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Quantifying reputation and success in art

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In areas of human activity where performance is difficult to quantify in an objective fashion, reputation and networks of influence play a key role in determining access to resources and rewards. To understand the role of these factors, we reconstructed the exhibition history of half a million artists, mapping out the coexhibition network that captures the movement of art between institutions. Centrality within this network captured institutional prestige, allowing us to explore the career trajectory of individual artists in terms of access to coveted institutions. Early access to prestigious central institutions offered life-long access to high-prestige venues and reduced dropout rate. By contrast, starting at the network periphery resulted in a high dropout rate, limiting access to central institutions. A Markov model predicts the career trajectory of individual artists and documents the strong path and history dependence of valuation in art.

The Man with the Golden Helmet, an 18th-century painting attributed to Rembrandt, was Berlin's most famous artwork for decades. Once evidence emerged, in the 1980s, that the painting was not by Rembrandt, it lost much of its artistic and economic value, even though the artwork itself had not changed (*1*). Quality in art is elusive; art appeals to individual senses, pleasures, feelings, and emotions. Recognition depends on variables external to the work itself, like its attribution, the artist's body of work, the display venue, and the work's relationship to art history as a whole (*2*, *3*). Recognition and value are shaped by a network of experts, curators, collectors, and art historians whose judgments act as gatekeepers for museums, galleries, and auction houses (*4*). Given the fragmented and often secretive nature of transaction records, quantitative analyses of the art world have been difficult (*5*, *6*). Although artists' reputation is known to affect auction outcomes, our current understanding of these processes is based on small samples spanning short periods and limited to a country or region (*7*–*9*).

Our dataset was collected by Magnus (www.magnus.net) and combines information on artists' exhibitions, auction sales, and primary market quotes. It offers information on 497,796 exhibitions in 16,002 galleries, 289,677 exhibitions in 7568 museums, and 127,208 auctions in 1239 auction houses, spanning 143 countries and 36 years (1980 to 2016, fig. S1), allowing us to reconstruct the artistic career of 496,354 artists (see supplementary text S1 for additional description and validation and fig. S1a for an example) (*10*, *11*). The number of exhibitions for an artist followed a fat-tailed distribution; whereas 52% of the artists had one recorded show, a few high-profile artists were exhibited at an exceptional number of venues (fig. S1, c and d). Although half of the auctioned artworks sold for less than \$4000, the price for art was as high as \$110,500,000 (fig. S1f).

Prestigious institutions have access to well-regarded artists, and influential artists in turn tend to seek out prestigious institutions. Yet, institutional prestige is also highly subjective, determined by factors like history, leadership, resources, and geographic location. Given that major institutions act as art portfolios, we can uncover the slowly changing institutional prestige from frequent artwork exchanges, an approach called "adiabatic approximation" (*12*). For this, we define an order τ coexhibition network, whose nodes are museums and galleries, connected by weighted directed links (i, j) that represent the number of artists that exhibited first in i then in j within a window of τ exhibits (fig. S2, a and b) (*13*). The obtained order $\tau = \infty$ coexhibition network, connecting 16,002 galleries and 7568 museums as nodes via 19,031,332 links, incorporates all art movement in our dataset. A subset of this network revealed the clustering inherent in the art world (Fig. 1 and figs. S3 and S4). The network core was a dense community of major European and North American institutions, underlying their access to a common pool of artistic talents. Movement between the hubs in the core was exceptionally high: The link weight between Museum of Modern Art (MoMA) and Guggenheim was 33 times higher than expected if artists would move randomly between institutions (supplementary text S2.1), reflecting a highly concentrated movement of selected artists between a few prominent institutions. Multiple dense regional communities of institutions in Europe, Asia, South America, and Australia were relatively isolated from the core, indicating that members of these communities share artists mainly among themselves.

