or service. In relation to the *perception* of the brand, this also suggests that the price that people are willing to pay will likely be above market value when a recognisable brand is present on the good. In short, the willingness of people to pay more relies on how *exclusive* the brand is perceived. Studies on brand effects in the art market include the effect of, for example, artist's names on auction and gallery sales prices (e.g., Angelini et al., 2019; Oosterlinck & Radermecker, 2019). What makes these latter examples striking is the turn from cultural value (based on *intangible*

indicators) into economic value (*tangible* indicators of currency).[2] Therefore, these goods can provoke what might then be called a criminogenic *desire*. A desire of belonging to a powerful group of elites by displaying markers of distinction, these markers, in this case, can then very well be expensive watches, jewellery, and designer clothes. The increasing presence of these 'markers of distinction' as categories in specialised art crime databases signals the importance and relevance of this category of goods to be studied further.

3   Evolution: Data, Methods, and Analyses

The dataset used for our investigation aimed at analysing which type of objects are available on the platform, comes from the blog post by Compton (2015), who in turn obtained the data from a torrent file that was shared on Reddit in 2015, a few days after the Evolution marketplace was shut down (17 March 2015). The original data was downloaded by an anonymous user with a varying frequency since the creation of the marketplace in early 2014, and consists of two databases. The first consists of all the ads present in the marketplace at the moment of each of the data downloads was made, and the second covers all the sellers that ever operated in the marketplace. We decided to focus on the first of the two, given the aim of our investigation. Therefore, our starting database contains information about objects at sale in the marketplace, for each day the download of data was made. Some objects occur more than once in our dataset: this could be due to the fact that these objects' ads were present in successive downloaded days because they were not sold or because they were sold between two of the downloaded days, but the seller put the same object with the same description at sale in the same range of days. Other information available from the database are: price in Bitcoin, name of the seller, description of the object, date in which the data dump was made,[3] the Bitcoin-EUR and Bitcoin-USD exchange rates on that date, the reputation level of the seller, and the reputation number (that is, the number of feedback votes received by the seller), the percentage of positive feedback,[4] and the categories the goods or services were part of. Our data covers the period from 21 January 2014 to 17 March 2015.

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[2] Angelini and Castellani (2019) present a critical review on the link between these two values, with a focus on (potential) causal effects.

[3] The dates of the data dumps were not equally distanced, in particular in the first two months, when the download dates were very sparse. In our final data, the distance between one dump and the other goes between two and nine days.

[4] Between the start of Evolution as a marketplace until roughly the end of April 2014, the reputation system did not consist of a numerical value, but only of levels (Freshman, Junior, Senior, Expert, tentatively ordered by us since there is no way to check for this). From May 2014 onwards, the reputation system changed to a numerical value, starting from 0, as in most online marketplace in the legal market, that was associated with a reputation level based on these numbers (Level 1, Level 2, etc.).

As mentioned in the introduction, Evolution was an anonymous online marketplace where the majority of traded objects were drugs, but also other types of objects and services (e.g. weapons, murder for hire, and personal identification information) were on offer, totalling 1,121,087 objects identified by a unique id,[5] and divided into 81 categories, e.g. "Analgesics", "Explosives", and "Bank Logins". Among the available categories, we focused on the existing categories "Counterfeits", "Jewellery", and "Miscellaneous", since these categories are those who most likely contain conspicuous goods. The total number of observations from these three categories was 46,854. In checking the types of goods presented in this subset of the data, we added a series of new variables useful for the empirical analysis, which were the name of the brand of the object (if stated/applicable), a dummy variable equal to 1 if the object is a replica (if stated/applicable), and a variable that describes the sub-category of the object, with 141 different descriptions, among which we found "watches", "clothing", and "jewellery". At this step, we also created the price in EUR and the price in USD for each object, given the price in Bitcoin and the appropriate exchange rates at that time. The selection and the creation of the new variables were made based on the description of the object coming from the original database. In some cases, this description was not completely clear since it used abbreviations and other acronyms which were not directly attributable to any particular type of object linked to conspicuous goods. The dataset after this first manual selection process accounted for 37,478 observations.

In the next step, a series of data cleaning checks were carried out. We picked the statistical observations (hereafter 'observations') whose categories were most related to the focus of our analysis concerning conspicuous goods, dropping 10,085 observations. There were 46 sub-categories left among which we observed diamonds, jewellery, watches, and precious metals. We also removed all the objects with missing or null prices, dropping another 49 observations, so that we ended up with 27,344 objects for our analysis.

