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### The three stages of an auction: how do the bid dynamics influence auction prices? Evidence from live art auctions

Marie BLUM & Régis BLAZY

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**Université de Strasbourg**
**Pôle Européen de Gestion et d'Economie**
61 avenue de la Forêt Noire
67085 Strasbourg Cedex
http://large.em-strasbourg.eu/

Institut de Finance
de Strasbourg

# The three stages of an auction: how do the bid dynamics influence auction prices? Evidence from live art auctions

Régis BLAZY

LARGE – University of Strasbourg (France),
EM Strasbourg Business School,
Sciences Po Strasbourg
regis.blazy@unistra.fr

Marie BLUM

LARGE – University of Strasbourg (France),
Sciences Po Strasbourg

marie.blum@unistra.fr

**Abstract:**

This research examines whether and how the bid dynamics influence the final price, using a unique hand-collected database gathering bid dynamics of artworks auctioned live by a human auctioneer. Specifically, we study the degree of aggressiveness of bids and the pace of the auction resulting from the succession of bids, at the three main stages of an auction. We first find that bid dynamics are not neutral towards final auction prices. In line with our theoretical framework, this result confirms the importance of bidders' "fuzzy" reserve prices which explains why bidders adopt strategic behaviors. We then find that the auction price particularly benefits from the presence of "motivated" bidders, *i.e.* bidders who bid aggressively (high and quickly) to win the auction and do not seek for a bargain, especially at the beginning and end of the auction. At the end however, this positive impact of aggressive bidding may be attenuated by a despondency effect affecting some bidders. Moreover, we find that early arousal, which also contributes to provide valuable information on the artwork's common value, boosts the price. Lastly, we show that ultimate duels between bidders increase final prices. Overall, this paper proposes a primer conceptual framework of bidders' fuzzy reserves. This investigation contributes to the understanding of bidding behaviors by offering an easily understandable insight into bid dynamics, and by analyzing the case of live auctions of hedonic products that have received few attention until now.

**Keywords**: bid dynamics, auction price, fuzzy reserve prices, auction phases, live auctions, art market

(JEL Z11, D44)

# 1. Introduction

Auctions, although an ancient mode of exchange, have gained an increasing public attention these last two decades, especially due to the emergence of Internet auctions in the 1990s. They now account for a significant volume of economic activity and have become a mainstream form of trading. Auction markets have been the subject of a large body of academic research. This literature has mainly focused on how the different kinds of auction designs (e.g. English, Dutch, first-price and second-price sealed-bid auctions) affect revenues and efficiency. Factors such as differences in risk preferences, affiliation, information asymmetries or collusion have been explored in this research (see Klemperer 1999 for a review). The outbreak of online auctions has offered new research opportunities thanks to the huge amount of freely available field data. This stream of research has provided valuable insights into human bidding behaviour. Classical auction theory assumes bidder rationality, in other words that bidders enter an auction with a fixed valuation for the auctioned items defined ahead of auction, so that the final outcome of the auctions – the price – is determined by ex-ante calculations of bidders. However, empirical studies have provided significant evidence suggesting that bidding cannot be reduced to a maximization of expected utility, but rather that the dynamics of bidding behaviour matters.

Indeed, while an auction has been launched and is in progress, auction participants may be influenced by a number of value signals, such as the minimum bid and other participants' bids. Studies have shown that the opening bid (*i.e.* sellers are required to set a starting bid for their items) has a significant impact on the final auction price. Bajari and Hortacsu (2003), Häubl and Popkowski Leszczyc (2003), Lucking-Reiley et al. (2007) and Hou (2007) among others found a significant positive effect, explained as the result of the informative quality signal sent by the opening bid for items which are hard to estimate, whereas Ku et al. (2005, 2006) found a negative impact, due according to the authors to the attractive power of low starting bid that leads to bidding wars which can push up prices. Regarding other participants' bids, Dholakia and Soltysinski (2001), Dholakia et al. (2002) and Simonsohn and Ariely (2008) have shown that bidders herd into online auctions with more existing bids, ignoring comparable or even more attractive available auction item.

Moreover, researchers have pointed out that bidding involves emotional aspects and observe an auction fever phenomenon especially in ascending auctions (Ku et al. 2005, Jones 2011, Adam et al. 2011, Adam et al. 2015), described as "*an emotional state elicited in the course of one or more auctions that causes a bidder to deviate from an initially chosen bidding strategy*" (Adam et al. 2011, p. 204). Ku et al. (2005) explain that auction fever may stem from both bidder's escalation of commitment (*i.e.* individuals seek to view themselves positively which leads them to avoid giving up or admitting a mistake, so that they can continue bidding even when they have outreached their limits to fulfil the need to self-justify their previous bids) and bidder's competitive arousal (*i.e.* numerous factors can increase arousal, which in turn impairs decision-making, such as rivalry, the presence of an audience, time pressure and the uniqueness of being first). They found that Internet bidders who have exceeded their limits have spent more time in auctions than the ones who have not exceeded their limits, that bidders exceed their limits more in the later stages of auctions, more when few other bidders remain, and by greater amounts in live, *i.e.* in the presence of an audience, than in Internet auctions.

Time seems to also play an important role in determining bidding in dynamic auctions. In descending auctions, Katok and Kwasnica (2008) found that under time pressure, bidders place lower bids, whereas in ascending auctions, Ku et al. (2008) observe particularly high bids when bidders are confronted with high time pressure and high stakes, a result corroborated by Cheema et al. (2012). Roth and Ockenfels (2002) observe that a large part of bids is placed within the last minutes in hard-close online auctions (eBay©), a phenomenon called "sniping" that has been highlighted by many other studies (Bajari and Hortaçsu 2003, Ockenfels and Roth 2006, Borle et al. 2006, Cao et al. 2019, among others), which shows that a modification of the auction system such as the time limit affects bidding behavior. Houser and Wooders (2005), Glover and Raviv (2012) and Gray and Reiley (2013) find evidence of lower prices in sniped auctions. Besides, Haruvy and Popkowski Leszczyc (2010) find that short auctions result in higher prices compared to auctions with a longer duration, due to more jump bidding. Jump bidding, a well-established phenomenon in ascending auctions, consists of placing a bid larger than the minimum bidding increment required to be a winning bidder, which can be a result of impatience, strategic concerns, or can serve as a valuation signal as well as to signal an aggressive strategy. The literature have shown that the bid increment and the rules of bidding (allowing jump bidding or not) can have effects on the revenues of an auction (Isaac et al. 2005, Isaac et al. 2007) and that the choice of bids allow the bidders to communicate within the competitive structure of English auctions (Avery 1998, Easley and Tenorio 2004, Kwasnica and Katok 2007).

These studies all highlight the fact that the dynamics of bidding behaviour are far from being irrelevant, however they focus on summary statistics of the auction such as the number of bids, the percent of bids placed in the last minutes of an auction or the duration of an auction.

Other studies have sought to investigate further into the bid dynamics, *i.e.* the distribution of bids over the course of an item auction. A first stream of research has introduced advanced data visualisation of sequence of bids. Shmueli and Jank (2005) and Hyde et al. (2006) propose different visualisation methods and tools for bid histories, including complex types of visualisations for viewing bid data of concurrent auctions (on auction sites such as eBay©, many identical products are sold in simultaneous auctions, therefore being dependent and concurrent auctions). Shmueli et al. (2006) offer a tool for interactive visualisation of bidding data, which allows an interactive exploration of datasets with bid histories (time series) as well as auction attributes (cross-sectional data).

Another stream of literature consists of modelling bidding dynamics. Shmueli et al. (2007) elaborate a probabilistic model for the bid arrival process in online ascending auctions. Park and Bradlow (2005) have developed a dynamic model of bidding behavior in Internet single-item ascending auctions that addresses whether people will bid, who will bid, when they will bid, and how much they will bid for the entire sequence of bids on an auction item. Bradlow and Park (2007) explore how bidders' behaviors evolve over the course of an ascending auction by modelling auction data drawing upon the record-breaking literature in statistics with Bayesian data augmentation methods. Reddy and Dass (2006) have modelled online ascending art auction dynamics (107 lots) using functional data analysis in order to investigate the effect of different characteristics (related to the auction house/seller, the level of competition, the artist and the artwork) on bids movement during the entire auction. They find that the influence of these factors on the current bid level and on the velocity (rate of change in bids) vary over the duration of the auction, some being stronger or inexistant at various stages of the auction process (at the beginning of the auction, at the middle or at the end). Bapna et al. (2008) also use functional data modelling to explore the dynamics (price evolution and its first and second derivates meaning price speed and acceleration respectively) of the price formation process of online auctions on eBay©, investigating five kinds of explanatory factors of bid dynamics at various moments of an item auction. Wang et al. (2008) create a dynamic forecasting model for bids in online ascending auctions, based on functional data analysis, which operates during the live auction and forecasts bids not only at the auction end but also at a future time point of the ongoing auction. Jap and Naik (2008) provide models to predict bidding dynamics within business-to-business online reverse auction. Lastly, Ceyhan et al. (2011) model in the case of online peer-to-peer (P2P) lending services how the bid trajectories predict loan outcomes (*i.e.* loan funded vs. not funded, and loan paid back vs. not paid back). It turns out from these studies that the trajectories of bids say something about the auction outcome.

The focus of this paper is on traditional auctions, *i.e.* ascending auctions conducted on-site in the art market, for which we investigate if and how the degree of aggressiveness of bids and the pace of the sequence of bids (*i.e.* acceleration and deceleration phases) can predict the final outcome of the auction, that is the price. The sequence of bids refers to the entire series of bids placed by bidders over the duration of an item auction. Thus, this study examines how the pricing outcome is affected by the micro bid level at traditional auctions.

On-site outcry auctions differ from online auctions. First, traditional auctions occur in a close time frame, as each lot is auctioned within a few tens of seconds or in a matter of minutes (60 seconds is the time typically taken to sell a lot) whereas online auctions are opened for bidding over an extended time period, generally over several days. Second, bidders in live auctions tend to be more committed since they make themselves available for the exact moment and duration of the item auction they are interested in and can spend time to commute to auction house building, than online bidders who make less effort as they can bid from wherever and choose when they want to bid over the longer auction duration. Third, on-site auctions involve different ways of bidding, depending on the rules of the auction house: placing bids physically from the room, by purchase order addressed to the auction house in advance (the auctioneer is in charge of placing bids on the behalf of the person who left a purchase order), by phone, or on the Internet if the auction is broadcast live. Fourth, compared to online auction, on-site auctions involve the presence of a human auctioneer who conducts the auction and has an undeniable role of salesman to enhance bidding by increasing bidders' engagement and excitement with what is called the auctioneer's "chant" (Chipty et al. 2015, Lacetera et al. 2016). However, previous bid dynamics studies have largely relied on online auction. One reason of the paucity of research on on-site auctions is the challenge of obtaining accurate data on the timing and amount of all bids placed over the course of the item auction. Thus, there is a need for field studies to analyse bidding dynamics in on-site auctions in order to understand how the sequence of bids, which reflects bidders' and auctioneer's strategies specific to the on-site context, influence the price.

Moreover, we focus on the art market where the goods exchanged are hedonic and unique ones, whereas previous research on bidding dynamics on the Internet have explored markets of utilitarian or functional products, with the notable exception being the work of Reddy and Dass (2006). Yet, purchase of hedonic products such as art is steered by motivations which are completely different from those of functional product purchase, namely aesthetic pleasure, social status and financial investment. This contrast in motivations may result in different commitment levels of bidders. In addition, as art is an emotional asset, artworks involve both common and private value components for bidders, in contrast to utilitarian goods with an objective common value. This difference may also lead to different bidding behaviours.

The lack of bidding dynamics research on hedonic heterogeneous commodities is certainly due to the complexity of modelling bidding dynamics while controlling for the high variability between goods, each artwork being unique.

Considering the bidding dynamics of traditional auctions and of hedonic products such as art thus represents an improvement over previous studies. Our question of interest is whether the degree of aggressiveness of bids and the rhythm of the sequence of bids in an ascending on-site auction appear to be neutral regarding the final price, or if instead they actively predict the final outcome. We assume that if bid dynamics have an impact on prices, it is due to the fact that bidders' reserves (the highest price they are willing to pay for an item) are "fuzzy", *i.e.* reserves of bidders change during the lifetime of the auction. To answer our question, we analyse the curve of the sequence of bids from the starting bid to the final bid, the latter being the price paid by the winning bidder for the good (to which fees may be added). However, the online auction literature (Ariely and Simonson 2003, Chiang and Kung 2005, Shmueli and Jank 2005, Hyde et al. 2006) shows that bidding patterns depend on the phase of an item auction and scholars distinguish three main phases (*i.e.* moments) of an item auction: the beginning, the middle and the end of the auction. Indeed, bidders' strategies may vary depending on the auction stage, due to several contextual changes. We therefore construct indexes capturing the bid dynamics at each phase of the auction. We measure the degree of aggressiveness of bids as well as the pace of the auction resulting from the accumulation of bids for the three phases, in order to analyse their impact on the final price.

The fact that traditional art auction houses now permit bidders to join the auction online, broadcasting live the sale, has allowed us to record these sales and to manually collect data about the opening bid, the closing price, the bid arrival time and the amount of each bid, be it in the room, on phone, on purchase order, or on Internet. We note that we lack bidding information for confidentiality reasons such as the provenance of the bid placed, the number of bidders, bidders and sellers characteristics, which excludes any analysis of individual bidding behavior for this paper. We use a rich and hand-collected database of ascending auctions conducted on-site in the art market. Our dataset comprises 547 European comic artworks auctioned between March 2017 and May 2018 by six different auction houses. Our data include bid trajectories, final prices, sale characteristics, artist characteristics and artwork characteristics.

