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Third-party signals and sales to expert-agent buyers: Quality indicators in the contemporary visual arts market☆

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A B S T R A C T

This paper builds on a fine-grained longitudinal dataset detailing 22 years of contemporary visual art sales to corporate collectors. We focus on expert buyers who act as agents for the art collecting organizations who employ them. Our major findings show that third-party indicators of quality – reviews, awards, and gallery affiliations that have been received by visual artists over time – are positively related to sales. Moreover, this relationship persists far beyond the time when the signals were first conveyed. These results are interesting because compared to ordinary consumers, these expert buyers are assumed to make purchase decisions based on their professional knowledge of contemporary visual art that enables them to recognize quality that is only obvious to a trained "eye." However, we show that simple indicators of quality based on third-party signals strongly influence them. Our findings provide a much-needed understanding of the mechanisms guiding expert-agent buyers' purchase decisions, particularly in markets with high uncertainty about quality and high levels of innovation. We argue that third-party signals influence these expert-agent buyers because they prefer to make purchase decisions they can readily defend.

1. Introduction

The primary market for contemporary visual art is a domain with high uncertainty about the underlying quality of the products being transacted. We investigate this under-researched but economically and culturally relevant market, where artists sell their paintings, sculptures, or photographs to a *first* buyer (Singer & Lynch, 1994). Determining the quality of the artworks transacted on this market is notoriously difficult because objective measures for evaluation are largely lacking and aesthetic comparisons

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as alternative measures are highly subjective (Yogev, 2010). In addition, this market has an extreme oversupply of producers, uncertain demand, high levels of innovation, and imperfect and incomplete information about producers' quality (e.g., Becker, 1982; Caves, 2000; DiMaggio, 1987; Ertug, Yogev, Lee, & Hedström, 2016; Prinz, Piening, & Ehrmann, 2015; Velthuis, 2003).

These challenging competitive conditions in the primary art market are starkly different when compared to the secondary or art auction market, where the selected artworks that are sold almost always have provenance, which includes a chronology of ownership and information about sales prices paid by previous owners (e.g., Renneboog & Spaenjers, 2013). In contrast, historical performance data before the first sale of a particular work of art, on which buyers active on the primary market can base their purchase decisions on, is to the best of our knowledge non-existent.

One important category of buyer active in the primary art market are corporate collectors (Wu, 2003). Over half of the *Fortune* 500 companies and other corporations worldwide have a corporate art collection (Kottasz, Bennett, Savani, & Ali-Choudhury, 2008; Kottasz, Bennett, Savani, Mousley, & Ali-Choudhury, 2007). The collections themselves are mainly formed under the auspices of art curators (Martorella, 1990; Wu, 2003), who are employed by the art collecting organization and act as expert-agents on their behalf.

The core characteristics of the primary art market and especially the high uncertainty about quality make the role of expert-agent buyers, as experienced professionals in the high arts, indispensable. It is largely assumed that these buyers make purchase decisions based (almost) exclusively on their direct judgments. In other words, they are thought to be able to perceive quality earlier than others because of their technical qualifications and trained expert "eye." One might, therefore, expect that publicly available third-party signals will not significantly affect the buying behavior of these experts. However, such experts acting as agents for others in markets characterized by high uncertainty about quality and high levels of innovation are also likely to try and avoid the risk that in retrospect they will be held accountable by their employers for having made the "wrong" decisions. As a result, expert-agent buyers, just like ordinary consumers (Lee, Herr, Kardes, & Kim, 1999; Liu, Polman, Liu, & Jiao, 2018; Maglio, Trope, & Liberman, 2013; Polman, Effron, & Thomas, 2018), may be strongly affected by third-party signals.

Consequently, this study addresses the following main research question: Given that expert-agents in the contemporary visual arts are employed because of their professional ability to evaluate new art, to what extent is their purchase behavior associated with publicly observable third-party quality signals? In the subsequent sections, we propose two sub-questions that focus on (1) the quantity of third-party signals with - and without – weighting their source credibility scores, as well as (2) the period of time for which these signals remain effective.

The main contributions of this study to the literature are as follows. First, while a large body of marketing studies in the creative industries focus on the effects of third-party signals on buying behavior of ordinary consumers (e.g., Eliashberg & Shugan, 1997; Hennig-Thurau, Marchand, & Hiller, 2012), we highlight the under-researched role of the expert buyer (Legoux, Larocque, Laporte, Belmati, & Boquet, 2016). Specifically, we focus on expert-agent buyers who are employed by principals dealing with non-technological innovations where there are no unequivocal tests to compare product quality along pre-specified product features (Wijnberg, 2004). Second, we study the effect of the credibility of the sources from which these third-party signals originate because expert-agent buyers are expected to be better at filtering heterogeneous and multidimensional sources of information compared to ordinary buyers (Camerer & Johnson, 1991; Spence & Brucks, 1997). Third, by comparing recent or "point" signals (DeKinder & Kohli, 2008) with the accumulated "stock" of signals, we extend research about signal durability from the context of first-party signals, such as advertising and promotion (Batra & Keller, 2016; Köhler, Mantrala, Albers, & Kanuri, 2017; Mela, Gupta, & Lehmann, 1997), to that of signals conveyed by third parties.

To provide empirical evidence, we draw on a unique panel dataset consisting of 471 contemporary visual artists, e.g., painters, sculptors, and photographers, who are alumni from an internationally renowned fine arts program located in the Netherlands. We study their career trajectories over a 22-year observation period and analyze the extent to which third-party signals accumulated over time by an artist influences the probability of sales to expert-agent buyers purchasing art on behalf of their employer. In the next sections, we focus on the quantitative (number) and the qualitative dimensions (source credibility) of third-party signals – i.e., reviews, awards and gallery affiliations – and the decay rate of each kind of signal with different levels of credibility over time. We describe our empirical setting, followed by the data and our results. We conclude with a discussion, managerial implications, limitations, and avenues for future research.

2. Theoretical framework and research questions

2.1. Third-party signals

Third-party signals are often considered more trustworthy than signals (e.g., advertising) conveyed directly by the producer (Lampel & Shamsie, 2000; Pollock & Rindova, 2003). This is because third parties are subject to reputational and financial punishment if the signals they convey turn out to be inaccurate (Bergh, Connelly, Ketchen, & Shannon, 2014; Higgins & Gulati, 2003; Ippolito, 1990).

Signals from third-party sources help create (and maintain) structuring mechanisms, e.g., rankings or other segmentation, that enable relative comparisons among competing producers (e.g., Bergh et al., 2014; Connelly, Certo, Ireland, & Reutzel, 2011). For instance, in the marketing literature on the creative industries, critical reviews (e.g., Eliashberg & Shugan, 1997; Hennig-Thurau et al., 2012; Legoux et al., 2016) and award ceremonies such the Grammy awards in the music industry (Anand & Watson, 2004) and the Oscars in the movie industry (Gemser, Leenders, & Wijnberg, 2008), have been shown to shape market hierarchies. This, in turn, explicitly informs buyers about what is "good" and what not by demarcating boundaries that separate high-quality producers from those of lesser quality (Anand & Watson, 2004). Additionally, such ranking and segmentation mechanisms further abate uncertainty by reducing heterogeneous information into a common metric, which serves as a proxy of producers' quality in a competitive environment (Espeland & Stevens, 1998).

2.2. Expert-agent buyers and third-party signals

While a distinction has been made between novice and expert buyers (Camerer & Johnson, 1991; Wagner, Klein, & Keith, 2001), very little is known about the degree to which expert buyers take into account third-party signals in their buying decisions (Legoux et al., 2016). Expert buyers are individuals who have professional credentials and experience in the domain in which they are active (Camerer & Johnson, 1991). We focus on a specific kind of expert buyer, one who acts as an agent to a principal and makes purchase decisions on their behalf. Earlier studies have shown that expert buyers are especially good at judging the quality of highly complex and innovative products (Brucks, 1985; Johnson & Russo, 1984; Rao & Monroe, 1988; Shanteau, 1992; Wagner et al., 2001), because, for instance they are better at filtering out irrelevant sources information (Camerer & Johnson, 1991; Spence & Brucks, 1997).

Nevertheless, even expert-agent buyers may find it difficult to find cogent information, especially in a market environment characterized by high uncertainty about quality and high levels of innovation. For example, when judging the quality of artworks, expert-agent buyers may use various structuring mechanisms or rely on heuristics to aggregate heterogeneous information about producers from a number of different sources (Espeland & Stevens, 1998). One straightforward heuristic is to consider the quantity of each particular kind of signal about a producer, although source credibility of third parties conveying these signals could factor in as well.