Next, we validated the data, checking for potential issues with the variables. We first graphically investigated the prices of our objects and noticed that some of them presented a price which was excessively above the average of other prices for objects of the same sub-category; for example, we dropped a series of replica watches whose prices were above 9000 EUR, when the average price of similar watches was around 145 EUR.[6] This issue may be due to mistakes made by the sellers in reporting the price of the object. In total, we dropped 39 observations, remaining with 27,305. Then, we checked if all the reputation numbers were present, and we found that 22 observations had a N/A reputation number, so we dropped them since we could not identify the reason this information was missing, ending up with 27,283

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[5]Notice that each unique id is associated with a certain object that was up on the marketplace in a certain day.

[6]The figures are computed considering the lowest BTC to EUR exchange rate, so they should be taken as the lower boundaries of the ranges of these prices over time, since the exchange rate is highly volatile in the considered period.

Table 1 Descriptive statistics of continuous and dummy variables

Variable name	N	Mean	SD	Min	Max
Price (in BTC)	27,191	0.6637	1.7741	0.0183	39.0998
Price (in EUR)	27,191	168.85	436.16	3.72	9335.27
Price (in USD)	27,191	203.17	523.77	4.31	11,882.38
Reputation number	27,191	151.10	453.59	0	8416
Dummy variable name	N	%			
Replica	20,771	0.957			

The table reports the number of observations (N) for both types of variables, the mean, the standard deviation (SD), the minimum and maximum level for the continuous variables, and the frequency of 1 (in percentage) for the dummy variable. BTC prices are rounded to the fourth digit. EUR and USD prices are rounded to the second digit

observations. Lastly, we graphically investigated how the number of observations and prices were distributed overtime, noticing that some days presented very few observations with respect to all the other days (in particular, 17 October 2014, 07 November 2014, and 24 February 2015); each of these days had less than 40 objects on sale, when the previous and following days had, respectively, 241 and 210, 253 and 197, and 652 and 595. This issue may be due to problems in the downloading of data at the time of the dump and we decided to drop them since the data for each of these days very likely represented only a part of the objects present in the marketplace on those days. By dropping these observations, we reduced our dataset with 92 data points, ending up with a total of 27,191 objects for our analysis.[7] After the cleaning and validation, our data covers the period between the 10 August 2014 and the 17 March 2015. A series of descriptive statistics of the data are presented in Tables 1 and 2.

As we can see in Table 1, the overall price of the products in our database has a high dispersion, ranging from 3.27 EUR to 9335.27 EUR with an average price of 168,85 EUR. The reputation number of the sellers is equally volatile. The highest reputation number is 8416, whereas the lowest is 0, with an average number of 151.10. The standard deviation of the reputation number, explaining the dispersion of the data around the average, is 453.59. Most of the items in our categories, around 96 percent of those that we could identify as such, totalling 20,771 objects, are replicas, namely fake branded products sold as fakes on purpose.

Table 2 displays the ten most frequent brands and sub-categories together with their relative frequencies and average prices. Having selected those conspicuous goods, we can see that certain products are represented more than others. Watches are overrepresented, totalling almost 50 percent of the database (49.6 percent) with an average price of 219.78 EUR. This average price is higher than the average price

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[7]Notice that the number of dropped observations in this case would have been higher if we did not drop the N/A reputation number in the previous step, since all the dates before May 2014 presented very few observations with respect to the rest of the period. This might be due to the fact that the marketplace did not start 'at full power' from the beginning, but we have no means to test this hypothesis.

Table 2 Descriptive statistics of categorical variables

Sub-category	Relative frequency (%)	Average price (in EUR)	Brand	Relative frequency (%)	Average price (in EUR)
Watch	49.60	219.78	Rolex	14.73	184.02
Sunglasses	7.13	79.18	Omega	7.09	100.70
Necklace	6.61	108.66	Chanel	6.17	72.92
Bracelet	5.10	44.07	Audemars Piguet	5.75	298.72
Shoes	3.16	114.56	Cartier	5.19	59.60
Pen	3.00	48.81	Louis Vuitton	5.07	87.83
Jacket	2.80	159.61	Emporio Armani	4.43	96.28
Belt	2.68	56.72	Breitling	4.42	143.59
Earrings	2.45	29.20	Montblanc	4.35	51.11
Bag	2.34	147.26	Gucci	3.47	65.89