We confirm the existence of strategic behaviors over the course of the auction whose impact is not neutral on the outcome of the auction. In line with our theoretical framework, this result supports the significance of fuzzy reserves that give bidders reasons to bid aggressively or mildly. Regarding the aggressiveness of bids, we find that aggressive bidding has a significant and positive influence on the final price at each stage of the auction, but to a greater extent at the beginning of the auction. This is due to the presence of highly motivated bidders, who aim at winning the auction rather than preserving their surplus. At the end of the auction, this effect is slightly attenuated, as final duels seem to give rise to some despondency amongst bidders. As for the auction pace, we find that initial arousals which contribute to give information on the common value of the item substantially and positively affect the auction outcome. Moreover, acceleration of bids at the end, implying ultimate duels of bidders eager to win the auction, increases the final price. Our results confirm the prevalence of some effects (such as "motivation", "arousal" and "common value" effects) compared to others (such as "despondency" or "inclusive" effects).

The contribution of this paper is twofold. First, we bring to the literature a conceptual framework toward fuzzy reserves of bidders and their consequences. Second, we contribute to the body of literature on bidding dynamics by using indexes for the main moments of an auction that offer an easily understandable insight into the bid dynamics and their impact. We also provide a bid dynamics analysis of live auctions in brick-and-mortar auction houses with a human auctioneer, as well as of auctions of hedonic goods, which have been little explored so far.

The remainder of the paper proceeds as follows. Section 2 describes the hypotheses. Section 3 details the bid dynamics indexes. Section 4 presents the data and the methodology. Section 5 presents the results and robustness checks. Section 6 concludes.

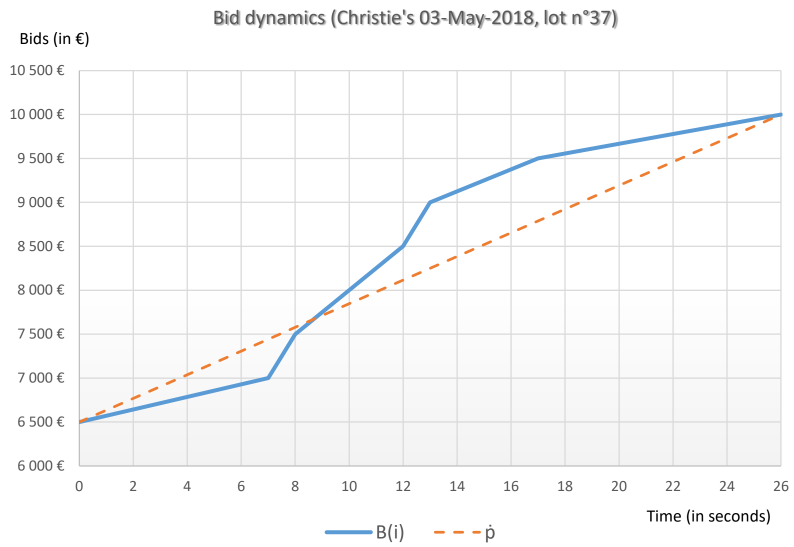
## 2. Hypotheses

English auctions can be viewed as a succession of ascending offers that appear at various dates. In such context, if the bidders were mere "robots" (*i.e.* following no specific strategy), the bids would increase linearly. Potential buyers would bid on regular time intervals, and the value of their bid would equal the next marginal bidding step, as proposed by the auctioneer. For instance, one may figure bidders raising their hand while the auctioneer proposes prices that correspond to the next increment: some hands would go down each time the price goes beyond some bidders' individual reserve (*i.e.* the highest price (s)he is ready to pay for the lot). In such situation, relating every bidding time with the corresponding bid would lead to a linear increase in offers until they ultimately reach the hammer price (*i.e.* the final auction price for which only one hand is left raised). We consider such situation as a benchmark: here, auctions are said "neutral" in the sense that they gather non-strategic bidders whose presence leads to a linear auction path (*i.e.* the curve linking all bids, in the plan that relates bid times to prices).

Our dataset however contradicts such prediction, as many lots for sale display non-linear auction paths (our descriptive statistics shown afterwards confirms this observation). Figure 1 illustrates this for a comic artwork (lot n°37) sold at Christie's, the 3rd of May 2018. This lot, introduced at 6 500€, reaches its final price (10 000€) 26 seconds later. The bold curve shows the actual evolution of bids across time, while the dashed line refers to the linear benchmark for this sale. Clearly, the bids evolve in a non-linear way, showing a S-shaped curve. During its initial stage, the sale is behind time (when compared to the benchmark), then accelerates, and slows down before the auction ends. We suspect such acceleration/slowing-down phases to stem from bidding strategies that evolve throughout the auction. As suggested later on, such strategies can have some influence on the final auction price.

**FIGURE 1**

Example of bid dynamics (Christie's, 03-May-2018, lot n°37)



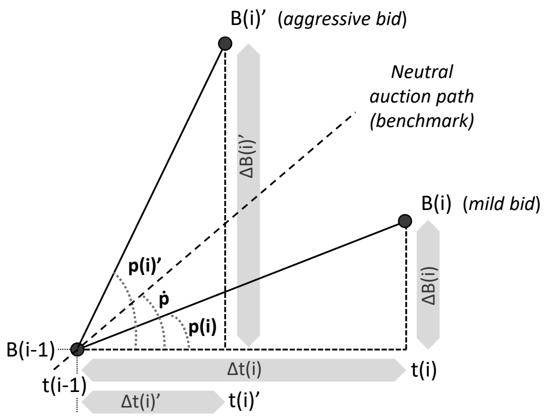

## 2.1. Individual bidding strategies

Let us consider a succession of N increasing bids, each indexed by $i \in [1;N]$. Every bidder (k) can bid several times during the auction without limitation. B(i) is the (i)th bid made at time t(i), in response to the (i-1)th previous competing bid, B(i-1) at time t(i-1). We denote as ΔB(i) the price increase between both offers (*i.e.* ΔB(i) is the difference B(i) - B(i-1)). Δt(i) is the time (in seconds) between both bids (*i.e.* Δt(i) equals t(i) - t(i-1)). We define p(i) as the ratio

ΔB(i)/Δt(i), which measures the "aggressive power" of the $i^{th}$ bid: the higher it is, the more forceful is the bid (*i.e.* the bidding step is boosted in a period of time). An aggressive[1] (respectively mild) bid means that p(i) exceeds (resp. is less than) the benchmark slope ($\dot{p}$) of the "neutral auction path", as defined before. Figure 2 illustrates this theoretical framework. The dashed line represents the benchmark slope ($\dot{p}$). A mild bidding strategy extends the bidding time while the price increases moderately. On the figure, this leads to a small slope p(i). At the opposite, an aggressive strategy boosts the slope (that raises from p(i) to p(i)'): such bid is aggressive in that sense that it reduces the bidding time while producing a price jump.

**FIGURE 2**

Aggressive *vs.* mild bidding strategies




The level of aggressiveness is a strategic choice made by every candidate buyer when deciding to (re)bid. We next explore the rationale explaining why (s)he may choose a high or a low p(i) when (re)bidding on a lot.

## 2.2. Fuzzy reserves

The rationale behind aggressive *vs.* mild bidding strategies lies on a core assumption on the bidders' reserves which we consider as "fuzzy reserves". Indeed, as explained by Cramton (1998), D'Souza and Prentice (2002), Heyman et al. (2004) and Hou (2007), bidders may not fully respect their initial reserve throughout the auction. Following this avenue, it seems realistic to expect the bidders' maximum reserves to increase (more or less notably, depending

[1] An "aggressive bid", as defined here, differs from a "jump bid", although both notions are close. Namely, in English auctions, a jump bid corresponds to an offer that exceeds the minimal amount allowed by the auctioneer.

on each bidder's individual profile) while the auction is going on. Several reasons can explain such behavior. First, individuals can face difficulty in assessing the value of an item for sale, especially for common value goods or particular objects (D'Souza and Prentice 2002, Ku et al. 2005). This is particularly true for art objects, as art goods hold a common value component (for resale) and bidders can have imperfect information about the objects, which are unique. Thus, other bids may reveal information about the common value of the good and its quality. Some bidders interpret previous high offers as signs of stronger interest towards the lot (and may therefore readjust their valuation). Second, participating in an auction may be considered as a competitive game by bidders and, as a result, bidders may feel a strong desire to beat their rivals and win. This phenomenon, called the "uniqueness of being first" and highlighted by Ku et al. (2005), Malhotra et al. (2008) and Adam et al. (2015), can generate emotional arousal which then impair decision-making and may thus lead to overbidding. Third, in the context of an artwork sale, the uniqueness of the lots at sale makes them one-of-a-kind opportunities. While the auction goes on and gets closer to the end, the feeling that "when it's gone, it's gone" may increase the perceived value for bidders wishing to avoid after-sale regrets. Indeed, auction participants may anticipate how they will feel about losing the item after the auction, what Ariely and Simonson (2003) call the "loser's curse". Fourth, having more time to think during the auction gives the bidders the opportunity to reallocate some other purchases plans (e.g. other auctioned lots, and/or alternative scheduled expenses) to increase their chances of winning the auction. Such recalculation requires time while readjusting a budget and/or planned purchases. Of course, pure rational players should have made such computation prior to the auction. From that view, last-minute increases of reserve limits may be the sign of behavioral bias among the bidders who may adopt some myopic strategies, while bidding on a lot. Overall, fuzzy bidders can elevate (more or less, depending on individual profiles) their initial reserve during the auction: *i)* the longer it takes to sell the lot, and/or *ii)* the higher the previous offers, the more likely fuzzy reserves will subsequently increase. Of course, this process goes on up to a certain point, until they reach their hard budget constraint, which cannot expand further.

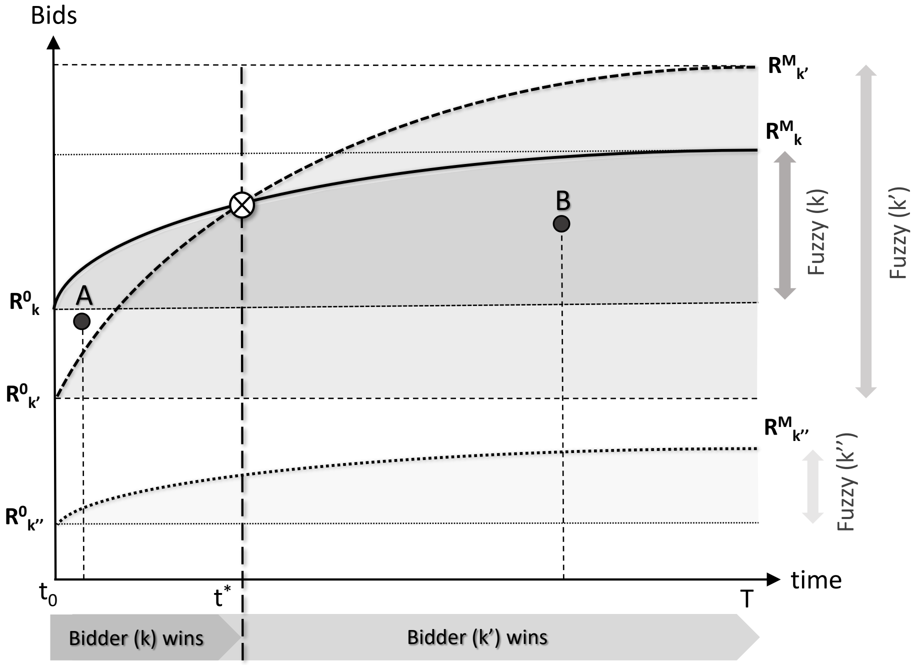
Figure 3 illustrates fuzzy reserves when three bidders (k, k', k'') compete. Suppose, for instance, that all bidders increase their fuzzy reserves in a concave way.[2] When the auction begins (at time $t_0$), the reserve of bidder (k) equals $R^0_k$; which is higher than $R^0_{k'}$ and $R^0_{k''}$, the reserves of the opponents (k' and k''). While the auction is going on, bidder (k) can always outbid (k''), but the situation gets more complicated regarding (k'). Indeed, bidder (k') is

[2] This assumption is for illustration purpose only. The same reasoning can extend to more complex evolutions.

fuzzier than (k) (*i.e.* his/her reserve increases in a larger proportion during the sale). Under this case, the initial situation may reverse during the auction. From time $t^*$, bidder (k') values more the lot than (k), so that his/her reserve is now higher. At the end of the auction, the reserves of (k) and (k') equal respectively $R^M_k$ and $R^M_{k'}$, where the latter exceeds the former. During the auction, bidder (k) has a chance to win the lot until time ($t^*$) (point "A" reflects such situation: in "A", (k)'s offer still exceeds his/her opponent's reserve). After this time limit, the situation reverses as any future attempt can be outbid by (k') (see point "B" for example). Obviously, fuzzy reserve curves are private information (one may even consider that fuzzy bidders discover the evolution of their own reserve as the auction progresses). In that context, ($t^*$) can be assessed only, but never discovered. To sum it up, the longer it takes to bid, the higher is everyone's own reserve, but with a rising risk that opponents increase their reserves even more.

**FIGURE 3**

Fuzzy reserves (three bidders, k, k', k'')




Under the "fuzzy reserves" assumption, playing a high bid in a short time-frame (*i.e.* raising p(i)) increases the chances to kill competition, as such strategy prevents the other (fuzzy) bidders to have enough time to update their own reserves to a higher level. A bidder can play such strategy all the more easily than (s)he is far from his/her own reserve, *i.e.* (s)he still has strong dissuasive power, which might disappear while the auction is going on. Obviously, this strategy has two major drawbacks. Firstly, whereas boosting the current bid increases the chances of winning the auction, the resulting increase of p(i) undermines eventually the bidder's individual surplus (*i.e.* the difference between his/her own reserve and the final auction price). Secondly, when the high level of p(i) stems from a fast bid, the bidder prevents him-/herself to heighten his/her own (fuzzy) reserve as (s)he shortens time for reflection. Overall, a bidder must arbitrate between two extreme strategies. On the one hand, (s)he can choose a mild-bidding strategy (*i.e.* low p(i)) that preserves his/her surplus but at the risk of giving more time to the competitors to also increase their fuzzy reserves.[3] On the other hand, (s)he can opt for an aggressive-bidding strategy (*i.e.* high p(i)) that reduces competition, thus leading to higher chances of winning the auction, but at the cost of lower individual surplus.

Depending on the number and timing of aggressive/mild bidding strategies, the auction may deviate from its neutral path (*i.e.* linear increase of bids). Such accelerations/slowdowns might generate delays/advances within the auction dynamics. We expect such strategies to have various consequences depending on the time when they take place.

