

# Information Asymmetry in Art Auctions: Modeling the Effect of Enhanced Attribute Resolution

Eugene Shcherbinin<sup>1,2</sup> and Gemini 3 Pro<sup>3</sup>

<sup>1</sup>London School of Economics (LSE)

<sup>2</sup>Bloomsbury Technology , [eugene.shcherbinin@bloombergtech.com](mailto:eugene.shcherbinin@bloombergtech.com)

<sup>3</sup>AI Co-author

January 27, 2026

## Abstract

This whitepaper outlines a theoretical framework for analyzing the impact of improved information technology (referred to herein as the “Virginia” mechanism) on bidder behavior in art auctions. By modeling the valuation process as a function of imperfect knowledge regarding artwork attributes, we derive three key economic implications of reducing estimation error: (1) convergence of perceived value to fundamental value, (2) mitigation of bid shading (reduction of the Winner’s Curse), and (3) increased allocative efficiency.

## 1 Introduction

Auctions for heterogeneous goods, such as fine art, are characterized by significant information asymmetry and uncertainty. Bidders must estimate their private value based on imperfect signals regarding the artwork’s provenance, condition, and market standing. This paper models the introduction of a technology that strictly reduces the noise in these signals and analyzes the resulting equilibrium effects.

## 2 The Model Setup

We consider a standard auction environment with risk-neutral bidders. The true valuation of an item for bidder  $i$ , denoted as  $P_i$ , is derived from intrinsic and extrinsic factors.

**Definition 1** (Valuation Function). *Let the true willingness to pay  $P_i$  be defined as:*

$$P_i = g(f(k_i, X), Y) \tag{1}$$

Where:

- $k_i$ : The bidder’s perfect knowledge/intelligence regarding the art.
- $X$ : The true intrinsic attributes of the artwork.
- $Y$ : Extrinsic market factors.
- $f(\cdot)$ : The interpretation function mapping attributes to utility.
- $g(\cdot)$ : The pricing function.

## 2.1 Imperfect Information (Status Quo)

In the absence of technology, the bidder does not observe  $k_i$  or  $X$  perfectly. Instead, they observe estimates  $\hat{k}_i$  and  $\hat{X}$ . Thus, their *estimated* valuation is:

$$\hat{P}_i = g(f(\hat{k}_i, \hat{X}), \hat{Y}) \quad (2)$$

## 2.2 The “Virginia” Technology Intervention

We introduce a technology mechanism denoted by the superscript  $v$ . This technology provides enhanced data, resulting in a refined knowledge set  $k_i^v$ . The tech-enhanced valuation is:

$$P_i^v = g(f(k_i^v, \hat{X}), \hat{Y}) \quad (3)$$

**The Efficiency Condition:** The fundamental assumption of the model is that the technology strictly reduces the estimation error in the knowledge vector:

$$\|k_i - k_i^v\| < \|k_i - \hat{k}_i\| \quad (4)$$

## 3 Theoretical Implications

Based on the condition in Inequality (4), we derive the following results regarding market outcomes.

**Proposition 1** (Reduction of Valuation Variance). *Assuming  $g(\cdot)$  and  $f(\cdot)$  are differentiable and monotonic, the technology reduces the divergence between the perceived value and the fundamental value.*

*Proof.* By applying a first-order Taylor expansion around the true knowledge  $k_i$ , the valuation error can be approximated as:

$$|P_{est} - P_{true}| \approx |\nabla g \cdot \nabla f \cdot (k_{est} - k_{true})|$$

Given the condition  $\|k_i - k_i^v\| < \|k_i - \hat{k}_i\|$ , it follows that:

$$|P_i^v - P_i| < |\hat{P}_i - P_i| \quad (5)$$

The variance of the valuation distribution around the true mean is strictly lower under the technological regime.  $\square$

**Proposition 2** (Mitigation of the Winner’s Curse). *The introduction of the technology leads to less aggressive bid shading, resulting in bids that are closer to the bidder’s true valuation.*

*Proof.* In a common-value or interdependent-value setting, the optimal bid  $b_i$  is defined by the expected valuation conditional on winning, minus a shading factor  $\lambda$  which is a function of uncertainty (variance  $\sigma^2$ ):

$$b_i = E[P_i | \text{win}] - \lambda(\sigma^2)$$

Since the technology reduces the error variance ( $\sigma_v^2 < \sigma_{\hat{v}}^2$ ), and  $\lambda'(\sigma^2) > 0$ , the shading factor decreases. Consequently,  $b_i^v > b_i$  (holding expectation constant), implying higher revenue realization for the seller and reduced fear of overpayment for the buyer.  $\square$

**Proposition 3** (Allocative Efficiency). *The technology increases the probability that the item is awarded to the bidder with the highest fundamental valuation  $P_i$ , rather than the bidder with the largest positive estimation error.*

*Proof.* Let  $i^*$  be the bidder with the highest true  $P$ . Without technology, it is possible for a bidder  $j$  with lower true value ( $P_j < P_{i^*}$ ) to win if their estimation error  $\epsilon_j$  is sufficiently large and positive ( $\hat{P}_j = P_j + \epsilon_j > \hat{P}_{i^*}$ ).

As  $k_i^v \rightarrow k_i$ , the noise term  $\epsilon \rightarrow 0$ . The correlation between the bid rank and the true valuation rank approaches 1. This ensures that the asset is allocated to the agent who values it most in fundamental terms, maximizing total welfare.  $\square$

## 4 Conclusion

The model demonstrates that the integration of the “Virginia” technology into the auction mechanism serves to de-risk the transaction for all parties. By reducing the informational distance between the agent’s estimate and the artwork’s true attributes, the market achieves tighter price discovery and superior allocative efficiency.