The table reports the ten most frequent brands and sub-categories, together with their relative frequencies and average price. The values are rounded to the second digit

of the total objects in the database, making watches also amongst the higher price categories of the marketplace. As mentioned previously, watches have become their own distinct sub-category within specialised art crime databases. It therefore does not come as a surprise that Evolutions largest category of conspicuous goods is indeed wristwatches. When combining those conspicuous goods that we can categorise as jewellery,[8] we see a total of 13.2 percent of the marketplace dedicated to these items. The various categories also have strong differences in prices, which overlaps with what we see in Table 1. Concerning brands, there is less of a concentration in one group, although the popular watch brand "Rolex" has the highest number of incidents with 14.73 percent with an average price of 184.04 EUR. There are high differences also in the brand sub-categories, with the brand Audemars Piguet having an average price of 298.72 EUR and Montblanc of 51.11 EUR.

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[8]Combining the categories necklace (6.61 percent), bracelet (5.10 percent), and earrings (2.45 percent). Other less represented sub-categories which can be considered as jewels are ring (1.40 percent), cufflinks (0.34 percent), ring and necklace (0.18 percent), keyring (0.07 percent), and money clips (0.01 percent). Some sellers also sold branded boxes of necklaces and bracelets, and these accounted for 0.23 percent of total observations, and branded boxes of watches, accounting for 1.53 percent of all observations.

4   Results

In determining how a market like this one works, we can focus on the demand, on the supply, or on both. In our case, we have no information about the demand, or in that sense about the consumers and we have no means of inferring it in any way,[9] therefore we decided to focus on the supply of the market, from August 2014 up to the closure of the marketplace in March 2015. What we do know however, is the amount of pieces the sellers have sold. This gives us an indication as to what the market demands, regardless. Therefore, we developed two types of analyses: the first studies the time dynamics of this marketplace with a particular focus on the behaviour of the sellers and on the feedback system, while the second aims to understand which of the variables are more important in explaining the price of the objects traded in this market.

4.1   Trends in Price Dynamics

Concerning the time dynamics, we wanted to check if a trend is present in both price dynamics and number of observations. Since the marketplace increased in renown overtime, and it is likely that some sellers (and hence buyers, since this type of market is likely to be supply-driven) moved to Evolution after *Operation Onymous*, we expected to observe both an increase in total price of all objects available in the marketplace and number of objects available, as measures of the importance of the market overtime. In checking if this is the case, one should recall that the data points are irregularly spaced (see footnote 3) and use a particular method to smooth the graph, that is, to remove fluctuations in the figures which are not strictly linked with the trend of the variable we want to analyse. In particular, we used a median filter to smooth the graph, preserving sharp edges in the signal (Ataman et al., 1981; Tukey, 1971). Figures 1 and 2 report the median filtered time series for the price in EUR and for the number of observations, respectively.[10]

From the two figures, it is clear that a strong increasing trend is present in both prices and number of objects at sale in the Evolution marketplace, throughout the considered period. While the number of objects increases almost linearly from Mid-November 2014 onwards, the sum of prices of all the items at sale starts increasing in the same period, then has a small reduction at the beginning of

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[9]We cannot know how many of these objects were sold, since we only observed the ads of the sellers and information of consumers is not available. What we can observe is the reputation number as a noisy measure of completed transactions. Inferring remains complex because we cannot assert how many points of the reputation number comes from our examined categories, and how many are from other categories. However, this information is not reproducible from the original dataset.

[10]The median is computed over a moving window of 10 periods, the signal level is estimated at the end of each time window. The computation was implemented using the R package by Fried et al. (2019).