### 2.3. Changing context with the auction stages

The impact of bidding strategies changes significantly with the stage of the auction, either at its beginning or at its end. We now discuss these contextual changes, separating the beginning and end phases of an auction (with the midpoint considered an intermediate case).

When the auction starts, the number of potential bidders is at its highest. However, this does not mean that competition is the toughest. Indeed, two factors counterbalance the level of competition stemming from numerous bidders (if any). First, the proportion of potential buyers with small or moderate initial reserves (reflecting their low interest and/or limited budget) is *ceteris paribus* higher. For the most motivated bidders, such competitors are rather easy to discourage (although their identity remains private information). Second, everyone's fuzzy reserves have not increased yet. Another consequence of a high number of bidders is that strategic interactions are relatively low at the beginning of the auction (bidders become interactive Nash-players when they are fewer). A consequence is that the bids of one potential buyer are less of a signal to others: at that point, bidders reveal less information by choosing a certain level of p(i) because they are (to some extent) drowned in the mass. Furthermore, the early stage of the auction is a moment when everyone's *ex-ante* bidding latitude is at its highest.

[3] Following such strategy also increases the risk that a rushing auctioneer ends the auction rapidly, thus bypassing bidders who are too slow to react.

Indeed, the upset price is low in ascending auctions (*i.e.* such upset price is far from the bidders' initial reserve).[4] Last, the level of information on actual competition is low when the auction starts, as few bidders have started bidding, thus showing some interest about the auctioned lot.

It might seem confusing to mention the "end of an auction" whereas there is no *ex-ante* time limitation to English auctions. That said, from an *ex-post* perspective (*i.e.* once the auction is over), analyzing the ending dynamics of a (closed) auction is a straightforward task. From that view, the context of the sale reverses and important features arise when an auction ends. On the one hand, the remaining bidders (with the highest reserves) are the toughest ones. When being fuzzy, their reserves have even had enough time to increase up to that moment. On the other hand, the bidders' ability to keep increasing their bids narrows while the competing offers get closer to their own (updated) reserve. This is even truer when their (hard) budget constraint cannot expand anymore (no matter the time given for this). Furthermore, the number of remaining bidders is lower when the auction ends.[5] As strategic interactions are stronger with fewer bidders, one can expect Nash-strategies to be more prevalent at this time. Namely, the last bidders make conjectures on the strategies of their opponents, and decide, for each conjecture, their best answer. In such context, each p(i) ratio becomes a signal likely to change the players' beliefs. Last, the level of information is higher when the auction ends, as every bidder has been observing the (aggressive/mild) strategies of their competitors, especially the latest ones.

Now that we have analyzed the buyers' bidding strategies under the changing context of an auction, we question how such strategies may alter the final price.

## 2.4. Tested hypotheses

In that section, we first analyze the influence of an acceleration of bids due to punctual aggressive strategies (*i.e.* p(i) increases) (section 2.4.1). Then, we wonder to which extent the price may also depend on an accumulation of aggressive/mild offers, thus generating advances/delays, and catch-up/slowing down effect in the pace of the auction (section 2.4.2).

[4] This is not always verified *ex-post*, as fuzzy reserves can increase later on, throughout the auction.
[5] However, late bidders may join the ongoing auction too. Besides, some bidders may hide during the previous stages of the auction.

### 2.4.1. Influence of punctual aggressive bids on the price

We discuss here the expected influence of punctual aggressive bids on the final auction price, *i.e.* how an increase of p(i) (observed at time t(i)) can alter the ultimate bid B(N), *i.e.* the hammer price observed at time t(N).[6] The bid dynamics locally accelerate (respectively slow down) when the mentioned slope increases (resp. decreases). As the bidding context changes throughout the auction, we distinguish hereafter two polar moments: the start and the end of the auction.

#### A. *Early stage of an auction*

When an auction starts, the relatively high number of potential buyers requires focusing on the most dominant strategy among them.

Choosing a high p(i) reflects an aggressive bidding strategy, which characterizes high motivation towards the lot, as it maximizes a bidder's chances to win the auction before the competitors' fuzzy reserves start rising. Obviously, the bidders who follow such strategy do not aim to drive a bargain (as they voluntary reduce the gap between their bid and their reserve), but rather to discourage competitors before they become dangerous. Choosing a high p(i) has an immediate consequence (compared to neutral bidding): by minimizing their surplus, aggressive bidders maximize their chances to win the auction, which, as a result, boosts the hammer price.[7] This leads to our first hypothesis (H1a).

> **H1a.** *[Motivation] When an auction starts, aggressive bids may boost the final auction price, i.e. a rise of p(i) may have a positive influence on B(N). Such effect reflects early "motivation" from bidders.*

A second immediate consequence appears however: if aggressive bidding is successful, a significant number of competitors can be discouraged rapidly, at the early stage of the auction. Here, fewer bidders are given the chance to stay further in the competition, and will not participate to the future growth of fuzzy reserves, if any (higher values of p(i) also reduce the auction time, which gives the early-discouraged bidders even fewer opportunities to readjust

[6] We make the implicit assumption that the ultimate bid is high enough to sell the lot. In other words, there is not selling reserve.
[7] Thus taking the risk of paying more than the second highest bid in case of opponents whose reserve would have never exceeded the bidder's one. In such (uncertain) situation, following the neutral auction path would have led the bidder to win the lot anyway, while paying the second highest bid.

their reserves afterwards).[8] In a nutshell, the level of competition is expected to decrease when the rise of p(i) is high enough to discourage bidders, especially those entering an auction with low initial reserves. As a result, less competition between potential buyers leads to a lower hammer price: the more bidders being discouraged, the stronger is the effect. This brings (H1b), as an alternative to (H1a).

> **H1b.** *[Despondency] When an auction starts, aggressive bids may undermine the final auction price, i.e. a rise of p(i) may exert a negative influence on B(N). Such effect reflects early "despondency" among bidders.*

### *B. Last stage of an auction*

During the last stage of an auction, the immediate consequences of aggressive bidding are similar to the ones discussed in the previous section (*i.e.* motivation *vs.* despondency effects can boost *vs.* undermine the hammer price).[9] Nevertheless, further consequences may arise when an auction ends, as strategic interactions increase while bidders are fewer. This justifies a focus on the best responses of each bidder based on conjectures about the latest competitors, especially in terms of the threat they pose. There are several reasons why bidders may (or may not) view an offer as dangerous. Firstly, the art-collecting community is a small world. Some bidders have a strong/weak reputation, which is common knowledge.[10] Secondly, the magnitude and timing of previous bids are cumulative signals (the latest being the most visible ones): bidders[11] signal their type by sending a succession of ratios p(i) during the auction. The participants use such signals to revise and assess the potential danger of any recent bid. Thirdly, the absolute level of bids also alters the bidders' beliefs about opponents, especially when symbolic thresholds have been outreached (the population of buyers obviously changes when the bids go beyond 5 000 €, 100 000 €, or 1+ million €).

Let us consider a bidder having chosen a high p(i), thus playing an aggressive strategy while the auction ends. At this stage of the sale, such decision is a strong signal, observed easily

[8] Moreover, Avery (1998) says that a bidder using jump bidding as an aggressive strategy aims at sending the message to others that (s)he has the highest value for the good and that competing with her/him puts them at risk of overbidding and losing money (*i.e.* suffering from the winner's curse) if (s)he drops out.

[9] Although the higher level of offers at this point of the auction makes it more likely that bidders are (*ceteris paribus*) closer to their hard budget constraint.

[10] At least for non-anonymous bids, which excludes Internet/phone/purchase order offers.

[11] In most auctions, each online registered buyer is given an ID number, so that it remains possible for the others to identify the bidder, despite ignoring his/her precise identity. As for offers by phone, there is one auction house staff member per call, so it remains also possible for the others to identify from which staff member over the phone the bids come from.

by opponents.[12] Here, the nature of the next offers depend mainly on the conjectures made by the remaining competitors. Suppose some of them fear that *i)* the aggressive bidder has not reached his/her reserve yet, *ii)* such reserve remains fuzzy enough to keep increasing if the auction goes on. Then, the bidder's opponents may decide to stake everything on, and strike back by playing aggressively too, which is the best way to discourage a dangerous offer[13] (of course, the ability to play such strategy is limited by the buyers' own (hard) budget constraint). In other terms, bidding high quickly saves the last chances to grab the lot, and can be the ultimate answer for competitors being the most motivated and/or whose financial latitude is narrowing. This strategy is rational when followed by bidders who are convinced that others can win the auction if it lasts too long. Overall, final bidding duels may appear when a set of players believes that a current bid is dangerous (*i.e.* it can elevate even more).[14] This can amplify the immediate consequences of aggressive bidding, as competitors bid to the maximum afterwards. This leads to (H2a).

> **H2a.** *[Amplification] When the auction ends, the consequences of aggressive bidding (cf. motivation (H1a) vs. despondency (H1b)) can amplify when opposing bidders identify such bid as dangerous, thus leading to "final bidding duels".*

Now, H2a has some counterarguments. Suppose that when facing an aggressive bid, competitors now believe that the bidder behind such offer has (nearly) reached his/her hard budget constraint (which cannot be exceeded, except in case of irresponsible bids, which we exclude from our analytical framework). Here, the best response of the opponents is to make incremental (mild) bids afterwards in order to maximize their surplus: raising further their bids is useless as they assume the current bidder to have exhausted his/her bidding margin. Hence, when a set of buyers see the current bid as a non-threatening offer, a high p(i) may be followed by milder bids, which can cancel/mitigate the consequences of aggressiveness. Namely, mild responses *i)* no longer boost the offers (thus terminating "motivation effects"), *ii)* expand time (thus tempering "despondency effects"). This leads to (H2b), as an alternative to (H2a).

[12] Among whom are bidders approaching their non-expandable hard budget constraint.

[13] Indeed, playing a low p(i) (to maximize one's individual surplus) is of less interest. On the contrary, while facing dangerous competitors, a high p(i) is the only answer left to win the lot (which includes bidders whose financial margin is shrinking with higher bids).

[14] At the end of the auction, these bidding duels can even be reinforced by a surge of pride among certain duelists deciding to increase their reserve even more to win the fight.

**H2b.** *[Cancellation/Mitigation] When the auction ends, the consequences of aggressive bidding (cf. motivation (H1a) vs. despondency (H1b)) can disappear/narrow when opposing bidders are confident, thus leading to "final de-escalating".*

Table 1 gathers our hypotheses on the impact of aggressive bids (*i.e.* p(i) ratios) on the hammer price (B(N)). We split them depending on the considered auction stage. When the auction ends, we distinguish the immediate consequences of aggressive bidding (high p(i)) from the further effects (competitors' strategic responses). The signs in brackets indicate the expected influence on the hammer price.

**TABLE 1**

Synthesis of hypotheses (expected influence of aggressive bids)

<table>
<tr><td rowspan="3">Auction starts:<br>Aggressive bidding<br>► p(i)↑</td><td colspan="3">Auction ends: Aggressive bidding ► p(i)↑</td></tr>
<tr><td rowspan="2">Immediate consequence</td><td colspan="2">Further effects (competitors' strategic responses)</td></tr>
<tr><td>Opponents' beliefs →<br>Dangerous bid</td><td>Opponent's beliefs →<br>Non-dangerous bid</td></tr>
<tr><td>H1a: Early motivation (+)</td><td>Late motivation (+)</td><td>H2a: Final duels<br>→ amplified (+) impact</td><td>H2b: Confidence<br>→ cancelled (+) impact</td></tr>
<tr><td>H1b: Early despondency (-)</td><td>Late despondency (-)</td><td>H2a: Final duels<br>→ amplified (-) impact</td><td>H2b: Confidence<br>→ mitigated (-) impact</td></tr>
</table>

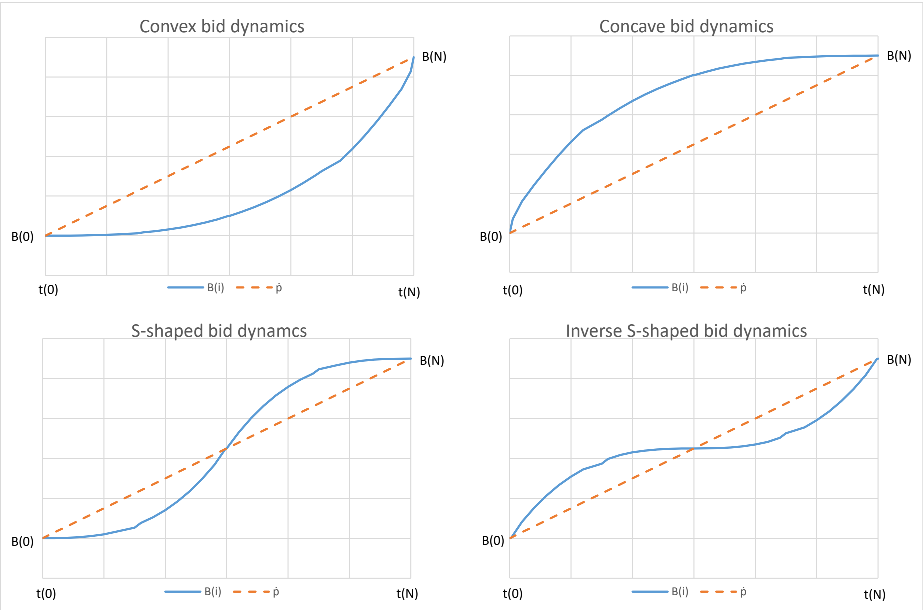
## 2.4.2. Influence of the pace of an auction on the price

At a given time, an aggressive bid punctually accelerates the pace of an auction, while a mild one leads to punctual deceleration. Therefore, the way succeeding aggressive/mild bids accumulate over time can modify the pace of the auction. Fast-paced auctions may stem from a steady succession of aggressive offers (many motivated buyers), or to one extremely aggressive early offer ("wipe them out" strategy). At the opposite, slow-paced sales may be due to succeeding mild bids (numerous bargain seekers) or to one soft late offer ("wait and see" strategy). When such strategies prevail at the beginning of an auction, the bid dynamics can evolve behind or ahead of "normal pace" (*i.e.* the pace of a linear auction deriving from automatic bids: *see supra*). When the auction ends, previous delays (respectively advances) lead consequently to catch-up (resp. slowing down) effects, when compared to linear (neutral) dynamics.