Source credibility has been shown to be a determinant of the strength and impact of the signal (Pornpitakpan, 2004; Sternhal, Dholakia, & Leavitt, 1978). Expertise and trustworthiness are constituent parts of source credibility. While expertise refers to the extent to which a source is perceived to have knowledge and experience (Hovland, Janis, & Kelly, 1953; Ohanian, 1990), trustworthiness refers to the extent to which buyers perceive a source to be honest and dependable (Hovland et al., 1953; Meyer, 1988; Newell & Goldsmith, 2001; Ohanian, 1990). Precisely because expert-agent buyers are assumed to be highly skilled professionals, who can efficiently filter relevant information, they are likely to be sensitive to the source credibility of third parties transmitting the signals.

As the level of expertise increases (Bettman & Park, 1980), and the amount of knowledge about options increases, the more likely decisions will also be based on qualitative dimensions of sources (Fiedler, 2007). Consequently, just as for ordinary consumers, one might expect that the effect of third-party signals on expert-agent buyers depends on the credibility of the sources transmitting these signals. This is based on the assumption that especially in markets with numerous varieties of products and an oversupply of producers, such as in the primary art market, expert-agent buyers will attempt to limit their cognitive effort by putting more focus on third-party signals with higher source credibility. While looking for a greater number of signals of a particular kind can be considered as a strong quality indicator in its own right and used as a relatively easy basis for comparisons within the same product category, incorporating source credibility may make it easier to justify their decisions. Especially, as is the case with expert-agent buyers, they can be held to account by their employers for their purchases. Based on the arguments above, we frame the first research question:

RQ1: To what extent are third-party signals about a focal producer associated with that producer's likelihood of a sale to expert-agent buyers?

2.3. Point versus stock of third-party signals

Previous research has made a distinction between short versus long-term effects of first-party signals on buyer sales behavior (Batra & Keller, 2016; for a meta-analysis see Köhler et al., 2017). For example, Mela et al. (1997) use distributed lag Koyck models with decay parameters to study carryover effects, or find out how long particular advertising and promotion activities affect buyer behavior. This enables scholars to compare recent, so-called “point signals,” i.e., signals about a producer at a single point in time (DeKinder & Kohli, 2008) to the “stock of signals,” i.e., signals about a producer accumulated over time.

Although effects of first-party signals, such as advertising and promotion, on sales tend to last less than a year (Köhler et al., 2017; Mela et al., 1997), one might expect third-party signals to have longer lasting effects on expert-agent buyer behavior. While some studies show that the effects of third-party signals deteriorate when sales performance becomes available (Rao, Greve, & Davis, 2001), others provide evidence of their durability, even in the presence of sales information (Pollock & Gulati, 2007). Since expert-agent buyers use more heterogeneous and multidimensional information, while at the same time third-party signals tend to remain available in the public domain, one would expect expert-agent buyers to use an extended time window for considering third-party signals, as well as the credibility of the sources from which they originate, when making purchasing decisions. Accordingly, we formulate the second research question:

RQ2: How rapidly does the association between third-party signals about a focal producer with that producer's likelihood of a sale to expert-agent buyers decay over time?

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3. Empirical setting

3.1. Primary market for contemporary visual art

The contemporary art market is comprised of a network of visual artists, gallery owners, curators, museum directors, and art collectors. Extant research has investigated the effects of audience-specific reputations of artists (Ertug, Yogev, Lee & Hedström, 2016) and their network centrality (Fraiberger, Sinatra, Resch, Riedl, & Barabási, 2018) as predictors of financial or reputational success. There is also a rich research history in economics that focuses on the determinants of auction prices and investment performance (e.g., Goetzmann, 1993; Mei & Moses, 2002; Renneboog & Spaenjers, 2013).

We focus on the primary art market, where artworks are sold directly by the artist or through the mediation of an art gallery to the first buyer (Singer & Lynch, 1994) for a couple of reasons. First, corporate collectors are predominately interested in purchasing art from emerging artists (Wu, 2003), and these artists are chiefly active in this market. Second, the primary art market is characterized as having the highest degree of uncertainty about the quality of the artist (Becker, 1982; Caves, 2000; DiMaggio, 1987), and third-party signals can be particularly helpful in reducing uncertainty by providing information about artists' quality (Yogev, 2010). This market functions as a 'dealer-critic system' (White & White, 1993), which means that third-party signals both reflect and helps constitute the reputation of an artist (Caves, 2000; Ertug et al., 2016; Hirsch, 1972; Prinz et al., 2015; Velthuis, 2003).

3.2. Prestigious art residency

We study the career trajectories of visual artists that attended the Rijksakademie van Beeldende Kunsten (RABK) located in the Netherlands. The RABK is a highly prestigious and internationally acclaimed art residency program offering 2 years of financial support and studio space to accepted applicants. In the late 1980s, the RABK began its transition from a classical art academy to becoming a two-year artists' residency program.

The RABK invests heavily in talent scouting and development, which starts with a highly competitive and rigorous selection process. For example, in 2008, 23 of the 1415 artists who applied were accepted, and more than two-thirds came from outside the Netherlands. More than 95% of the accepted applicants have received a bachelor and/or master degree in fine arts or a related discipline, and have at least two to five year's experience as autonomous visual artists (Rijksakademie van Beeldende Kunsten, 2017).

RABK tracks the careers of their alumni; we received these raw data consisting of reviews, award records, listings of exhibitions, art fairs, and gallery information for all 471 visual artists that were at RABK from 1990 to 2012. Upon retrieval, we first verified these data by checking artists' curricula vitae (CV) on their websites. The verification process took place from September to December 2012. Most artists use their CV to provide a comprehensive listing of their professional history, including art education, and achievements, such as awards, reviews, art exhibitions and representation at art fairs. Second, we cross-validated these data for accuracy by checking art market news platforms such as artnet.com and artfacts.com. Third, we collected the complete set of sales data, from 22 participating organizations with corporate collections. This resulted in a unique and very comprehensive dataset, as no sales data were reported in the original RABK data. We note that our dataset is not a sample of alumni but rather includes all artists who completed the residency program during our observation period.

3.3. Corporate art collectors

Corporate collections include are all art owned by organizations whose core business activity is not preservation, research and communication of contemporary visual art (Martorella, 1990; Weil, 1990). Historically, museums have played a major role in determining what art became institutionalized, although corporate collections have increasingly gained credibility and authority in determining the value of art (Wu, 2003). While the corporate elite, such as the CEO or senior partners, usually initiate corporate collections (Wu, 2003), the collections themselves are managed by art curators (Martorella, 1990; Wu, 2003), who act as expert-agent buyers for the art collecting organization that employs them. This category of art buyer is active in the primary art market (Wu, 2003). *Re*-selling an artwork that was part of an existing collection, while it may occur under very particular circumstances, is not a common practice among corporate collectors in general, and specifically, not for the corporate collections that we study here.

We conducted a review of the websites of the corporations' art collections in our data and found that, in addition to including photographs of the artworks in their collection, they also list third-party quality signals received by artists throughout their career. We interpret this to mean that the expert-agent buyers we study are at the very least aware of these signals and recognize them as indicators of quality. Furthermore, the size of the group makes it possible to collect comprehensive data about their purchases; in fact, the data in this study cover 77% of all sales to corporate collections in the Netherlands during our observation period (Netherlands Association of Corporate Art Collections, 2017. www.vbcn.nl/EN/).

4. Empirical strategy

4.1. Overview

The dependent variable in the empirical analysis is the sales of an artist in a particular year. We explain the variation in sales by one-year lagged review, lagged award and lagged gallery affiliation signals as well as a vector of control variables. We measure sales by the count (number) of artworks sold by an artist in a year, while each kind of signal can be quantified by the count

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(number) and the source credibility level of the third-party signals, calculated as a yearly total by the artist. The vector of control variables includes, among other things, cohort and discipline fixed effects and is described in more detail in Section 4.6.

We include one-year lagged rather than contemporaneous signal variables for several reasons. First, using contemporaneous values of signals can result in incorrect chronological order of events if a signal occurs later in the calendar year than a sale. Second, there is likely a lagged response or awareness with respect to the occurrence of signals. Third, by using lagged signals, we avoid reverse causality.