Fig. 1 Median filter for
total value of products
per day
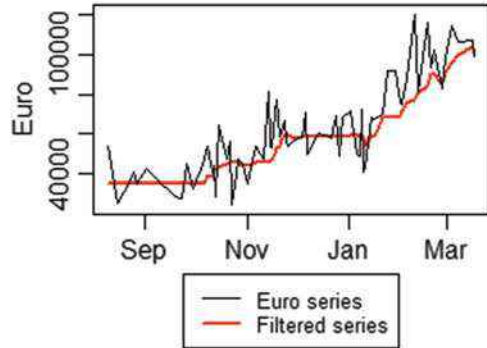
Fig. 2 Median filter for
total number of objects
per day
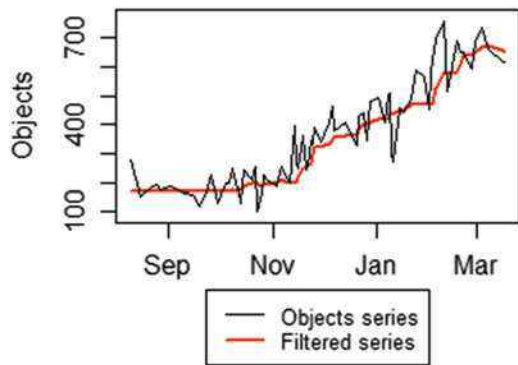
January 2015, and then starts increasing again from the second part of January 2015 until the closure of the marketplace. A tentative explanation of this is that, after *Operation Onymous*, several sellers moved to Evolution from other similar marketplaces, increasing the number of ads, but the average price decreased, meaning that the supplied goods presented a lower price. There can be different explanations for this. One explanation could be that sellers with generally lower prices entered the market, and the buyers then moved from the previous sellers to these new sellers. However, in principle, the old sellers might also have left the marketplace, so the price went down and the number of sellers (or the saturation of the market) is the same, or even lower.

4.2 Seller Behaviour Concerning Number of Objects and Total Price

Another way to look at the supply side of this marketplace is to consider how the sellers behaved with respect to the number of objects they supplied on the

marketplace and to their total price, as a measure of the potential trade flow that each agent could obtain if every object in his/her inventory was sold.

Figure 3 reports the logarithm of the sum of the prices of all the objects each seller put on sale (in blue, on the y axis on the left) and the logarithm of the number of objects at sale (in red, on the y axis on the right).[11]

Figure 3 suggests that not all the sellers behave in the same way, and this is strictly linked to the fact that very different types of objects are part of our dataset. In other words, the average price (which is higher the farther two points in the graph are from each other) can be very different and influenced by the specialization of each seller in a certain type of objects or his/her diversification strategy carried on by focusing on different types of objects. Indeed, the result of the Pearson's Chi-squared test on the contingency of sellers and sub-categories suggests that both specialised sellers as well as sellers that offer more types of objects exist, and this is also confirmed by a network analysis we do not report here, but is available upon request.

4.3 Reputation

Figure 4 reports the logarithm of the reputation number each seller obtained from August 2014 to March 2015 (in blue, on the y axis on the left) and the logarithm of the number of objects at sale (in red, on the y axis on the right). Notice that the number of vendors is smaller than the one in Fig. 3; this is because we focused on those who obtained at least one (1) feedback in the considered period.

Figure 4 indicates that different sellers, under the point of view of the number of completed trades, operate in the marketplace: some sellers have a high number of reviews even though the number of objects at sale are not too high, and the converse combination is also found among other sellers. This suggests that a high number of ads is not strictly linked with a high number of completed trades (and then a high reputation number), even though we must consider that some of these sellers might be selling objects associated with categories we did not consider influencing their reputation score.

4.4 Indicators for Pricing

The second part of the analysis focuses on the variables that play a major role in explaining the price of the objects. One of the simpler ways to check for this kind of relationship in an empirical way is by using an ordinary least squares (OLS)