Figure 4 describes four alternate fictive cases showing several combinations of advances/delays and catch-up/slowdown effects, occurring at the beginning and/or at the end of the sale. The first configuration illustrates a convex auction, (*i.e.* starting slowly, which generates catching-up effects in the end). Here, the bidding curve is always below the linear (neutral) auction path. The second graph shows the reverse: concave auctions accelerate in the beginning, and decelerate afterwards. Here, all bids are above the non-strategic auction path. The third configuration (S-shaped auction) is more complex: after initial delays, the bid dynamics suddenly accelerate at midpoint, so that the auction becomes ahead of pace, just before converging late towards the linear path (*i.e.* a final slowdown). The fourth graph illustrates the reverse situation: an inverse S-shaped auction boosts when starting and ending, while decelerating at midpoint.

**FIGURE 4**

Auction pace (4 configurations)




There is a chance that the hammer price also depends on such non-linear dynamics affecting the pace of an auction. We now investigate this latter question by comparing the actual bid dynamics to the neutral auction path. One may observe various phases in the ongoing auction, either behind or ahead of pace: we expect such advances/delays to have various influences on the auction outcome, depending on whether they occur at the beginning or at the end of the sale.

### A. *Early stage of an auction*

Let us focus on the early stage of an auction. At this moment, the pace of the sale may be either fast or slow depending on the nature of successive offers and the way they accumulate over time. We now distinguish both cases.

Let us consider a sale ahead of pace, while the auction begins. Let us remind here that fuzzy reserves are likely to increase when bidders have observed high previous offers (cf. "common value component" and "arousal" effects mentioned earlier). This actually happens when the auction accelerates early. This latter effect boosts the upcoming reserves of fuzzy bidders', hence the final price. A counterargument prevails however. *Ceteris paribus*, an early acceleration of bids mechanically shortens the total auction time, thus reducing further opportunities to increase everyone's reserves (*i.e.* rushing effect). We expect a negative influence on the hammer price at this level. Hypothesis H3 combines the two opposite influences.

> **H3.** *When the auction starts, being ahead of pace has contrasted influence onto the final auction price depending on the strongest effect, between common value / arousal (H3a) vs. rushing (H3b). Such influence may be positive (respectively negative) when the former is stronger (resp. weaker) than the latter.*

Let us consider the alternative case now, *i.e.* a sale behind pace during the early stage of the auction (due to the presence of bargain seekers or "wait-and-see" individual strategies). Here, the expected impact on the final price is twofold. It can be positive at first. The reason is symmetrical to the previous arguments. Namely, a slow start to the sale extends the overall auction time, thus giving (fuzzy) bidders more opportunities to update their reserves, and therefore to join/stay in the race. Overall, an initial wait has some inclusive consequences that end up boosting competition, with more chances to reach a higher price at the end of the sale (*i.e.* inclusive effect). In contrast, early delays may also have negligible impact on the hammer price, as the absence of high early offers discourages (fuzzy) bidders to elevate their reserves further (*i.e.* indifference effect). H4 summarizes both effects.

> **H4.** *When the auction starts, being behind pace has contrasted influence onto the final auction price depending on the strongest effect, between inclusion (H4a) vs. indifference (H4b). Such influence may be positive (respectively null) when the former is stronger (resp. weaker) than the latter.*

### *B. Last stage of an auction*

Let us discuss now the last stage of an auction. At this moment, strategic interactions are stronger while remaining bidders are fewer. Again, we distinguish two polar cases, depending on the shape of the curve of bid dynamics (cf. presence of catch-up *vs.* slowing down effects). Both cases (and their related hypotheses) are discussed below.

We first consider catch-up effects at the end of sale (that mechanically follow earlier delays). This situation occurs when final bids accelerate due to the prevalence of late aggressive offers (it happens when duels emerge, now that competitors interact strategically). Indeed, the slowdown preceding final acceleration makes competitors even more dangerous as offers have remained contained for some time. This reinforces the belief that competition remains fierce and strengthens the incentive for some bidders to end the wait by going all in. At this point, the accumulation of aggressive responses amplifies the consequences of (previous) aggressive bidding (see H2a). Regarding the ensuing influence on the hammer price, one can mention two opposite effects (stemming directly from the previous arguments). On one side, stronger motivation among bidders can boost the price (as they strategically minimize their surplus to maximize their chances of winning the auction). On another side, a succession of aggressive bids has discouraging effects too. Indeed, the acceleration of bids reduces the time for reflection, leaving even less opportunity to increase (fuzzy) reserves. This latter effect can undermine the price.[15] H5 sums up these arguments.

> **H5.** *Late catch-up effects are the sign of final strategic duels (i.e. bids accelerate): "late motivation" may increase the final price (H5a). Yet, fast duels can discourage bidders too: i.e. "late despondency" may lead to a lower price (H5b).*

We last consider slowing down effects during the last phase of the sale (by construction, this situation occurs when the auction was ahead of schedule, followed then by mild final offers). Constrained bidders are mechanically closer to their hard budget limit at this point of the auction (especially those who have bid high before). *Ceteris paribus*, this raises the chances that some strategic bidders become confident about their opponents, and the threat they pose. As discussed before (see H2b), confident bidders are less aggressive, which tempers the consequences of previous (aggressive) bids on the hammer price. We then expect two distinct influences on such price. A positive one at first, as (fuzzy) bidders have more time to raise their

[15] In our view however, such negative influence is less likely when the auction ends, as fuzzy bidders have had enough time to increase their reserves, making them more difficult to discourage.

reserves while the auction decelerates. Then, a slowing down pace can (re)include bidders into the race, leading ultimately to a higher price.[16] When reaching the end however, decelerating (mild) offers may no longer boost the sale outcome. The reason is straightforward: confident bidders do not need to trim their surplus to win the auction. Both arguments lead to H6.

> **H6.** *Late slowdowns generate "inclusive effects" towards bidders who can stay in the auction, thus raising the final price (H6a). Yet, such price may not be impacted anymore, as slowdowns also reflect "confident bidding" strategies (H6b).*

Table 2 gathers our hypotheses on how the auction pace (catch-up/slowing down affects) influences the hammer price (B(N)). We separate the start from the end of an auction. The signs in parentheses signal the expected influence.

**TABLE 2**

Synthesis of hypotheses (expected influence of changes in the auction pace)

| Auction starts | | Auction ends | |
|---|---|---|---|
| Auction ahead of pace | Auction behind pace | Late catch-up (duels) | Late slowdown |
| H3a: Common value / Arousal effects (+)<br>H3b: Rushing effects (-) | H4a: Inclusive effects (+)<br>H4b: Indifference (no impact) | H5a: Late motivation (+)<br>H5b: Late despondency (-) | H6a: Inclusive effects (+)<br>H6b: Confidence (no impact) |

Once the hypotheses have been presented, we will detail in the next section our indexes related to the bid dynamics which allow to test for these hypotheses.

## 3. Bid dynamics indexes

This section introduces our indexes on bid dynamics. Those aim to summarize such dynamics during the three major phases of an auction, *i.e.* when the sale starts, ends, and is at midpoint. As discussed before, the context drastically changes depending on the considered phase, which requires separating them. We compute six indexes in total, of two types. The first set of indexes (three indexes) captures the degree of aggressiveness of bids, at the start (S),

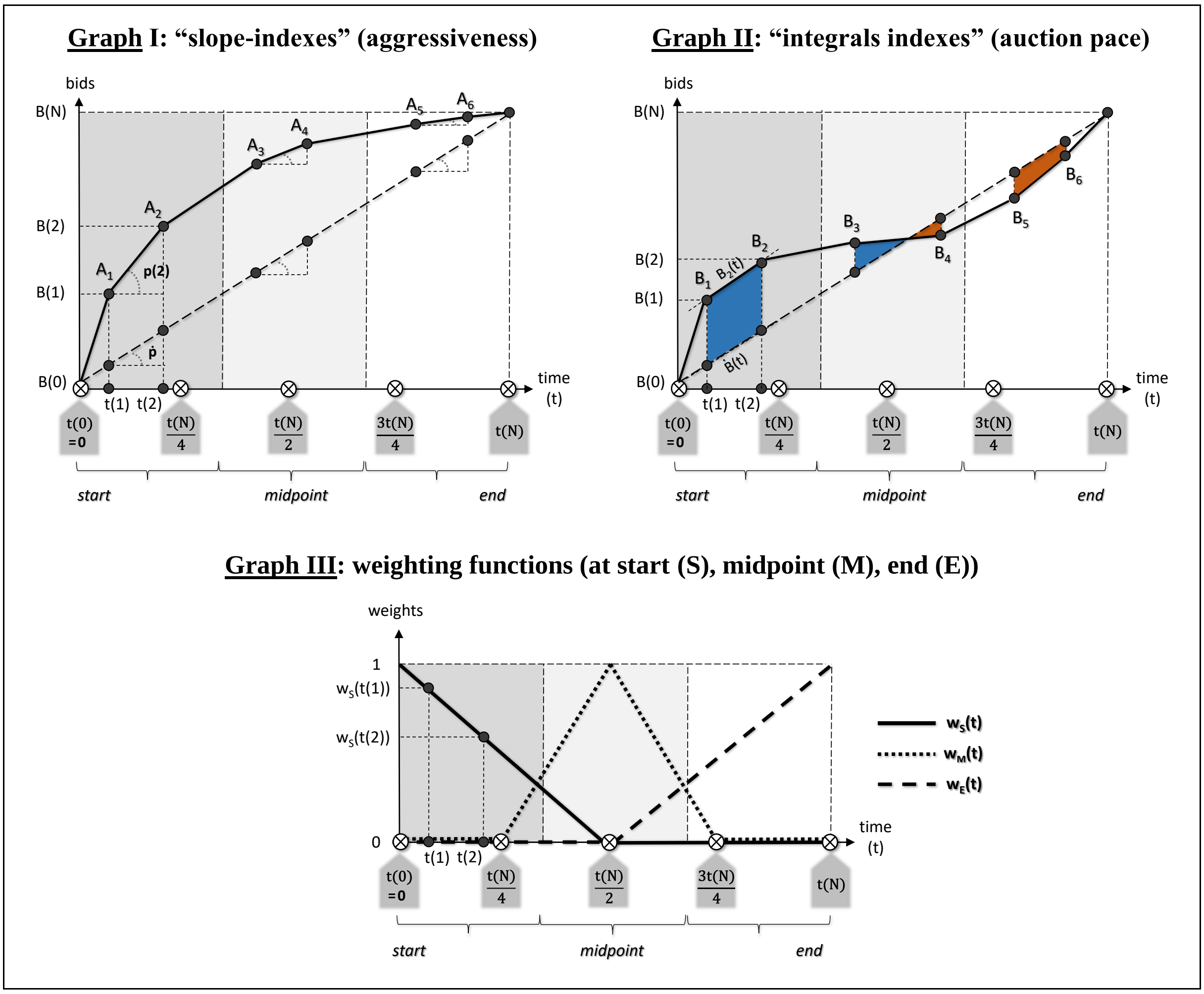
[16] That said, we do not expect such positive influence to dominate when the auction ends, as higher bids at that point may no longer attract competitors who have (almost) exhausted their financial margin.

midpoint (M), end (E) of the auction, denoted respectively $IBID\_SL_{(S)}$, $IBID\_SL_{(M)}$, $IBID\_SL_{(E)}$.[17] The second set (three indexes) measures advances/delays of the auction pace, again computed for the three main phases of the sale. We denote them $IBID\_IN_{(S)}$, $IBID\_IN_{(M)}$, $IBID\_IN_{(E)}$.[18]

Figure 5 illustrates how our indexes actually work. The two first graphs (I and II) relate to each category of index: *i)* aggressiveness, *ii)* auction pace. Both graphs synchronize with the third one (III) showing how indexes are weighted differently depending on the phase of the sale.

**FIGURE 5**

Weighted indexes accounting for bid dynamics (aggressiveness and auction pace)




[17] IBID stands for "Index-Bidding". "SL" stems from the fact that the level of bidding aggressiveness is measured as a difference in slopes. "(S)/(M)/(E)" relates to the auction time (start, midpoint, end). Each index is computed in relative terms (*i.e.* divided by a constant benchmark).

[18] The naming is similar to the three previous indexes. Here, "IN" stems from the fact that we compute differences in integrals to capture the pace changes during the sale.

Let us first consider "IBID_SL" indexes that summarize how aggressive bids are. Graph I illustrates a succession of seven offers, from B(1) (first bid) to B(N) ($7^{th}$ bid that leads to the hammer price), while B(0) represents the auction starting price at time t(0) = 0. Let us consider two offers: B(2) that follows B(1), made at times t(2) and t(1) respectively (points $A_2$ and $A_1$ correspond to their crossing points). We measure how aggressive offer B(2) is by computing slope p(2) (as seen above: p(2) = (B(2)-B(1))/(t(2)-t(1)) = ΔB(2)/Δt(2)).[19] Then, we compare p(2) to (ṗ), the invariant slope attached to the neutral auction path. Namely, we compute the difference p(2)-ṗ, which gets normalized by dividing by constant (ṗ).

At this level, one must introduce weighting functions, denoted $w_j(t(i))$, to account for the time the $i^{th}$ bid (B(i)) was made (remind there are three indexes, one for each auction phase). Suppose that we first compute $IBID\_SL_{(S)}$, *i.e.* the index attached to the starting stage of the sale. Here, the weighting function corresponds to the plain curve appearing in graph III. This curve ($w_S(t)$) linearly declines from one at time 0, to zero at time t(N)/2 (*i.e.* the midpoint of the sale). Hence, offer B(2) has a lower weight than B(1) as it comes later. Beyond midpoint time, any subsequent bid has null weight (indeed, the latter bids are closer to the end of the auction). The second (small-dotted) curve ($w_M(t)$) represents the weights describing the mid-stage of the sale. Those weights are maximized (equal to 1) at time t(N)/2, and decrease when moving away from this point: they are null at times t(N)/4 and 3t(N)/4. Here, a bid made at midpoint has the maximum weight when computing $IBID\_SL_{(M)}$. The third (broad-dashed) increasing curve ($w_E(t)$) shows how weights accounting for the last stage of the auction increase from zero (at time t(N)/2) to one (at time t(N)). Therefore, an offer made at time t(N) has the strongest weight as regards $IBID\_SL_{(E)}$.