As the dependent variable is a count, we use the Poisson Pseudo Maximum Likelihood estimator (PPML) for our main analysis. We supplement the coefficient estimates with robust standard errors clustered at the artist level to account for heteroscedasticity and possible non-independence across same artist observations. An important advantage of PPML is that it accommodates the case of a dependent variable with many zero values (Silva & Tenreyro, 2011). The sign of the coefficients is equal to the sign of their marginal effects. The marginal effects, however, depend on the value of the regressors due to the nonlinearity of the Poisson regression model.

Since our data includes annual, individual-level data for all artists completing the RABK program, we constructed a yearly panel dataset. We observe annual sales and signals for N = 471 artists over the observation period 1990–2012. We code sales and signals as zero in years without a registered event. Based on an extensive review of all curriculum vitae, we confirm that all individuals are active as artists during the observation years. Furthermore, we code sales and signals as not available for observations before 1990 as well as any observations before an individual's starting year at the bachelor level art education, which we define as the start of their career. This makes the panel data unbalanced; the average number of periods per individual is 15 with a minimum of 5 (2008 cohort) and a maximum of 22 periods (first year of collecting data).

4.2. Model and estimation

We use a geometric lag structure that assumes that the impact of signals (reviews, awards, and gallery affiliations) on sales declines geometrically with time. We illustrate this method by omitting control variables and considering only one signal (Z) and sales (S):

$$S_{it} = \beta\left(Z_{i,t-1} + \alpha Z_{i,t-2} + \alpha^2 Z_{i,t-3} + \ldots\right) + \varepsilon_{it} \tag{1}$$

where i denotes the individual artist and t is a particular year. As mentioned before, for various reasons, we model current sales in year t (labeled S_{it}) as a function of past signals ($Z_{i,t-1}$ and further lagged values).

Regarding the error term, we assume that the lagged signals are predetermined regressors, i.e. $E(\varepsilon_{it} | Z_{i,t-1}, Z_{i,t-2}, \ldots) = 0$. An explanatory variable is predetermined when it is not correlated with current and future shocks, but it may be correlated with past error terms (see e.g., Windmeijer, 2008). Because of timing, the lagged signals can be viewed as predetermined regressors. For consistent PPML estimation, predetermined signals are a sufficient condition. This assumption does not rule out that the error term is serially correlated and also allows for general patterns of both cross-section and time series heteroscedasticity.

While using lagged signals mitigates endogeneity concerns due to reverse causality, note that by assumption we rule out possible endogeneity caused by omitted variables bias. A major concern is unobserved heterogeneity, i.e., signals, as well as sales, may be driven by the same unobserved factors. In this case, lagged signals become endogenous rather than predetermined regressors. In Section 5.1 we will address in more detail this issue of unobserved heterogeneity in various ways. We perform Generalized Method of Moments (GMM) estimation treating the lagged signals as endogenous regressors. Furthermore, regarding PPML estimation, we include artists' entrance scores at the time of selection as an additional control variable, and we add fixed effects at the level of the individual artist. In short, our robustness checks do not reveal an endogeneity problem due to unobserved heterogeneity. Given that we have observational data, however, one should be cautious when interpreting the results as being causal.

Returning to Eq. (1) and recognizing that:

$$\alpha S_{i,t-1} = \alpha\beta\left(Z_{i,t-2} + \alpha Z_{i,t-3} + \alpha^2 Z_{i,t-4} + \ldots\right) + \alpha\varepsilon_{i,t-1} \tag{2}$$

we have a more parsimonious representation of Eq. (1):

$$S_{it} = \beta Z_{i,t-1} + \alpha S_{i,t-1} + \varepsilon_{it} - \alpha\varepsilon_{i,t-1} \tag{3}$$

Note that the geometric lag model (3) has a MA(1) component in the error term.

The geometric lag model used here is equivalent to the Adstock model developed in the advertising literature to measure the impact of advertising expenditures on sales (Broadbent, 1993; Danaher, Bonfrer, & Dhar, 2008; Dinner, Van Heerde, & Neslin, 2014; Leone, 1995). The Adstock model is used to model advertising carryover, in which advertising from previous periods influences current sales. The Adstock model introduces the notion of the stock of signals at the start of year t (labeled $X_{i,t-1}$),

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which is defined as the following exponentially smoothed expression of most recent signals ($Z_{i,t-1}$) and the earlier stock of signals ($X_{i,t-2}$):

$$X_{i,t-1} = (1-\alpha)Z_{i,t-1} + \alpha X_{i,t-2} \tag{4}$$

where $0 \le \alpha < 1$ is the weight of the stock of signals in period *t-2* (smoothing factor) and $Z_{i,t-1}$ is the signal count for artist *i* in the last period *t-1*. By repeated substitution, we see that the stock of signals at the start of year *t* is the exponentially weighted moving average of most recent signals and past signals:

$$X_{i,t-1} = (1-\alpha)Z_{i,t-1} + (1-\alpha)\alpha Z_{i,t-2} + (1-\alpha)\alpha^2 Z_{i,t-3} + \ldots \tag{5}$$

When $\alpha < 0.5$ recent signals are more relevant than past signals and vice versa.

Substituting Eq. (5) into Eq. (1) current sales can be expressed as a function of the lagged stock of signals:

$$S_{it} = \theta \mathrm{X}_{\mathrm{i,t-1}} + \varepsilon_{\mathrm{it}} \tag{6}$$

where $\theta = \beta/(1-\alpha)$. Note that θ is the long-run (including carry-over) effect, while β is the short-run (immediate) impact (Danaher et al., 2008).

To estimate the parameters either Eq. (3) or Eq. (6) can be used. Note that, unlike Eq. (6), the error term in Eq. (3) is MA(1). Neglecting this serial correlation results in endogeneity bias as lagged sales $S_{i,t-1}$ is correlated with $\varepsilon_{i,t-1}$, which is part of the MA (1) error term. We, therefore, follow the Adstock literature and estimate representation (6) of the geometric lag model.

To estimate α, Danaher et al. (2008) and Dinner et al. (2014) propose a grid search, varying α from 0 to 1 in increments of 0.01, looking for the value of α that results in the best goodness of fit as measured, for example, by AIC or BIC.[1] The model we use to do this includes the lagged signal counts[2] as predictor variables, equivalent to Model 2 in Table 2, discussed below. Having estimated α we next construct the smoothed lagged signal $X_{i,t-1}$ according to Eq. (4) and estimate Eq. (6) by PPML to retrieve an estimate of θ.

4.3. Dependent variable

Our dependent variable is the count (number) of sales. The sales count is simply the total number of sales made to corporate collectors by an artist in a particular year. The results are robust if we transform our dependent variable of sales count into a binary variable, measuring if a sale was made or not in a given year (see Section 5.1 for a discussion of alternatives). It should be noted that the distribution of success among artists active in the primary art market is highly skewed (Caves, 2000), with only 146 individuals in our dataset selling to a corporate collection. Of those who ever sold, 78% sold one or two artworks during our 22-year observation period (see Section 4.8).

4.4. Explanatory variables

Our three explanatory variables measuring signals are the number of reviews, awards, and gallery affiliations. First, for each kind of third-party signal, we construct a variable measuring the total number of signals in a given year. Second, we also create a variable measuring the credibility level of signals. The source credibility score for each kind of signal is the sum of the credibility levels for each signal that an artist received in a year.

The credibility levels of the signals were determined by two independent art experts and one of the authors, using validated scales measuring the source credibility construct (see Section 4.5). If an artist did not receive a particular kind of signal in a given year, then a value of zero was given for both count and credibility.

Reviews written by professional art critics are broadly interpreted as anything from a discourse about an artist's oeuvre to critiquing national and international exhibitions that are published in either art journals or national/ international newspapers. In the contemporary visual arts, the probability of a particular artist being reviewed is much smaller than in other creative industries, and those that are reviewed are generally positive. A study of the 169 professional art critics in the United States, found that 70% deliberately eschew writing negative reviews (Szántó, 2002). Professional art critics prefer to publish neutral descriptions of exhibitions instead of negative reviews (Elkins, 2003).

To verify if these findings are generalizable to our data, we took a random sample of 125 reviews from 125 individual artists in our data and asked two independent judges to quantify the positive and negative tenor of each review. Additionally, we used a computer program called Linguistic Inquiry and Word Count (LIWC) to quantify the number of positive and negative words in each review (Pennebaker, Booth, Booth, & Francis, 2007). The results from the judges as well as LIWC confirmed the results from previous studies showing that 76% and 74% of the reviews rated by humans and analyzed by LIWC, respectively, had a

[1] We also allow for smoothing parameters which differ by signal, but we find the estimates to be very close to each other. Allowing for different α by signal, therefore, hardly changes the estimation results.