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[11]We reported these values in logarithmic form since the high variability of these values (see Table 1) would impede a graphical comparison otherwise.
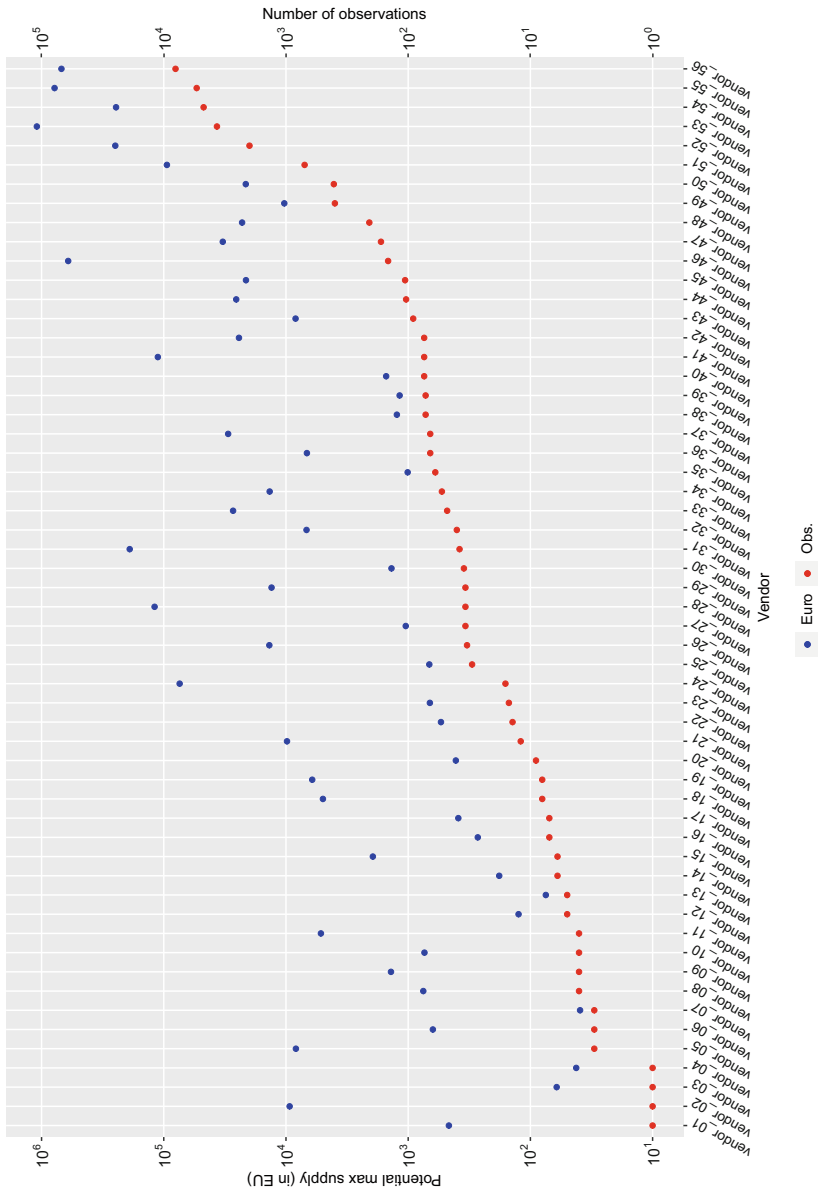
Fig. 3 Logarithm of the sum of prices for all objetcts each seller put on sale (in blue on the x-axis) and the logarithm of the number of objects at sale (in red on the y-axis)
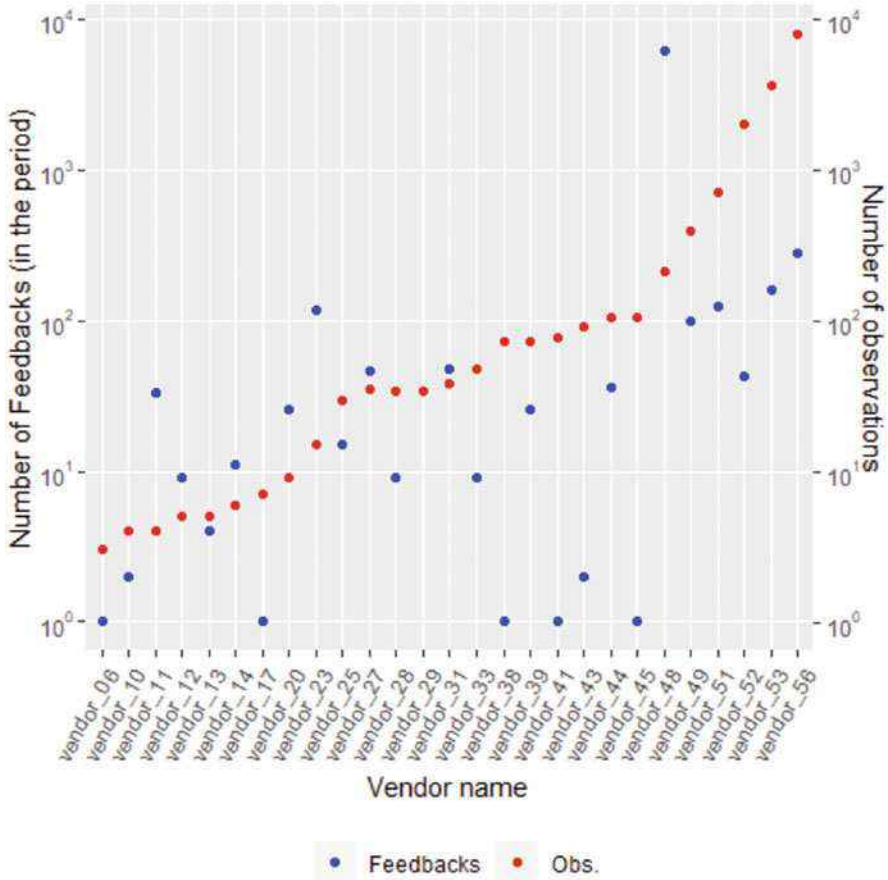
Fig. 4 Logratithm of reputation number each seller obtained from August 2014 to March 2015 (in blue on the y-axis) and the logarithm of the number of objects at sale (in red, on the y axis)