Equation (1) gives the computation of $IBID\_SL_{(j)}$ indexes, where (j) represents one of the three main phases of the auction: j = {S} (starting auction), j = {M} (auction at midpoint), j = {E} (ending auction).

$$IBID\_SL_{(j)} = \sum_{i=1}^{N} \frac{p(i) - \dot{p}}{\dot{p}} \cdot w_j\big(t(i)\big) \tag{1}$$

*with:*

$$p(i) = \frac{\Delta B(i)}{\Delta t(i)} = \frac{B(i) - B(i-1)}{t(i) - t(i-1)} \quad \text{and} \quad \dot{p} = \frac{B(N) - B(0)}{t(N) - t(0)} = \frac{B(N) - B(0)}{t(N)}$$

[19] We could do the same computation, when comparing B(1) to B(0), B(3) to B(2), etc. until B(7) to B(6).

$$w_j(t) = \begin{cases} 1 - \frac{2}{t(N)} \cdot t \ , \forall t < \frac{t(N)}{2} & \text{(0 otherwise), when } j = \{S\} \\ -1 + \frac{4}{t(N)} \cdot t \ , \forall t \in \left[\frac{t(N)}{4}; \frac{t(N)}{2}\right] & \\ & \text{(0 otherwise), when } j = \{M\} \\ 3 - \frac{4}{t(N)} \cdot t \ , \forall t \in \left[\frac{t(N)}{2}; \frac{3t(N)}{4}\right] & \\ -1 + \frac{2}{t(N)} \cdot t \ , \forall t > \frac{t(N)}{2} & \text{(0 otherwise), when } j = \{E\} \end{cases}$$

Let us now consider "IBID_IN" indexes that recap the pace of the auction. Graph II shows seven succeeding offers (from B(1) to B(7)), forming an inverse S-shaped bidding curve. We focus on point $B_2$ (t(2);B(2)) following $B_1$ (t(1);B(1)). Both points cross the times and amounts of the two first bids. We denote as $B_2$(t) the line that links both points (by construction, its slope is p(2)). We also consider $\dot{B}$(t), the line showing the neutral auction path. By definition, this latter line has a slope equal to ($\dot{p}$) and passes through points (t(0);B(0)) and (t(N);B(N)). Once bid n°2 is made, the sale is all the more ahead of pace as line $B_2$(t) is above line $\dot{B}$(t). The area between both lines is positive (respectively negative) when the sale is ahead of (resp. behind) the neutral auction path, our benchmark. On Graph II, the former (resp. latter) case corresponds to the blue (resp. red) regions. On the (continuous) time interval [t(1);t(2)], such area corresponds to the integral of $B_2$(t)-$\dot{B}$(t). We normalize this difference by dividing by the constant value B(N)-B(0) (*i.e.* the two extreme offers).

As for the previous index, such integral is weighted by function $w_j$(t) on the considered time interval (with j set to {S},{M},{E} depending on the considered auction phase: see Graph III). Overall, the resulting $IBID\_IN_{(j)}$ indexes aggregate the weighted integrals on all bids (from the first (B(1)) to the last one (B(N)). This leads to equations (2a) (general formula) and (2b) (explicit formula).

$$IBID\_IN_{(j)} = \sum_{i=1}^{N} \int_{t(i-1)}^{t(i)} \frac{B_i(t) - \dot{B}(t)}{B(N) - B(0)} \cdot w_j(t) dt \tag{2a}$$

*with:*

$B_i(t)$: line passing through points $(t(i-1); B(i-1))$ and $(t(i); B(i)) \rightarrow$ slope $= p(i)$

$\dot{B}(t)$: line passing through $(t(0); B(0))$ and $(t(N); B(N)) \rightarrow$ slope $= \dot{p}$ and $t(0) = 0$

$w_j(t)$: weighting function, as defined above (j∈$[S; M; E]$)

*Hence the explicit formula:*

$$IBID\_IN_{(j)} = \sum_{i=1}^{N} \int_{t(i-1)}^{t(i)} \frac{B(i) - p(i)t(i) - B(0) + (p(i) - \dot{p})t}{B(N) - B(0)} \cdot w_j(t)dt \qquad (2b)$$

A major difference with the "IBID_SL" index is that "IBID_IN" is invariant to the number of bids actually made, as it considers a continuous bid dynamics, thus capturing the general rhythm of an auction, which should not depend on how many offers were made during the sale.

Appendix 1 provides several simulated scenarios, and shows how "IBID_SL" and "IBID_IN" indexes vary with the shape of various (fictitious) auctions. As expected, all indexes take on zero values when bids align with the neutral auction path.

## 4. Data and methodology

We first present our sample (4.1.) and the data collection (4.2.), then the variables and descriptive statistics (4.3.), lastly the model (4.4.).

### 4.1. The sample

Our dataset consists of prices, sequences of bids and characteristics of 547 art lots sold at auction between March 2017 and May 2018 by six different auction houses. These lots were auctioned following the traditional type of auction used on the art market, *i.e.* the ascending-bid auction, also called the open, oral or English auction. Regarding the auction houses we selected in our sample, they organize their auction sales on-site, with a professional auctioneer conducting the sale. The auctioneer opens the auction by announcing a starting price and bidders call out prices successively until only one bidder remains, and that bidder acquires the product at the last price (s)he announces. Bidders can bid from the room, by phone, on the Internet, or with purchase order.

We focus on the European comic art market, *i.e.* the lots of our sample are original comic artworks auctioned in Paris and Brussels between March 2017 and May 2018. All main brick-and-mortar auction houses which organize dedicated sales on a regular basis are represented in our sample, apart from Vermot et Associés, since this auction house does not provide all images of the lots for sale. We count 40% of our sampled lots auctioned at Christie's, 20% at Artcurial, 9% at Coutau-Bégarie, 10% at Cornette de Saint Cyr, 12% at Millon and 9% at Huberty-Breyne. This distribution thus includes 40% of lots from prestigious sales (Christie's sales) with an average mean-estimate (midpoint between high and low pre-sale estimates) of 13 939 €, 20% of lots from top range to mid-range market (Artcurial sale) with an average mean-estimate of 6 294 € and 40% of lots from mid-range to low-end market (sales by Coutau-Bégarie, Cornette de Saint Cyr, Millon and Huberty-Breyne) with an average mean-estimate of 1 053 €. The auction sales by Millon and Huberty-Breyne took place in Brussels, the others in Paris.

We remove nine transactions that can be classified as outliers from our sample, as our indexes take extreme values for these observations. Therefore, the present analysis is restricted to 538 artworks.

## 4.2. Data collection

We construct an original dataset by collecting manually all information about prices, sequences of bids, characteristics of the sale environment and of the lots.

The information about the sequences of bids were gathered from video recordings of the auction sales. Indeed, as mentioned above, the auction houses of our sample allow to bid online, and therefore transmit live their sales on the Drouot Live platform (for Coutau-Bégarie, Cornette de Saint Cyr, Millon and Huberty-Breyne), or on their own live platforms (for Christie's and Artcurial). Thus, we record the auction sales thanks to the software *ActivePresenter*©. These videos enable us to collect the timing and the amount of each bid, from the starting price to the final price.

To control for the heterogeneity of the artworks, we gather data about their characteristics, by using catalogues provided by auction houses to customers before sale. These catalogues present each lot for sale with a description and an image of it. For some variables related to the artist or to the popularity of the artwork, we also use the specialized comic website Bédéthèque©[20].

Finally, to control for the heterogeneity of the auction sales, we gather data on the sale environment, using the catalogues, the videos of the sales and by screening the websites of French and Belgian auction houses that regularly organize original comic dedicated sales.

[20] https://www.bedetheque.com/

## 4.3. The variables and descriptive statistics

Descriptive statistics are given in Table 3. The dependent variable is the auction price of each artwork. We consider the hammer price, *i.e.* the last bid of the auction which is the price paid by the winning bidder to which transaction costs are added afterwards. The explanatory variables are organised in three categories. The average hammer price in our sample is 7 064 €, while half of our lots have been hammered under 3 000 €. Hammer prices range from a low price of 60 € to a high price of 200 000 €. The mean price per square centimetre is 6.33 € when the median is 2.35 €. Prices for one square centimetre of artwork range from 0.04 € to 143.61 €.

The first set of variables – and our variables of interest – consists of our bid dynamics indexes at the different phases of the auction, as detailed in section 3. We have two types of indexes: the first type ($IBID\_SL_{(j)}$) tells about the degree of aggressiveness of punctual bids and the second type ($IBID\_IN_{(j)}$) reflects phases of acceleration or deceleration in the auction of a lot. For each of this type, there is an index for the beginning, middle and end of the auction.

Regarding $IBID\_SL_{(j)}$, a positive value of this index means an aggressive bid, whereas a negative value accounts for a mild bid. On average for our 538 auctioned lots, this index at the start of the auction takes the value of 3.24, so that we generally observe aggressive bids at the beginning of the auction. The median of this index at the beginning is yet below, at 0.44, which means that our sample includes lots with particularly aggressive bids at the beginning. Indeed, we observe that the maximum value of the index at the start of the auction is 64.73, while the minimum value is -2.87. During the middle of the auction, the degree of aggressiveness of bids is generally lower: the index ranges from -1.51 to 34.01, with an average value of 1.42. At the end of the auction, bids are more aggressive on average than at the middle of the auction but less than at the beginning of the auction (average index of 1.84), although the index takes its highest value (71.01) at the end of the auction.

With respect to $IBID\_IN_{(j)}$, a positive value reflects an auction ahead of pace and a negative value indicates an auction behind pace. At the beginning of the auction, we observe that auction is on average slightly in advance compared to pace of the linear auction, as the mean value for this index is 0.07. Yet, the bid dynamics of more than half of our sampled lots are starting slowly (median at -0.11 for this index at the beginning). This means that the pace for some of our auctioned lots is particularly fast at the beginning, explaining why we observe a positive average index at the starting phase. At the middle of the auction, the mean index is positive (at 0.20) so that the auction dynamics are on average ahead of pace. At the end of the auction, the average index is slightly negative (-0.05). This means that on average the auctions are behind of pace, which corresponds to catch-up effects. Yet, the median index for the end of the auction is just above zero (0.03) so that the bid dynamics of slightly more than half of our auctioned lots are slowing down. Again, it appears that our average index at the end is driven by some of our auctioned lots characterized by important late catch-up effects.

The next set of variables gathered relates to the sale characteristics, in order to control for the heterogeneity in the auction sale environment. We include a dummy variable that equals 1 when sales are held by Christie's (and 0 otherwise), as they are prestigious comic art sales organized by a leading auction house. Many studies have shown that this auction house, along with Sotheby's, systematically obtains higher prices compared to other auction houses (Pesando 1993, De la Barre *et al*. 1994, Renneboog and Van Houtte 2002, Hodgson and Vorkink 2004, among others). The nature of the sale (prestigious or not) and the reputation of the auction house may attract different bidders and induce distinct strategies. In our sample, 40% of the lots are auctioned by Christie's. Moreover, we account for the level of competition with other similar sales by introducing the variable *other sales* that captures the number of other sales dedicated to comic art 15 days before and after the sale. The given supply of artworks for sale might indeed change bidders' behaviour. For the auction sales of our sample, the number of competing sales varies between 0 and 4, being on average of 1.64. Then, auction houses sometimes add a positive comment in the lot description of the catalogue like "beautiful piece of art" or "exceptional quality". This concerns 58% of our lots. We include a dummy variable *positive comment* that equals 1 if the description contains such a comment (0 otherwise), as praise of a lot can influence bidders. We also take into account the lot order (in percentage of the total number of lots), as bidding is likely to differ when the lot is among the first to be presented for sale or among the last. Indeed, bidders' energy, excitement and interest for the auction as well as the auctioneer's performance and patience might change over the period of the auction sale. In addition, we generate a variable (*number lots author*) to captures the number of lots per artist for sale. We can actually think that when bidders have the choice between different lots from an artist they are interested in, they will bid differently compared to a situation when they only have one chance to acquire an artwork from this artist. Half of our lots are sold with at least two other lots from the same artist in the same auction sale. The range of lots per artist goes from 1 to 32, as for two sales of our sample, a part was dedicated to an artist. Last, we include two variables related to the live auction. The first one stands for the duration of the lot description, *i.e.* the number of seconds taken by the expert/auctioneer to describe the lot which will be auctioned. Half of the descriptions are read in less than 5 seconds and the reading time ranges from 1 to 39 seconds. The second variable measures the average time in seconds between each bid for a lot. This time is one average of a bit more than 6 seconds for our sampled lots and for half of the lots, the average time between bids is less than 5 seconds.

The third set of variables aims at controlling for the heterogeneity between artworks, including characteristics of the artist and of the work. The first variable captures the artist's recognition, taking the form of a dummy equaling 1 if the artist has received an award in her/his life, 0 if not. It is well-recognized that one of the most important price determinant on the art market is the reputation and quality of the artist. In our sample, 24% of the lots have been created by an artist that has been honoured by an award for his/her career. Then, we generate a variable accounting for the living status of the artist, a dummy which takes the value of 1 if the artist is deceased, 0 if (s)he is still alive at the time of the auction sale. A positive effect of the artist's death on price has often been found (Agnello and Pierce 1996, Ekelund et al. 2000, Higgs and Worthington 2005). Art lots from deceased artist represent 38% of our sample.