[2] The stock S_{it} in the first year of the artist's career is chosen to be the signal count in that first year.

positive tenor. Less than 5% of the reviews analyzed by the judges were perceived (by them) to be somewhat more negative than positive in tenor. While only 2% of those analyzed using LIWC had more negative than positive words. The rest of the reviews were largely descriptive and communicated practical information about exhibitions.

Awards range from Dutch national art awards such as the Prix de Rome to internationally recognized art awards such as the Turner Prize. Although jury members selecting award winners and art critics writing reviews can derive reputational benefits - e.g., being the first to discover a new star talent, from the awards they bestow and reviews they write - a gallery owner is often interested in both the artistic contribution and potential of the artist as well as the evolving art market and financial gains to be made. As such, gallery owners are both promoters and service providers because they select artists, monitor their professional development and convey signals about them to the public, while also selling the artworks to art collectors (Velthuis, 2003). One of the strategies an art gallery can use to promote artists is to host a gallery show for the focal artist, while another strategy is to attend annual art fairs. Art Basel, Frieze, and Artissima are examples of international art fairs that provide selected art galleries a platform to exhibit artists and to sell artworks (Yogev & Grund, 2012). We operationalize affiliation as an artist's association with a gallery hosting an art exhibition or representing an artist at an art fair. Earlier research has shown that affiliations signal quality (e.g., Rindova, Williamson, Petkova, & Sever, 2005; Washington & Zajac, 2005) by the suggestion to buyers that the producer is worthy of the association (Khaire, 2010).

4.5. Signal credibility levels

Using a multi-item and validated scale underlying the credibility construct (Ohanian, 1990), we scored the credibility level of 967 different kinds of third-party sources. Following Stanford, Tauber, Fogg, and Marable (2002), we first took a sample of 200 third-party sources from our data and asked three well-informed judges to rate these sources on credibility using a 5 point Likert measurement. The scale itself consisted of the following six items: trustworthiness, honesty, dependability, experience, expertise, and how knowledgeable a source is (Ohanian, 1990). If a judge did not know the source and could not provide a rating based on a quick Internet search, then a 'do not know source' option could be checked. Two art experts, each with more than 18 years of experience in the field, served as judges; the third judge is one of the authors who also has a degree in fine arts.

The internal validity of the six items measured was high, with a Cronbach's alpha of 0.98. Inter-rater reliability among the three judges was calculated using a two-way random effects intraclass correlation statistic (Shrout & Fleiss, 1979). The intraclass correlation was 0.74, ($p < .001$), suggesting uniformity among the judges' ratings (Bravo & Potvin, 1990). Based on the construct's high internal validity and internal consistency, the third judge continued to rate the remaining 767 sources. The results of our main models presented in Section 5 are robust to the results if we estimate regressions including only the signal credibility scores for the 200 third-party sources rated by all three judges (see Table E of the Online Appendix).

4.6. Control variables

In addition to the explanatory variables described above, we include a number of control variables. First, we construct a set of dummy variables to measure the effect of being in the same cohort (Merluzzi & Phillips, 2016). Second, to allow for discipline fixed effects, we create binary indicators for each of the six artistic disciplines: drawing, installation, painting, photography,

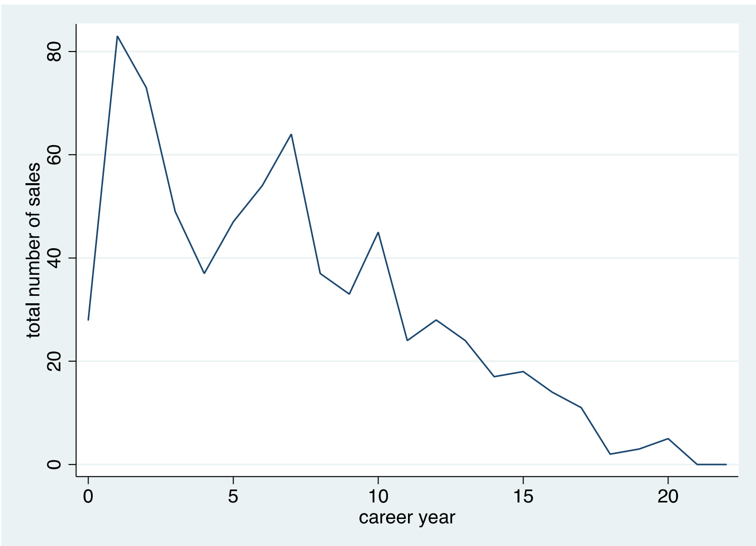

Fig. 1. Total sales to corporate art collectors by career year.

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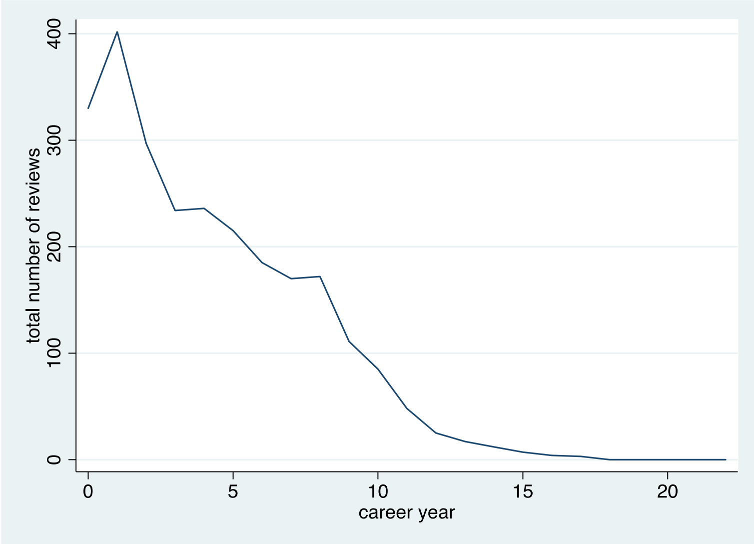

Fig. 2. Total number of reviews by career year.

sculpture, and video-film. Miscellaneous, a basket category for other disciplines, e.g., graphics and book making, is the base. Third, we create binary indicators to control for gender (1 equals female) and nationality (1 equals Dutch).

4.7. Unobserved heterogeneity

While using lagged signals reduces endogeneity concerns due to simultaneity, our estimates could still be biased due to omitted variables. For instance, unobserved quality of the artists, which are correlated with both sales and signals, could bias the coefficients of the lagged signals. We address this potential omitted variable bias in several robustness checks. First, we use GMM estimation treating lagged signals as endogenous regressors. Second, regarding the PPML estimation, we include artists' entrance scores at the time of selection to control for innate talent and quality. Third, we conduct a robustness check where we include fixed effects (FE) at the level of the individual artist. As we show in Section 5.1, our main results for our two research questions still hold through these alternative approaches.

4.8. Summary statistics

In the period 1990–2012, we observe 452 sales to corporate collectors, 1409 reviews, 547 awards, and 284 gallery affiliations. The majority of the 471 artists in our sample received at least one review (399) or award (272). However, only 146 artists ever sold an artwork to corporate collectors, and only 132 had a gallery affiliation. Fig. 1 shows that the peak in sales to corporate art collectors is immediately after finishing RABK. Figs. 2 and 3 show the peak in reviews and awards, respectively, occurs right after finishing RABK, while Fig. 4 shows that gallery affiliations happen later in the artists' careers.

Of those artists who sold one or more artworks, 44% are female, and 73% are Dutch. In total, 87% of the artworks sold are paintings (45%), sculptures (16%), photographs (13%) and drawings (13%). The remaining sales are distributed among the following disciplines: video art (6%), installations (4%), and miscellaneous, e.g., graphics and bookmaking (3%). Of the artists who sold an artwork, 78% have either one or two sales throughout their career while 22% of the artists sold three or more artworks, indicating a highly-skewed distribution of success.[3] With respect to the signals, on a 1 (low credibility) to 5 (high credibility) scale, the average score for review source credibility is 3.28, award source credibility is 2.79, and affiliation source credibility is 2.92, based only on artists who were recipients of these signals.

In Table 1, we show bivariate correlations among the sales count and the lagged signals (both count and credibility measures). It can be seen that there are moderate correlations between the dependent variable and each of the lagged signals. Furthermore, count and credibility of a particular signal are highly correlated. This is because the variable lagged signal source credibility, which is defined as the stock of the weighted sum of source credibility scores for each kind of signal in a given year, is a variable that already includes (implicitly) both the quantity and the quality of signals received in a given year.

[3] In our data, the maximum price paid for an artwork sold to a corporate collector is € 120,000 the minimum € 155 the mean € 4968 and the median €2635.