regression (see Wooldridge, 2006). What we want to check is if a series of explanatory variables (such as the brand associated with the product, the object being a replica or authentic piece, etc.) has an impact on the prices of the goods, and if this impact is positive or negative. The direction of the effect (positive versus negative) and its statistical significance (meaning if the effect is indeed significantly different from zero and thus not by chance) will give us hints about what could be the behaviour and beliefs of the sellers in fixing the prices.

In what follows, we will implement the OLS model on different subsamples of our data.[12] The model we are going to use is as follows:

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[12] In our analysis, we pool the data at cross-sectional level, meaning that we do not consider time dynamics. This is because our data is irregularly spaced with respect to time and an approach to consider time dynamics with this type of data would be too complex.

Table 3 Regression results

Dependent variable: log(Price in EUR)	(1)	(2)	(3)	(4)	(5)
Intercept	4.068 [0.247] ***	6.109 [0.035] ***	8.479 [0.061] ***	4.984 [0.103] ***	2.570 [0.166] ***
log(Reputation number + 1)	−0.171 [0.003] ***	−0.187 [0.004] ***	−0.045 [0.004] ***	0.044 [0.005] ***	0.049 [0.030]
Replica dummy		−0.298 [0.024] ***		−0.940 [0.046] ***	
Brand dummy variables	Yes	Yes	Yes	Yes	–
Sub-categories dummy variables	Yes	–	Yes	Yes	Yes
Number of observations	26,507	9915	4440	3326	684
Adjusted R²	0.693	0.484	0.690	0.882	0.847

It is standard practice for the referencing of tests of significance to work with this three-step model. Even despite the fact that we only have levels of significance that are *** (equals <0.001), it is normal for transparency of the results that the other values (equalling both <0.05 and <0.01) to be mentioned, even if non of the statistical results belong to these two values (being */**). Therefore, these values should remain in the legend of table 3 as well. This is standard practice.
*p < 0.05
**p < 0.01
***p < 0.001

$$P_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_k x_{k,i} + e_i$$

where the price of the object i, P_i, is explained by k variables ($x_{1,\,i}, x_{2,\,i}, \ldots, x_{k,\,i}$). What we estimate here are the β-s, the coefficients that indicate how each variable is related with the dependent variable P_i. The results of the various OLS regression models we implemented are reported in Table 3.

The values are rounded to three digits and the standard deviation is presented within brackets. Model (1) is computed on all *branded objects*, model (2) on *branded watches* only, model (3) on *jewellery*, model (4) on *branded clothes*, and model (5) on *unbranded objects*.

As we can see, reputation is negatively related to prices in Model 1. Since we primarily consider the supply, it might be the case that those sellers that provide lower-priced items sell more, creating a higher reputation for these respective sellers. Brands impact in Model 1 is statistically significant, some with higher effect than others (consistently with Table 2). When we turn to our biggest conspicuous good in the database, watches, the pattern is similar to what we witnessed in Model 1: the replica dummy variable has a strong negative effect on price.

Jewellery (Model 3) presents the same link between reputation and price that we found in Models 1 and 2. In this model, the dummy variable for the replica is not considered since all the objects in our dataset that are part of jewellery categories are either a replica, or an object whose authenticity is not mentioned in the description.