We then account for the popularity of the artwork, with a variable indicating the number of publications the comic artwork has been subject to. Indeed, comic artworks have an "hybrid" nature : they are unique works of art drawn by an artist and at the same time they are commercial goods gathered and published in the form of comic books for the purpose of being sold on a large scale. Thus, the number of publications of the comic book from which the artwork stems – the median number of publications is 2 in our sample – reveals the popularity of the artwork. We also consider the presence of the artist's signature, a proof of authenticity, taking the form of a dummy variable which equals 1 if the artwork is signed, 0 if not. In our sample, 62% of the lots are signed. Finally, we include physical attributes of the artworks that are considered to be determinants of the price: the size (represented in surface area in square meter), the condition of the artwork (dummy variable), the type of comic artwork (dummies for the different types), the medium (dummies for each medium) and the subject matter(s) (dummies for the various topics). The average size for an artwork in our sample is 0,19 square meters. 8% of the artworks are damaged, *i.e.* being affected by retouching, patches, tears or yellowing. With respect to the type of comic art, 11% of our artworks are coverpages, 28% are illustrations and 61% are other types, mainly boards and a few drafts. "Other types" is omitted in our regressions to serve as a benchmark. As for the medium, most of the artworks (84%) are inked, 40% have been painted, 17% include pencil strokes and a few (4%) have been done with feltpen, pasting or mixed medium. In our regressions, the reference category is the ink medium. The represented topics of our artworks are numerous, the most common (depicted in more than 20% of our artworks) being action, adventure/suspense, archetypes, genre scenes and social interaction.

**TABLE 3**

Descriptive statistics

| Variables | | Mean | Median | Std Dev | Min | Max |
|---|---|---|---|---|---|---|
| **Price** | | | | | | |
| Hammer price | | 7 064.80 | 3 000.00 | 14 390.93 | 60.00 | 200 000.00 |
| Price buyer's premium incl. | | 8 888.75 | 3 761.00 | 17 856.12 | 76.00 | 242 500.00 |
| Price per cm2 | | 6.33 | 2.35 | 13.41 | 0.04 | 143.61 |
| **IBID indexes** | | | | | | |
| IBID_SL(START) | | 3.24 | 0.44 | 8.43 | -2.87 | 64.73 |
| IBID_SL(MIDDLE) | | 1.42 | 0.33 | 3.22 | -1.51 | 34.01 |
| IBID_SL(END) | | 1.84 | 0.33 | 6.29 | -1.38 | 71.01 |
| IBID_IN(START) | | 0.07 | -0.11 | 1.02 | -3.73 | 6.32 |
| IBID_IN(MIDDLE) | | 0.20 | 0.00 | 1.59 | -11.93 | 7.45 |
| IBID_IN(END) | | -0.05 | 0.03 | 1.04 | -7.00 | 3.94 |
| **Control variables related to the sale context** | | | | | | |
| Christies (0/1) | | 0.40 | 0 | 0.49 | 0 | 1 |
| Other sales | | 1.64 | 1 | 1.32 | 0 | 4 |
| Description time | | 5.60 | 5 | 3.36 | 1 | 39 |
| Mean time between bids | | 6.46 | 4.89 | 6.21 | 0.32 | 62.00 |
| Positive comment (0/1) | | 0.58 | 1 | 0.49 | 0 | 1 |
| Lot order (% of total number of lots) | | 0.49 | 0.49 | 0.29 | 0.01 | 1.00 |
| Number lots author | | 5.12 | 3 | 7.27 | 1 | 32 |
| **Control variables related to the artist and lot** | | | | | | |
| Artist's Award (0/1) | | 0.24 | 0 | 0.43 | 0 | 1 |
| Death (0/1) | | 0.38 | 0 | 0.49 | 0 | 1 |
| Number of publications | | 4.92 | 2 | 8.81 | 0 | 141 |
| Signature (0/1) | | 0.62 | 1 | 0.49 | 0 | 1 |
| Size (m2) | | 0.19 | 0.15 | 0.22 | 0.01 | 2.44 |
| Condition (0/1) | | 0.08 | 0 | 0.27 | 0 | 1 |
| Type (0/1): | Coverpage | 0.11 | 0 | 0.31 | 0 | 1 |
| | Illustration | 0.28 | 0 | 0.45 | 0 | 1 |
| | Other | 0.61 | 1 | 0.49 | 0 | 1 |
| Medium (0/1): | Ink | 0.84 | 1 | 0.37 | 0 | 1 |
| | Paint | 0.40 | 0 | 0.49 | 0 | 1 |
| | Pencil | 0.17 | 0 | 0.38 | 0 | 1 |
| | Feltpen | 0.04 | 0 | 0.19 | 0 | 1 |
| | Pasting/mixed medium | 0.04 | 0 | 0.18 | 0 | 1 |
| Subject matter (0/1) | Action | 0.21 | 0 | 0.41 | 0 | 1 |
| | Ads | 0.02 | 0 | 0.15 | 0 | 1 |
| | Adventure/suspens | 0.24 | 0 | 0.43 | 0 | 1 |
| | Archetypes | 0.24 | 0 | 0.43 | 0 | 1 |
| | Arts | 0.04 | 0 | 0.20 | 0 | 1 |
| | Death | 0.03 | 0 | 0.16 | 0 | 1 |
| | Erotism | 0.16 | 0 | 0.37 | 0 | 1 |
| | Fantasy/Magic | 0.12 | 0 | 0.33 | 0 | 1 |
| | Genre | 0.24 | 0 | 0.43 | 0 | 1 |
| | Historical context | 0.10 | 0 | 0.30 | 0 | 1 |
| | Homage | 0.04 | 0 | 0.20 | 0 | 1 |
| | Humor | 0.16 | 0 | 0.37 | 0 | 1 |
| | Interaction | 0.21 | 0 | 0.41 | 0 | 1 |
| | Landscape | 0.19 | 0 | 0.39 | 0 | 1 |
| | Love | 0.05 | 0 | 0.23 | 0 | 1 |
| | Portrait | 0.15 | 0 | 0.36 | 0 | 1 |
| | Science-fiction/high-tech | 0.09 | 0 | 0.29 | 0 | 1 |
| | War/violence | 0.11 | 0 | 0.31 | 0 | 1 |

### 4.4. The model

The analysis with indexes by phase of the sequence of bids allows to keep a simple model, in order to shed light on the influence on prices of punctual bids' aggressiveness and of the auction pace at the main moments of a sale. We use the hedonic regression methodology, commonly found in studies on the art market. Our model relates hammer prices (log) to our bid dynamics indexes, while controlling for a wide range of hedonic characteristics such as the sale environment, artist and work features. Our specifications are the following (one for each type of index, $IBID\_SL_{(j)}$ and $IBID\_IN_{(j)}$, to avoid any risk of multicollinearity):

$$\ln p_i = \alpha + \sum_j \beta_j IBID\_SL_{(j),i} + \sum_m \gamma_m Sale_{m,i} + \sum_n \delta_n Artist_{n,i} + \sum_p \theta_p Artwork_{p,i} + \varepsilon_i \quad (3)$$

$$\ln p_i = a + \sum_j b_j IBID\_IN_{(j),i} + \sum_m c_m Sale_{m,i} + \sum_n d_n Artist_{n,i} + \sum_p f_p Artwork_{p,i} + e_i \quad (4)$$

where $\ln p_i$ is the log of the hammer price of artwork $i$ ($i$ = 1, …, $N$), $IBID_{SL(j),i}$ is the index value capturing the degree of aggressiveness of bids at phase $j$ ($j$ ={S},{M},{E}) of artwork $i$, $IBID_{IN(j),i}$ is the index value measuring the advance/delay of the auction pace at phase $j$ ($j$ ={S},{M},{E}) of artwork $i$, $Sale_{m,i}$ is sale-level attribute $m$ ($m$=1, …, $M$), $Artist_{n,i}$ is the measurable artist-related attribute $n$ ($n$= 1,…, $N$) of artwork $i$, $Artwork_{p,i}$ is artwork-specific feature $p$ ($p$=1, …, $P$), $\beta, \gamma, \delta, \theta, b, c, d$ and $f$ are unknown coefficients that represent the implicit prices of the linked characteristics, and $\varepsilon_i$ and $e_i$ are the error terms.

## 5. Results and robustness checks

### 5.1. Results

Table 4 shows our OLS estimates on two models. Model 1 focuses on the aggressiveness of offers ("IBID_SL" indexes). Model 2 relates to the pace of the auction

("IBID_IN" indexes). Overall, VIF statistics (1.35 and 1.49 on average for models 1 and 2 respectively, with a maximum value of 3.27) confirm that such risk does not affect our estimates on separate models. Both regressions rely on 538 observations (auctioned lots) and use identical control variables (context of the sale, artist profile and lot features).

We first discuss the estimates on our test-variables (*i.e.* bid dynamics indexes). We focus on their sign and magnitude, as OLS parameters also account for marginal effects.

In Model 1, all "IBID_SL" indexes accounting for bidders' aggressiveness are significant and positive; whatever the considered stage (*i.e.* "start"," midpoint", "end"). This noteworthy finding confirms that bidding strategies are not neutral on the outcome of the auction (neutral strategies would have led to non-significant estimates, for all indexes). Following our theoretical framework, this confirms the importance of fuzzy reserves that give (fuzzy) bidders rationale to bid aggressively *vs.* mildly. Aggressive bidding during the early stage of the auction has the most significant influence (1% level) and shows a higher magnitude (1.9%) than when the auction ends (1.2%).[21] Aggressiveness has similar influence on price at the midpoint of the sale (2.2%) but is less significant (10% level) than at the beginning or end. These estimates confirm hypothesis (H1a) and reject its alternative (H1b). Precisely, early motivation among potential buyers (that leads them to bid aggressively) has the strongest positive impact on the hammer price.

This effect lasts until the end of the auction ($IBID\_SL_{(E)}$ remains positive), but its magnitude becomes 40% lower *in fine*. In our view, such narrowing magnitude can reveal the following mechanism. Remind that aggressiveness has two opposite influences: one is positive due to motivation, another one is negative because of despondency. This latter (depressing) effect can be exacerbated in case of ultimate strategic duels (see H2a). Hence, the smaller (positive) impact of $IBID\_SL_{(E)}$.

Overall, we find that <u>motivation (H1a) has stronger impact on the final price than despondency (H1b)</u>. By shortening time (cf. "late despondency" effect), ultimate duels (H2a) seem to attenuate the positive influence of aggressiveness when the auction ends.

[21] These percentages show how the final price (in log) increases after a 1% increase of the considered index.

**TABLE 4**

OLS regressions: Dependent variable: hammer price (N=538)

| Variables | | Model 1 | Model 2 |
|---|---|---|---|
| IBID_SL(START) | | 0.019 *** | |
| IBID_SL(MIDPOINT) | | 0.022 * | |
| IBID_SL(END) | | 0.012 ** | |
| IBID_IN(START) | | | 0.129 ** |
| IBID_IN(MIDPOINT) | | | 0.013 |
| IBID_IN(END) | | | -0.138 ** |
| **Control variables related to the sale context** | | | |
| Christies (0/1) | | 1.388 *** | 1.397 *** |
| Other sales | | -0.693 *** | -0.727 *** |
| Description time | | 0.034 *** | 0.036 *** |
| Mean time between bids | | 0.019 *** | 0.018 *** |
| Positive comment | | 0.483 *** | 0.448 *** |
| Lot order (% of total number of lots) | | 0.173 | 0.132 |
| Number lots author | | 0.322 *** | 0.328 *** |
| **Control variables related to the artist and lot** | | | |
| Artist's Award (0/1) | | 0.748 *** | 0.795 *** |
| Death (0/1) | | -0.047 | -0.025 |
| Number of publications | | 0.450 *** | 0.472 *** |
| Signature (0/1) | | 0.059 | 0.065 |
| Size (m2) | | 0.305 *** | 0.333 *** |
| Condition (0/1) | | -0.123 | -0.152 |
| Type (0/1): | Coverpage | 0.657 *** | 0.663 *** |
| | Illustration | 0.532 *** | 0.598 *** |
| Medium (0/1): | Paint | 0.247 *** | 0.264 *** |
| | Pencil | 0.249 ** | 0.272 *** |
| | Feltpen | 0.336 * | 0.340 * |
| | Pasting/mixed medium | 0.109 | 0.149 |
| Subject matter (0/1) | Action | 0.151 | 0.153 |
| | Ads | 0.139 | 0.076 |
| | Adventure/suspens | 0.126 | 0.105 |
| | Archetypes | 0.092 | 0.097 |
| | Arts | 0.603 *** | 0.645 *** |
| | Death | 0.103 | 0.012 |
| | Erotism | -0.106 | -0.109 |
| | Fantasy/Magic | 0.156 | 0.106 |
| | Genre | 0.320 *** | 0.296 *** |
| | Historical context | 0.165 | 0.143 |
| | Homage | 0.289 | 0.241 |
| | Humor | 0.106 | 0.115 |
| | Interaction | -0.073 | -0.067 |
| | Landscape | 0.157 | 0.136 |
| | Love | 0.329 * | 0.317 * |
| | Portrait | 0.265 ** | 0.246 * |
| | Science-fiction/high-tech | -0.235 * | -0.244 * |
| | War/violence | -0.083 | -0.080 |
| *Constant* | | 5.741 *** | 5.890 *** |
| F | | 34.92 | 33.48 |
| $R^2$ / Adjusted $R^2$ | | 0.738 / 0.716 | 0.729 / 0.708 |

***Statistically significant at 1% level, **Statistically significant at 5% level, *Statistically significant at 10% level

We now turn to Model 2 capturing how the auction pace influences the hammer price ("IBID_IN" indexes). Let us first consider a starting sale: we find that the higher $IBID\_IN_{(S)}$ (*i.e.* the more the auction is ahead of pace), the upper is the price. This finding – in line with hypothesis (H3a) – confirms the notable role of early arousals on the outcome of an auction. This finding also supports the argument that first offers reveal information about the common value of an artwork, which bidders internalize during the auction (D'Souza and Prentice 2002, Ku et al. 2005). Conversely, our estimates do not corroborate the negative influence on price of early rushing (H3b), nor any other alternative effects that would arise from slow bidding at the start, such as inclusion (H4a) or indifference (H4b: this latter effect would have led to insignificant estimates).