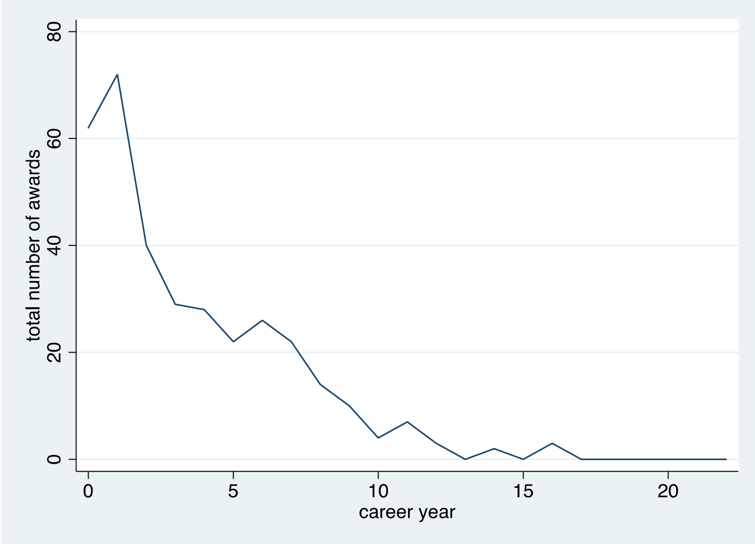

Fig. 3. Total number of awards by career year.

We foreshadow our estimation results by first looking at general patterns in the data. Fig. 5 shows the probability of having a sale in year t if a signal is received in t-1. For instance, if a producer receives a review in a given year then the probability that the producer will have a sale in the following year is 9.17%. In comparison, if a producer does not receive a review in a given year, the probability of having a sale in the following year is only 3.51%. For awards, the probabilities are 6.05% if an award is received and 4.41% if not; for gallery affiliations, 8.59% and 4.25% respectively. Consistent with our model of serial correlation, there is a 20.37% probability of a sale if there was a sale in the previous year, but drops to 2.96% if there was not a sale.

5. Results

In Table 2, we report the PPML parameter estimates and model selection criteria of Eq. (6). The first two models in Table 2 include the geometric lagged signal count for reviews, awards, and gallery affiliations. Model 1 includes these three explanatory variables without the control variables. Model 2 adds the control variables, namely dummy variables for gender and nationality, discipline fixed effects, and cohort fixed effects. As can be seen in Table 2, adding the control variables is beneficial; specifically,

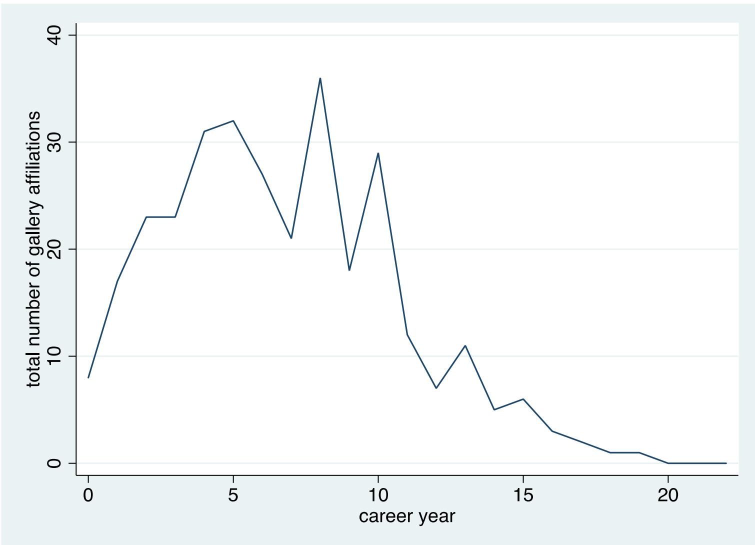

Fig. 4. Total number of gallery affiliations by career year In Figs. 2–4, the decline in the vertical axis is due, in part, to the decline in the number of artists who have that number of career years. That is, all artists have 5 career years, but very few have more than 20.

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Table 1
Correlation matrix.

		1.	2.	3.	4.	5.	6.	7.
1.	Sales count	1.0000						
2.	Geometric lagged review count	0.1701	1.0000					
3.	Geometric lagged review source credibility	0.1899	0.9900	1.0000				
4.	Geometric lagged award count	0.0850	0.2196	0.2165	1.0000			
5.	Geometric lagged award source credibility	0.1466	0.2993	0.3018	0.9338	1.0000		
6.	Geometric lagged affiliation count	0.1729	0.1673	0.1797	0.0535	0.0829	1.0000	
7.	Geometric lagged affiliation source credibility	0.1913	0.1896	0.2055	0.0499	0.0808	0.9695	1.0000

Bivariate correlations are all significant at $p < .001$.
$N = 8918$.
Note: Review, award and affiliation source credibility are variables that includes (implicitly) both the quantity of signals and the quality of sources conveying the signals received in a given year. This explains the observed high correlations between count and source credibility for each kind of signal. In the empirical analyses below we will therefore include either signal count or signal source credibility as explanatory variables; including both leads to multicollinearity issues.

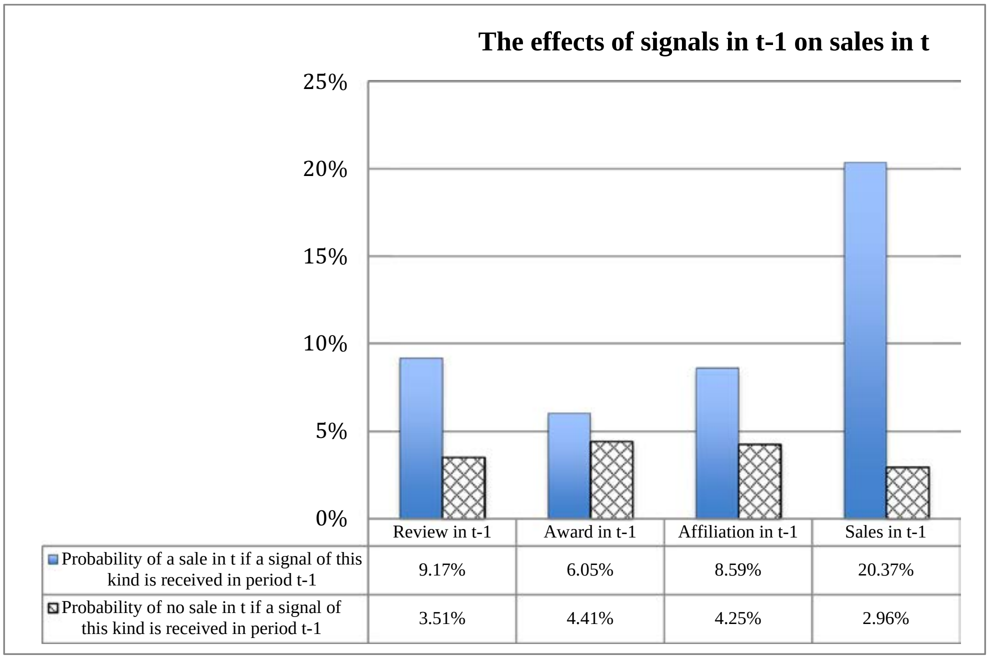

Fig. 5. Model free statistics.

Model 2 has the superior (lower) value of both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which are tests for comparing the explanatory power of nested models while also considering the number of parameters in each model.

Next, we turn to Model 3 in Table 2 which shows the exponentially smoothed source credibility variable that measures both the quantity and source credibility of third parties conveying signals, namely reviews, awards, and gallery affiliations. In Model 4, we add the control variables. Again, we see that adding these control variables is beneficial, i.e., Model 4 has the superior (lower) value of both AIC and BIC. Regarding our first research question, we find a significant positive association between the exponentially smoothed count of third-party signals of a particular kind, which have been accumulated in the past about an artist, and the number of sales in the subsequent year (see Model 2). These results are robust when weighing signals with their source credibility values (see Model 4).

In addressing our second research question, we consider the estimated value of $\alpha = 0.80$. As we discuss in Section 4.2, we perform a refined grid search to determine α and find that an estimate of $\alpha = 0.78$ provides the best fit in terms of AIC and BIC using Eq. (6) with the three signal count variables including control variables and fixed effects. If the pseudo R-squared is used as the criterion of fit, then $\alpha = 0.82$ provides the best fit. Consequently, we use $\alpha = 0.80$ throughout our analysis.[4] This result shows that the impact of recent signals extends beyond the period immediately following its occurrence. Because the estimated value of $\alpha > 0.5$, our findings show that the stock of third-party signals of a particular kind accumulated in the past about a

[4] This is confirmed by IV estimation of Eq. (3) using $S_{i,t-2}$ and $S_{i,t-3}$ as instruments for S_{t-1}, which results in an estimate of around 0.80.