Clothes (Model 4) behave differently than other branded objects since reputation impact is positive here. Namely high-reputation sellers are those with objects with higher prices, whereas replicas are sold at a lower price. This result might be linked to a different perception of risk of the buyer, which is taken into account by sellers. For example, buyers could perceive the risk differently with respect to the other described models. Namely: buyers perceive a higher risk for these other objects and therefore buy low-priced objects. Meaning that the reputation of the sellers that sell low-priced objects will be higher, and hence the negative direction is visible in the regression, whilst for clothing, this does not occur. Buyers purchase higher-priced objects and therefore the seller of high-priced objects has a higher reputation because they sell more, and this is confirmed by the positive direction in regression analysis. Of course, these are hypotheses of potential power dynamics. However, we have no way to confirm these with certainty. We could say however that clothes in this marketplace are perceived more as Veblen goods than other goods, since people buy high-price clothes, but low-price watches and jewellery.

When we look at objects without a specific brand (Model 5), presented as 'generic' products, the seller's reputation does not seem to be linked with his/her prices in a linear way. In fact, the estimated coefficient related to the seller's reputation is not statistically different from 0. There is a possibility here that these objects are considered as those objects with the highest perceived risk of scam. Additionally, we can argue that these objects are less important in signalling distinction as these specific objects are without brands. They consist mostly of gold, diamonds, and silver, which are objects that are more traditionally kept as 'storage' value, rather than something to display.

5   Analysis

The online anonymous marketplace Evolution showed us that indeed some of the discussed luxury objects are indeed treated as conspicuous goods, selling more frequently for higher prices than for lower ones, *ceteris paribus*. We can argue here that selling distinction through counterfeited luxury objects might be one of the explanations of the appeal of these objects, even if these objects turn out to be counterfeit. We argue that these products are 'objects of desire' that not only create a market for conspicuous consumption, but also a possible driver for criminal behaviour. Already signalling earlier on in this chapter that specialised law enforcement and commercial databases have increased their focus on these type of goods (as aptly visualised by the establishment of The Watch Register in 2015), it is important to note that these objects are indeed circulating in an underground illicit market, and that these are marketed using their brand and their 'exclusive' character. By analysing this marketplace, we can argue that the supply for these products run in the tens of thousands of objects, in just a single marketplace, arguing for these goods to receive increased academic scrutiny, in addition to the increasing focus of law enforcement and commercial databases for these goods.

What distinguishes these goods therefore is that they not only fulfil a material need, but possibly also a strong social need. Within the marketplace, these goods are often labelled as luxury products, and are distinguished as being 'exclusive', and thus priced based on their exclusivity. Being able to own or purchase conspicuous goods therefore signals not only the economic wealth of the individual, but also the prestige of the individual. In our analysis of the marketplace, we clearly see that the sellers have an eye for this, actively making use of the products' brands and offering them through a lens of 'exclusivity' and 'distinction'.

6   Conclusion

Research in art crime, observing some exceptions, has seen little use of statistical inferences, making for a small field of empirically grounded research data to draw upon. Art crime is often reported as the third, or even fourth largest criminal enterprise in the world, however the exact economic and criminal impact of this type of crime, remains unclear. The truth here is that the exact scale is unknown to almost anyone, so we often need to rely on anecdotal evidence or results of small-scale, in-depth studies that are difficult to infer to larger populations. Various factors contribute to this; however, it is mostly due to two specific factors. First, there is the issue of recording. For example, many national police databases rely on the *type* of crime, and not necessarily on the *objects* of theft. So, if a painting is stolen from a private accommodation, thefts are often labelled as property thefts. When a painting is stolen from a museum, it is still often considered as property theft (albeit from a public or commercial institution), however the label 'cultural property crime' or 'art crime' is more easily given. The second issue concerns determining, or rather understanding, the cultural value of these objects. Next to economic valuations of cultural objects, the exact cultural value of them is difficult to determine since there is no hard determination on how to evaluate this value, especially for non-specialists. Additionally, very little research has been undertaken concerning luxury products.

Of course, this was the very first step in developing art crime related research on this scale in an anonymous online marketplace on this specific category. To further enhance the understanding of these markets, and how their sellers fashion the sales of these goods, further research could explore the narratives of objects for sale (how are objects framed and marketed). Additionally, our formulae and methodology can be applied on notable art crime databases, such as Interpol's Stolen Works of Art Database or the Art Loss Register. Finally, our results, now specific to Evolution, could work differently in other online marketplaces; a comparison between the sellers' and consumers' behaviour of different dark marketplaces could give insights on the generalisability of the results of our analysis.

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