Thus, the initial stage of an auction appears crucial for the outcome of the auction. Nevertheless, such influence disappears afterwards, as we do not observe any significant influence of acceleration/deceleration phases in the middle of the sale. From that view, one can consider the midpoint time as a transition phase between initial advances/delays and final catching-up/slowing down phases. Overall, these transitory effects may compensate, with no definitive impact on the price.[22]

Last, what is happening during the last stage of the auction is remarkable: a higher $IBID\_IN_{(E)}$ index significantly decreases the price. Remind that this index is positive when the late bidding curve is above the neutral auction path, *i.e.* reflecting final slowdown. Conversely, it becomes negative in case of late catch-up. As this index is negative on average (-5%, cf. descriptive statistics), we discuss here the latter situation.[23] As suggested before, ultimate duels accelerate the pace of the sale, hence two opposite influences on the price. On the one hand, duels are the sign of (late) motivation among bidders, which may increase the price eventually (H5a). On the other hand, fast duels may discourage bidders quickly, with a reverse impact on price (H5b). The negative influence of $IBID\_IN_{(E)}$ (lower than zero in case of late catch-up) supports the former hypothesis (*i.e.* H5a).

In terms of magnitude, the (positive/negative) influence of the pace of an auction on the price is similar regardless of when they occur. Indeed, the corresponding estimates are close (provided they are significant): around 13-14% in absolute terms.

[22] This may also (partially) support hypothesis (H4b) according to which slowdowns can generate indifference among bidders, with no significant impact on the hammer price.

[23] The opposite extreme case would be a high and positive $IBID\_IN_{(E)}$ index (*i.e.* late slowdown). Here, we would expect either a positive influence (due to inclusive effects: H6a) or no impact at all (due to the presence of confident bidders: H6b). Our estimates reject both hypotheses as we find a significant and negative influence of $IBID\_IN_{(E)}$ on the price.

Table 5 gathers the hypotheses validated in Models 1 and 2. There are four of them (H1a, H2a, H3a, H5a). We can summarize them as follows. The auction outcome benefits from the presence of (early and late) “motivated bidders”, *i.e.* potential buyers who do not look for a bargain, but rather prompt to trim their surplus to win the auction. Initial arousals, which provide valuable information on the artwork’s common value, also boost the price. When the auction ends, final duels (slightly) temper the influence of punctual aggressiveness. Overall, those effects seem stronger than despondency or inclusive effects.

**TABLE 5**

Validated hypotheses (Models 1 and 2)

| Auction starts* | Auction ends* |
|---|---|
| **Aggressive bidding ► p(i)↑**<br>H1a: Early motivation (+) | **Aggressive bidding ► p(i)↑**<br>H1a remains valid (+) but attenuated by:<br>H2a (final duels) |
| **Auction ahead of pace**<br>H3a: Common value / Arousal effects (+) | **Late catch-up (duels)**<br>H5a: Late motivation (+) |

(*) The sign in parenthesis shows the observed influence on price.

As for the control variables, the sale context firstly plays a role in determining final prices. Artworks auctioned by Christie’s, those for which the auctioneer/expert has taken the time to read the description or those which are subject to positive comments all generally achieve higher prices than those auctioned by other auction houses, whose description has been partially or not read at all or which are not featured with positive comments. Also, artworks which are sold with other artworks from the same artist seem to benefit from an attraction effect of potential buyers interested by this artist which could explain why the number of lots of the same artist has a significant and positive influence upon prices. Moreover, the higher is the number of other similar sales close in time, the lower are auction prices. Lastly, the mean time between bids exhibits a positive relationship with the final price.

Secondly, artist’s and artwork’s characteristics contribute to auction prices. We unsurprisingly observe a highly significant and positive impact of the artist’s recognition (measured by the awarding of the artist or not during her/his life) on art prices. Likewise, our estimates show that the popularity of the artwork (assessed by the number of publications) has a significant and positive influence upon the price. A finding that has been reported by economists for a long time, namely that the size of an artwork plays a role in explaining art prices, is confirmed in our results: bigger artworks achieve on average higher prices. Regarding the physical attributes of the comic artworks, coverpages and illustrations call for a premium compared to boards. The paint, pencil and feltpen media result in increases in prices compared to the ink medium. Finally, we find that different subject matters have a significant effect on comic art prices. Topics that refer to the arts, to genre scenes, to love or portrait are positively associated with higher auction prices, whereas the science fiction/high-tech subject matter is associated with lower prices.

## 5.2. Robustness checks

The previous findings do not consider that the population of potential buyers may change with the types of auctioned lots, hence the strategies too. Indeed, fuzzy behaviors are likely to vary with the considered lot, from the cheapest ones to the most expensive and prestigious artworks. Furthermore, one does not expect bidding strategies to be the same depending on the overall duration of the sale. Obviously, longer auctions provide more time to readjust fuzzy reserves and give the bidders more information to revise their beliefs on the actual level of competition. We explore this avenue by estimating several models more, as robustness checks. In section 5.2.1, we focus on two sub-samples of auctioned lots, depending on their pre-sale estimates. In section 5.2.2, we analyze the robustness of our findings by separating sales depending on their duration.

### 5.2.1. Role of the experts' estimates

We focus here on two sub-samples of auctioned lots, depending on their average estimates, as it appears in the auction catalogues (those are set by the auction house's experts).

The first analyzed sub-sample consists of the 75% most expensive auctioned lots (*i.e.* artworks with a mean estimate above the first quartile). This gives a first group of 403 lots. Models 3 and 4 (Table 6, Appendix 2) give our estimates on this first set of observations. Model 3 shows that the positive influence of aggressive bids on the price restricts to the early stage of the auction. Namely, $IBID\_SL_{(S)}$ remains significant (1% level) and positive, in line with (H1a). Yet, the "motivation argument" that goes together with aggressive bidding loses its influence during the following stages of the auction, until its ending point ($IBID\_SL_{(E)}$ is not significant anymore in Model 3). In our view, this does not contradict the main framework. On the contrary, such result is quite logical as it relates to the bidders' strategic responses when the auction ends. We suggest the following interpretation. For the most expensive estimated lots, the ending phase of an auction corresponds to higher offers, in absolute value. *Ceteris paribus*, the chances that remaining bidders are close to their hard budget constraint are thus stronger. In such context, the room for aggressiveness becomes limited (more than at the beginning). Thus, the (late) "motivation argument" discussed earlier has less impact on the price, hence a non-significant $IBID\_SL_{(E)}$ index.

Considering now Model 4 (*i.e.* pace of the auction), we still find a negative influence of $IBID\_IN_{(E)}$ but at the 10% level only, while $IBID\_IN_{(S)}$ no longer exerts any influence. On our sample, final duels are more important than slowdowns (the average $IBID\_IN_{(E)}$ equals -5%), and this trend is even more pronounced for the most expensive lots (-8% for the 25% highest estimated ones). Thus, we interpret the negative influence of $IBID\_IN_{(E)}$ (*i.e.* the lower this index, the higher is the hammer price) as a consequence of exacerbated motivation during the duels that occurs when the auction ends.

Let us now focus on the second subsample that comprises 75% of the lowest estimated lots (*i.e.* artworks whose mean estimate is below the third quartile). This second group encompasses 407 lots. Models 5 and 6 in Table 6 (Appendix 2) relate to this second set of observations. Model 5 (*i.e.* aggressiveness of bids) shows results close to our main regression (Model 1). We note that the positive impact of "IBID_SL" indexes – while still observed at every stage of the auction – has more magnitude at the midpoint of the sale. Last, Model 6 does not confirm our hypotheses on the pace of the auction on this sub-population (no more "IBID_IN" indexes are significant). In other terms, for the cheapest lots, whereas aggressive bids still influence the price (especially when they occur at midpoint), the resulting changes in the pace of the auction no longer matter, probably because duels are less intense for "standard lots".[24]

### 5.2.2. Role of the sale duration

We focus here on two sub-samples, depending on the total sale duration. The first sub-sample consists of lots that took quite a long time to be sold (*i.e.* the 75% longest auctions), while the other gathers the 75% fastest sales. Table 7 (Appendix 2) provides the corresponding estimates. Model 7 and 8 relate to the longest auctions (402 observations), while Models 9 and 10 correspond to the fastest ones (406 observations).

[24] Another interpretation would be that slowdowns during the auction exert no impact on the hammer price, as predicted by hypotheses (H4b) and (H6b).

On all models, most of our hypotheses still prevail. Namely, we confirm that the final price of an auction is boosted by: *i)* early motivation among bidders, (H1a), *ii)* primary arousals generating information on common value (H3a), *iii)* late motivation through final duels (H5a). Let us focus first on punctual aggressiveness (cf. "IBID_SL" indexes in models 7 and 9). We observe that the boosting influence of aggressive bidding concentrates on the two extreme moments (*i.e.* start, end) of the longest auctions. Here, the way long auctions begin / terminate is of upmost importance, as extended time allow strategies to evolve and information to accumulate throughout the sale. At the opposite, such positive influence restricts to the early and middle stages of the fastest auctions, suggesting their outcome mostly depends on what happens at first. Now turning to the auction pace (cf. "IBID_IN" indexes), models 8 and 10 confirm the negative influence on price of $IBID\_IN_{(E)}$ index: *i.e.* whatever the duration, late catch-up effects (cf. prevalence of final duels) positively impact the auction outcome. The magnitude of such influence is stronger for the fastest auctions (-24% against -14%), reflecting the willingness of bidders to terminate rapidly the sale, which we interpret as a sign of strong motivation.

## 6. Conclusion

This paper investigates whether and how the bid dynamics influence the auction outcome, *i.e.* the final price. While the traditional auction theory assumes stable bidder valuations fixed ahead of the on-sale date, different empirical studies provide evidence suggesting that bidders adjust their reserves over the course of the auction. If bidders' reserves can be considered as "fuzzy", then bidders have a rationale to adopt bidding strategies in order to influence the auction outcome. Yet, these strategies are likely to have a different impact depending on the stage of the auction (beginning, middle, or end of the auction) as the auction context changes. As the sequence of bids reflects bidders' strategies, we explore such bid dynamics at the different phases of the auction and their impact on the hammer price. Using a unique hand-collected database of 547 lots auctioned live, we specifically focus on the degree of aggressiveness of bids as well as on the pace of the auction and we analyze how they can affect the pricing outcome.

We find that strategic behaviors of bidders exist and affect the final price, corroborating the stream of work pointing out that bid dynamics are not neutral with regard to the auction's outcome. According to our theoretical framework, this finding confirms the importance of fuzzy reserves that give bidders incentives to carefully think how they will (re)bid. We show that aggressive bidding has a significant and positive impact on the hammer price throughout the auction process, but this impact is the strongest at the beginning of the auction. This strategy is followed by bidders who are highly motivated by the prospect of winning the lot and who do not hunt for a bargain. At the end, final duels between motivated bidders may generate a despondency effect amongst bidders, for whom time is too short to readjust their reserves, which attenuates the positive impact of aggressiveness on final price. The motivation effect finally appears to be the strongest effect affecting final prices. Next, we also find that the pace of the auction, resulting from the succession of bids, influences the hammer price. Initial arousals, revealed by acceleration at the beginning of the auction and which may be interpreted by bidders as signals of strong interest towards the lot (*i.e.* they update the common-value component of their valuation), boost the price. Moreover, late catch-up effects, which follow earlier slowdowns and which are characterized by final duels with aggressive offers, contribute significantly and positively to prices. To conclude, motivation effects – coming from bidders whose priority is to win the auction at the expense of their surplus– seem to be the strongest ones compared to other effects such as despondency and inclusiveness.

The results of this research have implications for auction houses and bidders. Regarding the auctioneer who aims at maximising revenues, (s)he can use strategies to spur initial arousals and ultimate duels. He can encourage bidders to start bidding early and has strong incentives to report the bids (s)he sees in the room/at the phone/on the Internet as fast as possible to emphasize the aggressiveness of bids. When conducting a final acceleration of the auction, the auctioneer could emphasize this duel by threatening to close the auction if a bidder starts to slowdown the speed of the auction. With respect to bidders, they should be aware that the more aggressive they bid, the more the final price to acquire the good is likely to rise since bidders are likely to increase their reserves because of arousal effects and of reassessment of the common value component.

An avenue for further research would be to follow bidders over the course of live auctions in order to analyze their individual bidding behaviors. Further research may also investigate the fuzzy reserve functions of individuals, exploring for example what are the individual characteristics that influence this function or if the auction channel (from the room, phone, purchase order or Internet) has an influence. Another promising avenue for research lies in the investigation of other live auction markets to see if the effects of the bid dynamics on the final price at the three stages of the auction generalize across different kinds of goods.

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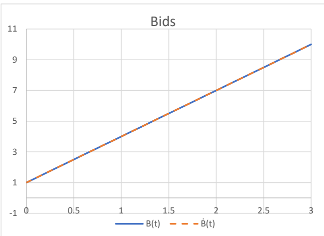
# Appendix

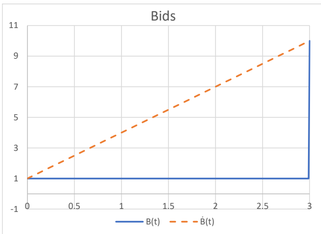
## Appendix 1. Simulations

We simulate here how our indexes behave depending on various (fictive) bid dynamics. Nine scenarios (Scen#0 to Scen#9) are considered. For simplification purpose, we consider a continuum of bids B(t), each being made at (continuous) time (t). The overall auction time is set to t(N)=3 (seconds). The plain line refers to the actual bids B(t), while the dashed line links together the benchmarks bids $\dot{B}(t)$ that follow the neutral auction path. Scen#0 is a benchmark: all auctions align to the neutral auction path. Scen#1 to Scen#4 display various bid dynamics showing no inflexion during the sale, from the most convex (Scen#1) to the most concave ones (Scen#4). Scen#5 to Scen#8 illustrate dynamics that are more complex: S-shaped curves (Scen#5 and #6) and inverse S-shaped curves (Scen#7 and #8).