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Table 2
Explaining the number of sales by geometric lagged signal counts and geometric lagged signal source credibility.

	Model 1	Model 2	Model 3	Model 4
Geometric lagged review count	0.559*** (0.067)	0.657*** (0.076)		
Geometric lagged award count	1.006*** (0.410)	1.399*** (0.210)		
Geometric lagged affiliation count	1.428*** (0.266)	2.211*** (0.294)		
Geometric lagged review source credibility			0.160*** (0.021)	0.198*** (0.023)
Geometric lagged award source credibility			0.525*** (0.101)	0.471*** (0.083)
Geometric lagged affiliation source credibility			0.530*** (0.091)	0.691*** (0.104)
Gender		−0.159 (0.230)		−0.118 (0.229)
Nationality		1.259*** (0.224)		1.157*** (0.226)
Drawing		2.465*** (0.600)		2.452*** (0.590)
Installation		1.836** (0.716)		1.838** (0.710)
Painting		2.157*** (0.485)		2.131*** (0.485)
Photography		1.355*** (0.570)		1.356*** (0.572)
Sculpture		1.606*** (0.540)		1.608*** (0.543)
Video-Film		0.064 (0.566)		0.103 (0.557)
N	8918	8918	8918	8918
Cohort fixed effects	No	Yes	No	Yes
BIC	5205	4609	5052	4555
AIC	5176	4375	5023	4321

Clustered standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.
Analysis based on PPML estimation.

producer has a stronger effect on sales to expert-agent buyers than third-party signals received in the previous year. Turning directly to our second research question about the decay rate of the signals, the annual decay rate is $(1\text{-}\alpha) = 0.20$ meaning that the effect of the signals declines at a rate of 20% per year.

5.1. Robustness checks

We conduct several robustness checks to test if our results are sensitive to alternative definitions of some of our key variables and with the functional forms that we use. We discuss results on functional form briefly in Section 5.1, while further results can be found in the Online Appendix.

Probably the most severe challenge to our estimation results is that both signals and sales are driven by the quality of the artists. In other words, the estimated significant relation between sales and signals may be spurious and omitting the underlying quality of the artists may have biased the estimation results. We have, therefore, conducted a number of robustness checks to rule out this alternative interpretation. We broadly classify this issue as omitted variable bias and discuss it in the next section.

5.2. Omitted variable bias

First, we have estimated the Poisson regression model by the Generalized Method of Moments (GMM) treating lagged signals as endogenous regressors. Finding valid instruments is a challenging task in most situations and that is true in our case as well. In our data, in particular, we do not have variables available, which are excluded from the sales equation and can provide the exogenous variation in lagged signals necessary for consistent GMM estimation. Given the longitudinal nature of the data, we, therefore, use further lagged values of the endogenous regressors as instrumental variables (see e.g., Windmeijer, 2008). More specifically, we instrument the lagged stock of signals in Eq. (6) with second and third lagged values ($X_{i,t-2}$ and $X_{i,t-3}$). Although commonly used in panel data analysis, obviously the validity of such moment conditions can be questioned, and we, therefore, exploit the Hansen test for over-identifying restrictions. The advantage of the GMM approach is that we can compare the Hansen test statistics between specifications assuming predetermined regressors and endogenous regressors. The difference of the Hansen statistics between these models is then used to test the validity of the assumption of predetermined regressors underlying consistent PPML estimation. The GMM results are reported in Table A of the online appendix. We find that the GMM estimates using endogenous lagged signals instead of predetermined lagged signals are very close to each other. Additionally, the moment conditions assuming predetermined lagged signals are not rejected, which validates the use of PPML as used in our main specifications.

Second, we control directly for an individuals' innate talent and quality by including artists' selection scores at the time of admission. Entrance score information is only available for five cohorts ($n = 111$), but for these years we have the scores for all artists accepted to the program. More details about the artist quality scores and PPML results adding this control variable (Table B) are presented in the Online Appendix. The results are consistent with our main models.

Third, assuming that artist quality is time invariant, we carry out fixed effects (FE) PPML estimation including artist-specific fixed effects. FE estimation is only feasible for the 146 artists (out of 471) for which we observe positive sales, so this potentially introduces selection bias since all artists are trying to sell their work, as we discussed earlier in the paper. Nevertheless, as shown in Table C of the Online Appendix, the results from FE estimation are broadly consistent with our main specifications. However, perhaps because of selection issues, the coefficient of gallery affiliation is no longer statistically significant.

5.3. Functional form

Table D of the Online Appendix reports estimation results using different functional forms, namely: probit, negative binomial, and linear regressions. In Table D, Model 1, we estimate a probit model where we replace the sales count with a binary variable to measure if a sale was made in a given year (1) or not (0). In Model 2, we estimate a negative binomial (instead of Poisson) regression on the sales count. In Model 3, we impose linearity and use the OLS estimator. Models 4 through 6 repeat these analyses using the signal credibility variables. The estimation results in Table D show that none of these modifications altered our main results.

In Table E, we conduct a Poisson regression analysis including only those third- party sources (200) that were scored by the two expert judges and one of the authors (see Section 4.5). The results for the three source credibility variables are qualitatively similar to our main models, hence do not reveal any systematic biases in the evaluations of the third judge.

6. Discussion

In this study, we present new empirical insights into the influence of third-party signals on sales to expert buyers purchasing contemporary visual art for their employers' corporate collection. We draw on a unique longitudinal dataset, which enables us to gain a better understanding of the mechanisms guiding their purchase decisions. In doing so, we are one of the first studies to quantify the drivers of artistic success in this under-researched yet economically and culturally relevant domain. Our aim, however, is not to explain each separate sale explicitly by each kind of signal, but rather to better understand the underlying data generating processes between signals and sales. We investigate the extent to which these processes have consequences that, in part, lead to success in markets characterized by an oversupply of producers of heterogeneous products.

We quantify the relative contribution of the different kinds of signals (reviews, awards, and gallery affiliation) and calculate the rate parameter of the Poisson distribution for different values of source credibility. The magnitude of the coefficients belonging to the signal counts (see Model 2 in Table 2) determines their relative importance for sales. Our results show that a gallery affiliation is most important for sales, while a review has the smallest impact. We use the coefficients to calculate the impact of a gallery affiliation and an award relative to receiving a review. We find that a gallery affiliation is more than three times as large, while an award is twice as large.[5] When we use source credibility of signals as the explanatory variable, the rank order results are virtually the same.[6]

While our results show that the relationship between signals and sales are robust when measured by the number of each particular kind of signal and when adjusted by source credibility, it may be worthwhile to reflect upon the implications of source credibility (see Model 4 in Table 2). As an example, we calculate the change in the rate parameter going from average source credibility to one standard deviation above average. For all three signals (reviews, awards and gallery affiliations) the average source credibility is around 3, while the standard deviation is around 1. The long-term impact on the likelihood of a sale increases the most for a one standard deviation increase above the mean in gallery affiliation source credibility (0.153). This is followed by a one standard deviation increase in award source credibility (0.076), and then review source credibility (0.009).

The value of our smoothing coefficient ($\alpha = 0.80$) shows that the past stock of third-party signals is more important than the recent signals. This result suggests that a signal has a significant effect several years after its initial occurrence. The half-life, i.e., the number of periods needed so that half of the impact of a signal has materialized, is slightly more than three years.[7] This is considerably longer than the reported longevity of advertising and other forms of promotion (Köhler et al., 2017). While the longevity of first-party signals, such as advertising, has been extensively examined and summarized in meta-analyses (e.g., Köhler et al., 2017), relatively little is known about the half-life of third-party signals that potential buyers may actively search for. We suppose that the long-term effects in our results might occur because expert agents, at least in cultural markets, are deliberately searching for such signals as compared to being passive recipients, as is the case in, for instance, advertising.

6.1. Managerial relevance

Our findings have several practical implications. First, producers who are aware of the factors guiding the heuristics expert buyers use when making purchases can make strategic decisions to invest part of their marketing budget in eliciting quality signals from third parties. This may set in motion self-reinforcing processes that further differentiate “winners” from the others (Azoulay, Stuart, & Wang, 2013; Merton, 1968; Sorenson & Waguespack, 2006), and influence exactly those buyers for whom this effort will provide them favorable economic returns (Fader, 2012; Rust & Verhoef, 2005). For example, in the cultural and creative industries influential third parties such as critics are often invited to attend high profile events such as art gallery openings, movie release parties, and fashion shows in the hope of eliciting (positive) evaluations of new products or producers through reviews (Currid, 2007).