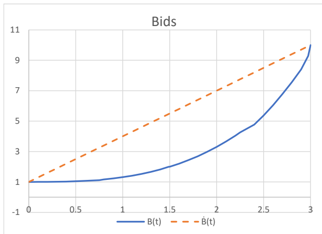
**Scen#0 (benchmark)**



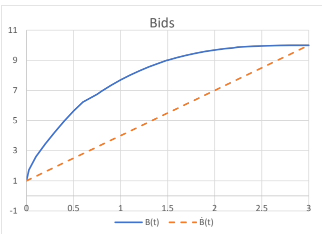

**Scen#1**



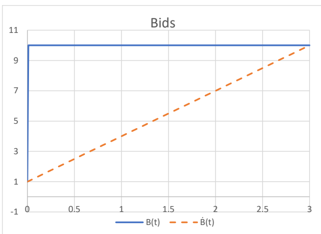

**Scen#2**



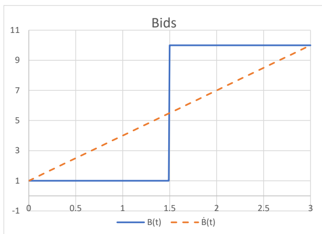

**Scen#3**



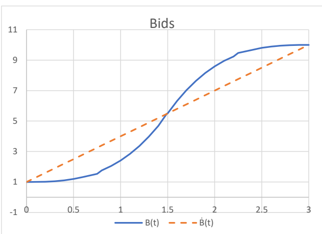

**Scen#4**



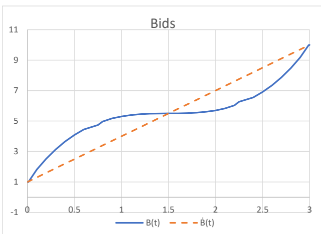

**Scen#5**



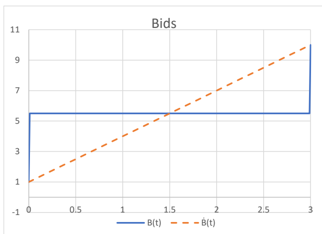

**Scen#6**



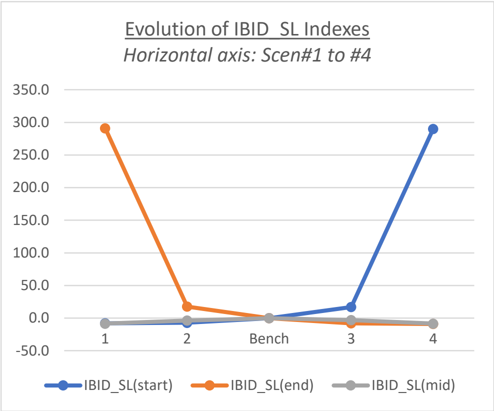

**Scen#7**



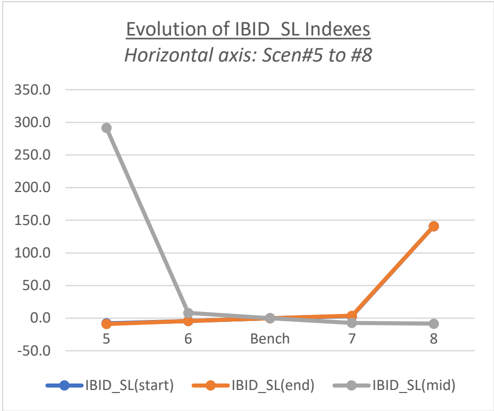

**Scen#8**



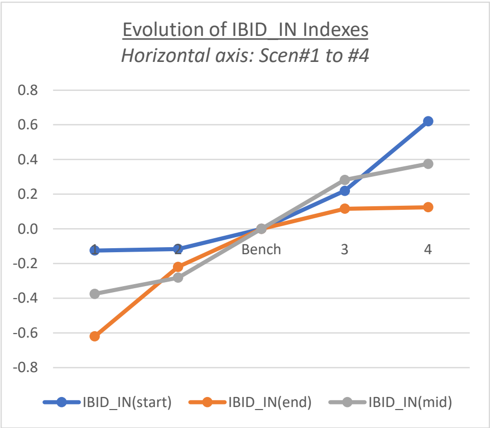
**Evolution of index IBID_SL (Scen#1 to #4)**



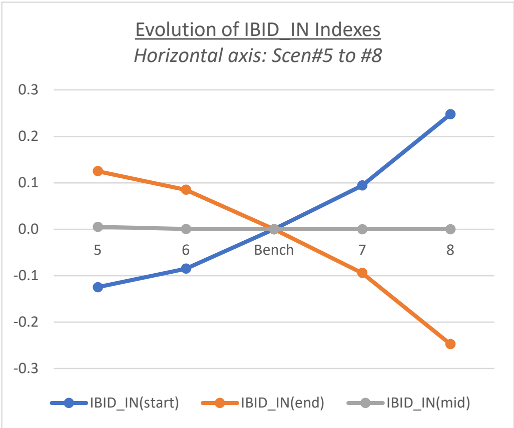

**Evolution of index IBID_SL (Scen#5 to #8)**




**Evolution of index IBID_IN (Scen#1 to #4)**




**Evolution of index IBID_IN (Scen#5 to #8)**



## Appendix 2. Robustness checks: estimates

## Appendix 2.A. Sub-samples: 75% highest/lowest mean estimated lots

### TABLE 6

Robustness check (OLS): Dependent var.: hammer price (subsamples: N=403 ▪ N=407)

| Variables | | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|
| IBID_SL(START) | | 0.012 *** | | 0.013 ** | |
| IBID_SL(MIDDLE) | | 0.014 | | 0.028 ** | |
| IBID_SL(END) | | 0.008 | | 0.013 * | |
| IBID_IN(START) | | | 0.091 | | 0.035 |
| IBID_IN(MIDDLE) | | | 0.005 | | 0.015 |
| IBID_IN(END) | | | -0.099 * | | -0.067 |
| **Control variables related to the sale context** | | | | | |
| Christies (0/1) | | 1.005 *** | 0.999 *** | 1.245 *** | 1.269 *** |
| Other sales | | -0.457 *** | -0.470 *** | -0.626 *** | -0.658 *** |
| Description time | | 0.049 *** | 0.051 *** | 0.019 | 0.020 |
| Mean time between bids | | 0.014 ** | 0.013 ** | 0.025 *** | 0.024 *** |
| Positive comment | | 0.237 ** | 0.199 * | 0.375 *** | 0.356 *** |
| Lot order (% of total number of lots) | | 0.186 | 0.159 | 0.164 | 0.128 |
| Number lots author | | 0.309 *** | 0.308 *** | 0.251 *** | 0.299 *** |
| **Control variables related to the artist and lot** | | | | | |
| Artist's Award (0/1) | | 0.434 *** | 0.463 *** | 0.756 *** | 0.763 *** |
| Death (0/1) | | 0.143 | 0.164 | -0.130 | -0.132 |
| Number of publications | | 0.390 *** | 0.409 *** | 0.303 *** | 0.299 *** |
| Signature (0/1) | | 0.050 | 0.056 | 0.132 | 0.142 |
| Size (m2) | | 0.263 *** | 0.281 *** | 0.213 *** | 0.229 *** |
| Condition (0/1) | | -0.196 | -0.220 | -0.183 | -0.202 |
| Type (0/1): | Coverpage | 0.510 *** | 0.507 *** | 0.476 *** | 0.495 *** |
| | Illustration | 0.408 *** | 0.456 *** | 0.395 *** | 0.409 *** |
| Medium (0/1): | Paint | 0.190 ** | 0.208 ** | 0.279 *** | 0.282 *** |
| | Pencil | 0.190 * | 0.199 * | 0.095 | 0.102 |
| | Feltpen | 0.237 | 0.231 | 0.229 | 0.190 |
| | Pasting/mixed medium | 0.130 | 0.146 | -0.075 | -0.081 |
| Subject matter (0/1) | Action | 0.146 | 0.142 | 0.172 | 0.194 * |
| | Ads | 0.248 | 0.209 | 0.247 | 0.254 |
| | Adventure/suspens | 0.011 | -0.013 | 0.206 * | 0.197 * |
| | Archetypes | 0.167 | 0.176 * | 0.079 | 0.098 |
| | Arts | 0.493 *** | 0.514 *** | 0.711 *** | 0.800 *** |
| | Death | 0.173 | 0.108 | 0.009 | -0.055 |
| | Erotism | 0.046 | 0.055 | -0.172 | -0.139 |
| | Fantasy/Magic | 0.139 | 0.101 | 0.110 | 0.051 |
| | Genre | 0.251 ** | 0.232 ** | 0.308 *** | 0.311 *** |
| | Historical context | 0.230 * | 0.215 | 0.089 | 0.085 |
| | Homage | 0.345 * | 0.309 | 0.213 | 0.219 |
| | Humor | 0.043 | 0.042 | 0.048 | 0.059 |
| | Interaction | -0.072 | -0.070 | -0.025 | -0.007 |
| | Landscape | 0.101 | 0.090 | 0.241 ** | 0.246 ** |
| | Love | 0.307 * | 0.299 * | 0.185 | 0.188 |
| | Portrait | 0.258 ** | 0.243 * | 0.208 | 0.170 |
| | Science-fiction/high-tech | -0.247 * | -0.246 * | -0.221 | -0.193 |
| | War/violence | 0.031 | 0.041 | -0.025 | -0.026 |
| *Constant* | | 6.273 *** | 6.380 *** | 5.805 *** | 5.901 *** |
| F | | 13.79 | 13.4 | 19.1 | 18.15 |
| $R^2$ / Adjusted $R^2$ | | 0.604 / 0.560 | 0.597 / 0.552 | 0.676 / 0.641 | 0.665 / 0.628 |

***Statistically significant at 1% level, **Statistically significant at 5% level, *Statistically significant at 10% level

## Appendix 2.B. Sub-samples: 75% longest/fastest auctions

### TABLE 7

Robustness check (OLS): Dependent var.: hammer price (subsamples: N=402 ▪ N=406)

| Variables | | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| IBID_SL(START) | | 0.018 *** | | 0.019 *** | |
| IBID_SL(MIDDLE) | | 0.016 | | 0.023 * | |
| IBID_SL(END) | | 0.025 *** | | 0.009 | |
| IBID_IN(START) | | | 0.089 | | 0.223 ** |
| IBID_IN(MIDDLE) | | | 0.021 | | 0.044 |
| IBID_IN(END) | | | -0.141 ** | | -0.236 *** |
| **Control variables related to the sale context** | | | | | |
| Christies (0/1) | | 1.362 *** | 1.350 *** | 1.548 *** | 1.598 *** |
| Other sales | | -0.675 *** | -0.689 *** | -0.734 *** | -0.755 *** |
| Description time | | 0.042 *** | 0.045 *** | 0.016 | 0.014 |
| Mean time between bids | | 0.014 ** | 0.013 * | 0.012 | 0.009 |
| Positive comment | | 0.354 *** | 0.301 ** | 0.414 *** | 0.386 *** |
| Lot order (% of total number of lots) | | 0.154 | 0.124 | 0.184 | 0.180 |
| Number lots author | | 0.253 *** | 0.262 *** | 0.307 *** | 0.316 *** |
| **Control variables related to the artist and lot** | | | | | |
| Artist's Award (0/1) | | 0.699 *** | 0.758 *** | 0.765 *** | 0.804 *** |
| Death (0/1) | | -0.074 | -0.064 | -0.108 | -0.080 |
| Number of publications | | 0.470 *** | 0.497 *** | 0.412 *** | 0.415 *** |
| Signature (0/1) | | -0.034 | -0.034 | 0.035 | 0.030 |
| Size (m2) | | 0.312 *** | 0.352 *** | 0.343 *** | 0.376 *** |
| Condition (0/1) | | -0.048 | -0.094 | -0.131 | -0.137 |
| Type (0/1): | Coverpage | 0.518 *** | 0.521 *** | 0.762 *** | 0.789 *** |
| | Illustration | 0.605 *** | 0.685 *** | 0.671 *** | 0.720 *** |
| Medium (0/1): | Paint | 0.218 ** | 0.256 ** | 0.183 | 0.177 |
| | Pencil | 0.284 ** | 0.306 ** | 0.267 ** | 0.302 ** |
| | Feltpen | 0.184 | 0.207 | 0.459 ** | 0.387 |
| | Pasting/mixed medium | 0.354 | 0.421 * | -0.064 | 0.014 |
| Subject matter (0/1) | Action | 0.232 * | 0.249 ** | 0.159 | 0.128 |
| | Ads | 0.243 | 0.207 | 0.015 | 0.003 |
| | Adventure/suspens | 0.026 | 0.027 | 0.216 * | 0.170 |
| | Archetypes | 0.196 * | 0.214 * | -0.025 | -0.054 |
| | Arts | 0.588 *** | 0.625 *** | 0.592 ** | 0.669 ** |
| | Death | 0.084 | -0.015 | 0.385 | 0.323 |
| | Erotism | -0.028 | -0.017 | -0.191 | -0.188 |
| | Fantasy/Magic | 0.195 | 0.151 | 0.067 | 0.001 |
| | Genre | 0.390 *** | 0.354 *** | 0.337 *** | 0.283 ** |
| | Historical context | 0.287 * | 0.273 * | 0.146 | 0.167 |
| | Homage | 0.220 | 0.130 | 0.142 | 0.103 |
| | Humor | 0.167 | 0.188 | 0.112 | 0.108 |
| | Interaction | -0.068 | -0.052 | -0.003 | -0.004 |
| | Landscape | 0.166 | 0.138 | 0.095 | 0.061 |
| | Love | 0.382 * | 0.390 * | 0.241 | 0.155 |
| | Portrait | 0.197 | 0.183 | 0.285 * | 0.237 |
| | Science-fiction/high-tech | -0.141 | -0.164 | -0.375 ** | -0.362 ** |
| | War/violence | -0.067 | -0.071 | -0.118 | -0.123 |
| *Constant* | | 5.970 *** | 6.123 *** | 6.022 *** | 6.217 *** |
| F | | 24.41 | 23.05 | 23.37 | 22.88 |
| $R^2$ / Adjusted $R^2$ | | 0.730 / 0.700 | 0.719 / 0.688 | 0.719 / 0.688 | 0.715 / 0.684 |

***Statistically significant at 1% level, **Statistically significant at 5% level, *Statistically significant at 10% level