Second, our results suggest that when deciding how much money and effort to invest in the development of third-party signals, managers need to recognize that these effects are often long-lasting. Thus, in making spending decisions and evaluating returns, a multi-year perspective is more appropriate than just focusing on immediate returns.

[5] For Model 2, Table 2, we find $2.211/0.657 = 3.365$ for a gallery affiliation and $1.399/0.657 = 2.129$ for an award.

[6] For Model 4, Table 2, we find $0.691/0.198 = 3.490$ for a gallery affiliation and $0.471/0.198 = 2.378$ for an award.

[7] The half-life is $\log(0.5)/\log(0.8) = 3.106$.

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Third, our data show, as expected, that most artists do not have annual sales. However, this lack of immediate success does not indicate that a signal did not have an effect or that having a signal is not influential. In markets such as the one we study, as well as others where only a small sample of innovations are successful, managers need to think in terms of changes in the probability of a sale and not merely actual sales.

6.2. Limitations and future research

This study has a number of limitations, which also point to further research opportunities. First, our study is only concerned with the top segment of the relevant market, which is to some extent unavoidable because of the unequal distribution of success in the cultural industries (Becker, 1982; Caves, 2000). This makes it difficult to analyze the effects of signals on sales for the vast majority of artists who often have very few signals and even fewer sales. Moreover, our results might be accentuated by the fact that our data concerns alumni from the premier art school in the Netherlands. Further research could explore datasets, possibly outside of the cultural and creative industries, where larger proportions of competitors can be studied.

Second, we did not focus on other qualitative dimensions of signals besides credibility. Valence, i.e., positive or negative tenor of the information conveyed by the signal, is an example of such a qualitative attribute. A number of recent meta-analyses show mixed findings of the effects of volume versus valence of signals - often focusing on reviews in specific industries - on sales performance (Babić Rosario, Sotgiu, Valck, & Bijmolt, 2016; Carrillat, Legoux, & Hadida, 2018; Floyd, Freling, Alhoqail, Cho, & Freling, 2014; You, Vadakkepatt, & Joshi, 2015). To explore the potential drivers of these mixed findings, the aforementioned meta-analyses also take into account long- versus short-term impact of these signal metrics (Carrillat et al., 2018), product characteristics such as their durability or utilitarian versus hedonic nature (Floyd et al., 2014), and industry level conditions such as competition (You et al., 2015). These mixed findings of recent meta-analyses suggest that the conditions under which volume versus valence matters warrant further research. Since the valence of signals in the context of our study is almost always positive, allowing us to abstract from the valence dimension, further research on expert-agent buyers should explore settings in which this condition does not hold.

Third, we suggest focusing on settings with signals from first as well as third-party sources and study interaction effects between different kinds of signals and the positive or negative tenor of the message they are conveying. While first-party signals will, of course, have a positive valence, other signals from third-parties can range from being highly positive to highly negative (see e.g., Mayzlin, 2006).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2019.11.001.

References

Anand, N., & Watson, M. R. (2004). Tournament rituals in the evolution of fields: The case of the Grammy Awards. *Academy of Management Journal*, *47*(1), 59–80.

Azoulay, P., Stuart, T., & Wang, Y. (2013). Matthew: Effect or fable? *Management Science*, *60*(1), 92–109.

Babić Rosario, A., Sotgiu, F., Valck, K. D., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297–318.

Batra, R., & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing*, *80*(6), 122–145.

Becker, H. S. (1982). *Art worlds.* Univ of California Press.

Bergh, D. D., Connelly, B. L., Ketchen, D. J., & Shannon, L. M. (2014). Signalling theory and equilibrium in strategic management research: An assessment and a research agenda. *Journal of Management Studies*, *51*(8), 1334–1360.

Bettman, J. R., & Park, C. W. (1980). Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis. *Journal of Consumer Research*, *7*, 234–248.

Bravo, G., & Potvin, L. (1990). Estimating the reliability of continuous measures with Cronbach's alpha or the intraclass correlation coefficient: Toward the integration of two traditions. *Journal of Clinical Epidemiol*, *44*(4/5), 381–390.

Broadbent, S. (1993). Advertising effects: More than short term. *Market Research Society Journal*, *35*(1), 1–11.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research*, *12*(1), 1–16.

Camerer, C. F., & Johnson, E. J. (1991). The process-performance paradox in expert judgment: How can experts know so much and predict so badly? In K. A. Ericsson, & J. Smith (Eds.), *Toward a general theory of expertise: Prospects and limits* (pp. 195–217). New York: Cambridge University Press.

Carrillat, F. A., Legoux, R., & Hadida, A. L. (2018). Debates and assumptions about motion picture performance: A meta-analysis. *Journal of the Academy of Marketing Science*, *46*(2), 273–299.

Caves, R. E. (2000). *Creative industries: Contracts between art and commerce.* Harvard University Press.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, *37*(1), 39–67.

Currid, E. (2007). The economics of a good party: Social mechanics and the legitimization of art/culture. *Journal of Economics and Finance*, *31*(3), 386–394.

Danaher, P. J., Bonfrer, A., & Dhar, S. (2008). The effect of competitive advertising interference on sales for packaged goods. *Journal of Marketing Research*, *45*(2), 211–225.

DeKinder, J. S., & Kohli, A. K. (2008). Flow signals: How patterns over time affect the acceptance of start-up firms. *Journal of Marketing*, *72*(5), 84–97.

DiMaggio, P. (1987). Classification in art. *American Sociological Review*, 440–455.

Dinner, I. M., Van Heerde, H. J., & Neslin, S. A. (2014). Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising. *Journal of Marketing Research*, *51*(5), 527–545.

Eliashberg, J., & Shugan, S. M. (1997). Film critics: Influencers or predictors? *The Journal of Marketing*, 68–78.

Elkins, J. (2003). *What happened to art criticism?* Chicago: Prickly Paradigm Press.

Ertug, G., Yogev, T., Lee, Y. G., & Hedström, P. (2016). The art of representation: How audience-specific reputations affect success in the contemporary art field. *Academy of Management Journal*, *59*(1), 113–134.

Espeland, W. N., & Stevens, M. L. (1998). Commensuration as a social process. *Annual Review of Sociology*, 313–343.

Fader, P. (2012). *Customer centricity, 2nd ed.* Philadelphia: Wharton Digital Press.

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Fiedler, K. (2007). Construal level theory as an integrative framework for behavioral decision-making research and consumer psychology. *Journal of Consumer Psychology*, *17*, 101–106.
Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, *90*(2), 217–232.
Fraiberger, S. P., Sinatra, R., Resch, M., Riedl, C., & Barabási, A. L. (2018). Quantifying reputation and success in art. *Science*, *362*(6416), 825–829.
Gemser, G., Leenders, M. A., & Wijnberg, N. M. (2008). Why some awards are more effective signals of quality than others: A study of movie awards. *Journal of Management*, *34*(1), 25–54.
Goetzmann, W. N. (1993). Accounting for taste: Art and the financial markets over three centuries. *The American Economic Review*, *83*(5), 1370–1376.
Hennig-Thurau, T., Marchand, A., & Hiller, B. (2012). The relationship between reviewer judgments and motion picture success: Re-analysis and extension. *Journal of Cultural Economics*, *36*(3), 249–283.
Higgins, M. C., & Gulati, R. (2003). Getting off to a good start: The effects of upper echelon affiliations on underwriter prestige. *Organization Science*, *14*(3), 244–263.
Hirsch, P. M. (1972). Processing fads and fashions: An organization-set analysis of cultural industry systems. *American Journal of Sociology*, *77*(4), 639–659.
Hovland, C., Janis, I., & Kelly, H. (1953). *Communication and persuasion.* New Haven, CT: Yale Univ. Press.
Ippolito, P. (1990). Bonding and non-bonding signals of product quality. *Journal of Business*, *63*(1), 41–60.
Johnson, E. J., & Russo, J. E. (1984). Product familiarity and learning new information. *Journal of Consumer Research*, *21*(June), 542–550.
Khaire, M. (2010). Young and no money? Never mind: The material impact of social resources on new venture growth. *Organization Science*, *21*(1), 168–185.
Köhler, C., Mantrala, M. K., Albers, S., & Kanuri, V. K. (2017). A meta-analysis of marketing communication carryover effects. *Journal of Marketing Research*, *54*(6), 990–1008.
Kottasz, R., Bennett, R., Savani, S., & Ali-Choudhury, R. (2008). The role of corporate art in the management of corporate identity. *Corporate Communications: An International Journal*, *13*(3), 235–254.
Kottasz, R., Bennett, R., Savani, S., Mousley, W., & Ali-Choudhury, R. (2007). The role of the corporate art collection in corporate identity management: The case of deutsche bank. *International Journal of Arts Management*, 19–31.
Lampel, J., & Shamsie, J. (2000). Critical push: Strategies for creating momentum in the motion picture industry. *Journal of Management*, *26*(2), 233–257.
Lee, H., Herr, P. M., Kardes, F. R., & Kim, C. (1999). Motivated search: Effects of choice accountability, issue involvement, and prior knowledge on information acquisition and use. *Journal of Business Research*, *45*(1), 75–88.
Legoux, R., Larocque, D., Laporte, S., Belmati, S., & Boquet, T. (2016). The effect of critical reviews on exhibitors' decisions: Do reviews affect the survival of a movie on screen? *International Journal of Research in Marketing*, *33*(2), 357–374.
Leone, R. P. (1995). Generalizing what is known about temporal aggregation and advertising carryover. *Marketing Science*, *14*(3_supplement), G141–G150.
Liu, Y., Polman, E., Liu, Y., & Jiao, J. (2018). Choosing for others and its relation to information search. *Organizational Behavior and Human Decision Processes*, *147*, 65–75.
Maglio, S. J., Trope, Y., & Liberman, N. (2013). The common currency of psychological distance. *Current Directions in Psychological Science*, *22*(4), 278–282.
Martorella, R. (1990). *Corporate art.* New Brunswick/London: Rutgers University Press.
Mayzlin, D. (2006). Promotional chat on the internet. *Marketing Science*, *25*(2), 155–163.
Mei, J., & Moses, M. (2002). Art as an investment and the underperformance of masterpieces. *American Economic Review*, *92*(5), 1656–1668.
Mela, C. F., Gupta, S., & Lehmann, D. R. (1997). The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research*, 248–261.
Merluzzi, J., & Phillips, D. J. (2016). The specialist discount: Negative returns for MBAs with focused profiles in investment banking. *Administrative Science Quarterly*, *61*(1), 87–124.
Merton, R. K. (1968). The Matthew effect in science. *Science*, *159*(3810), 56–63.
Meyer, P. (1988). Defining and measuring credibility of newspapers: Developing an index. *Journalism Quarterly*, *65*, 567–574.
Netherlands Association of Corporate Art Collections (2017). Homepage, (accessed September 15, 2017) [available at http:/www.vbcn.nl/EN/]. http://www.vbcn.nl
Newell, S. J., & Goldsmith, R. E. (2001). The development of a scale to measure perceived corporate credibility. *Journal of Business Research*, *52*, 235–247.
Ohanian, R. (1990). The impact of celebrity spokespersons' perceived image on consumers' intention to purchase. *Journal of Advertising Research*, *31*(1), 36–52.
Pennebaker, J.W., Booth, R. J. Booth, and M. E. Francis (2007), LIWC2007: Linguistic Inquiry and Word Count, (accessed October 10, 2013), [available at http://www.liwc.net/].
Pollock, T. G., & Gulati, R. (2007). Standing out from the crowd: The visibility-enhancing effects of IPO-related signals on alliance formation by entrepreneurial firms. *Strategic Organization*, *5*(4), 339–372.
Pollock, T. G., & Rindova, V. P. (2003). Media legitimation effects in the market for initial public offerings. *Academy of Management Journal*, *46*(5), 631–642.
Polman, E., Effron, D. A., & Thomas, M. R. (2018). Other people's money: Money's perceived purchasing power is smaller for others than for the self. *Journal of Consumer Research*, *45*(1), 109–125.
Pornpitakpan, C. (2004). The persuasiveness of source credibility: A critical review of five decades' evidence. *Journal of Applied Social Psychology*, *34*(2), 243–281.
Prinz, A., Piening, J., & Ehrmann, T. (2015). The success of art galleries: A dynamic model with competition and information effects. *Journal of Cultural Economics*, *39*(2), 153–176.
Rao, A. R., & Monroe, K. B. (1988). The moderating effect of prior knowledge on cue utilization in product evaluations. *Journal of Consumer Research*, *15*(2), 253–264.
Rao, H., Greve, H. R., & Davis, G. F. (2001). Fool's gold: Social proof in the initiation and abandonment of coverage by Wall Street analysts. *Administrative Science Quarterly*, *46*, 502–526.
Renneboog, L., & Spaenjers, C. (2013). Buying beauty: On prices and returns in the art market. *Management Science*, *59*(1), 36–53.
Rindova, V. P., Williamson, I. O., Petkova, A. P., & Sever, J. M. (2005). Being good or being known: An empirical examination of the dimensions, antecedents, and consequences of organizational reputation. *Academy of Management Journal*, *48*(6), 1033–1049.
Rust, R. T., & Verhoef, P. C. (2005). Optimizing the marketing interventions mix in intermediate-term CRM. *Marketing Science*, *24*(3), 477–489.
Shanteau, J. (1992). How much information does an expert use? Is it relevant? *Acta Psychologica*, *81*(1), 75–86.
Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, *86*(2), 420.
Silva, J. S., & Tenreyro, S. (2011). Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. *Economics Letters*, *112*(2), 220–222.
Singer, L., & Lynch, G. (1994). Public choice in the tertiary art market. *Journal of Cultural Economics*, *18*, 199–216.
Sorenson, O., & Waguespack, D. M. (2006). Social structure and exchange: Self-confirming dynamics in Hollywood. *Administrative Science Quarterly*, *51*(4), 560–589.
Spence, M. T., & Brucks, M. (1997). The moderating effects of problem characteristics on experts' and novices' judgements. *Journal of Marketing Research*, *34*(May), 233–247.
Stanford, J., Tauber, E., Fogg, B., & Marable, L. (2002). *Expert vs online consumers: A comparative credibility study of health and finance web sites.* (Consumer Web Watch Research Report).
Sternhal, B., Dholakia, R., & Leavitt, C. (1978). The persuasive effect of source credibility: Tests of cognitive response. *Journal of Customer Research*, *4*(4), 252–260.
Szántó, A. (2002). *The visual arts critic: A survey of art critics at general-interest publications in America.* New York: Columbia University.
Rijksakademie van Beeldende Kunsten (2017), Homepage, (accessed September 10, 2017), [available at http://www.rijksakademie.nl]. Annual report (2016) available at: https://www.rijksakademie.nl/ENG/rijksakademie/profiel/jaarverslagen/
Velthuis, O. (2003). Symbolic meanings of prices: Constructing the value of contemporary art in Amsterdam and New York galleries. *Theory and Society.*, *32*(2), 181–215.
Wagner, J. A., Klein, N. M., & Keith, J. E. (2001). Selling strategies: The effects of suggesting a decision structure to novice and expert buyers. *Journal of the Academy of Marketing Science*, *29*(3), 290–307.
Washington, M., & Zajac, E. J. (2005). Status evolution and competition: Theory and evidence. *Academy of Management Journal*, *48*(2), 282–296.
Weil, S. (1990). *Rethinking the museum and other meditations.* Washington D.C: Smithsonian Institute Press.
White, H. C., & White, C. A. (1993). *Canvases and careers: Institutional change in the French painting world.* University of Chicago Press.
Wijnberg, N. M. (2004). Innovation and organization: Value and competition in selection systems. *Organization Studies*, *25*(8), 1469–1490.

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Windmeijer, F. (2008). GMM for panel count data models. In M. Laszlo, & P. Sevestre (Eds.), *The econometrics of panel data: Fundamentals and recent developments in theory and practice* (pp. 603–624). Springer.
Wu, C. (2003). *Privatising culture: Corporate art intervention since the 1980s.* London: Verso.
Yogev, T. (2010). The social construction of quality: Status dynamics in the market for contemporary art. *Socio-Economic Review*, *8*(3), 511–536.
Yogev, T., & Grund, T. (2012). Network dynamics and market structure: The case of art fairs. *Sociological Focus*, *45*(1), 23–40.
You, Y., Vadakkepatt, G. G., & Joshi, A. (2015). A meta-analysis of electronic word-of-mouth elasticity. *Journal of Marketing*, *79*(2), 19–39.

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