A network-based ranking using each institution's eigenvector centrality (*14*) was strongly correlated with known prestige measures (supplementary text S2.4 and fig. S5): (i) $N = 9392$ institutions were independently assigned grades from A to D by a team of experts at Magnus based on criteria including longevity, the artists exhibited, size and quality of exhibition space, and art fair participation. A-rated institutions had high network-based ranking, whereas those rated D were at the bottom half (Fig. 2A). (ii) For each institution, we computed the maximum relative price taken across all the artworks exhibited, observing a high correlation between network-based ranks and economic value of the exhibited artists artworks (Fig. 2B). The top 10–ranked institutions had the highest cumulative sales values (Fig. 2C and fig. S6), indicating that the coexhibition network, though its construction is agnostic to price, identified institutions that have access to highly valued artists. In general, an institution's geographic distance to one of the 10 largest hubs showed no relationship with prestige (fig. S7, a and b). By contrast, the network-based distance of an institution to one of the top 10 institutions was closely linked to its prestige (fig. S7, c and d). Thus, network effects play a defining role in influencing the evolution of an artist's reputation and valuation.

To show that artistic careers can be interpreted within the context of the institutions to which they have access, we grouped artists by the average prestige of their first five exhibits. We assigned an artist a high initial reputation if her work was on average exhibited in the top 20% of institutions as defined by network ranking; an artist had low initial reputation if his work was shown on average in the bottom 40% (supplementary text S3.1). A decade after their fifth exhibit, 39% of the high–initial reputation artists continued to exhibit (Fig. 2D). For low–initial reputation artists, only 14% remained active 10 years later. Next, we selected 31,794 artists, born between 1950 and 1990 with at least 10 exhibitions (Fig. 2E). As a group, high–initial reputation artists had continuous access to high-prestige institutions during their entire career (Fig. 3A). Of the 4058 high–initial reputation artists, 58.6% remain in high-prestige territory until the end of their recorded career, and only 0.2% had the average prestige of their five most recent exhibits in the bottom 40% (Fig. 2F). This lock-in effect was largely absent for low–initial reputation artists: Their reception improved with time, advancing slowly to institutions of increasing prestige (Fig. 3A). Only 10.2% of low–initial reputation artists had the average prestige of their five most recent exhibits in the top 20% (Fig. 2F). Overall, initial reputation (first five exhibits) predicted success across a variety of measures: High–initial reputation artists had twice as many exhibitions as low–initial reputation artists (Fig. 2G); 49% of the exhibitions of high–initial reputation artists occurred outside of their home country, compared to 37% for low–initial reputation artists (Fig. 2G), and high–initial reputation artists showed more stability in institutional prestige (Fig. 2H). The work of a high–initial reputation artist was traded 4.7 times more often at auctions than that of a low–initial reputation artist (Fig. 2I), at a maximum price that was 5.2 times higher (Fig. 2I). We also collected 442,314 prices of artworks displayed in galleries, finding that the average maximum price of high–initial reputation artists was \$193,064, compared to \$40,476 for low–initial reputation artists (Fig. 2H). Thus, art careers were characterized by strong path dependence; artists starting in high-prestige institutions located at the center of the network showed a lower dropout rate and tended to maintain their status. By contrast, those starting at the periphery of the network showed a high dropout rate, but if they persisted, their access to top institutions gradually improved.

To model how reputation emerges in the art world, let $p\left[i_{\tau+1}\middle|i_\tau\right]$ be the probability that an artist, currently exhibited at institution i_τ, next exhibits at institution $i_{\tau+1}$. We assume that the only institutions $i_{\tau+1}$ reachable for the artist are those that have exhibited an artist from institution i_τ before. We can therefore model an artistic career as a random walk on the order $\tau = 1$ network (*15*, *16*), the probability of moving to $i_{\tau+1}$ being proportional to the number of previous artists who transitioned from i_τ to $i_{\tau+1}$ (fig. S2). We assume that the network captures the connections between curators and institutions, guiding access to specific institutions. Independently of where artists started their career, this model directs them toward institutions of median prestige (Fig. 3B), failing to capture the lock-in effect observed in real careers. This suggests that access to institutions also depends on the artist's previous exhibition history, not only on current exhibition venue. To consider an artist's previous exhibition history $i_1, i_2, \ldots, i_\tau$ (*17*), we write the probability of the $i_\tau \rightarrow i_{\tau+1}$ transition as

$$p\left[i_{\tau+1}\middle|i_\tau,\ldots,i_1\right] = K \times \mu\left[\pi_{i_{\tau+1}};m_\tau\right] \times p\left[i_{\tau+1}\middle|i_\tau\right] \quad (1)$$

where K is a normalization factor and the second term on the right-hand side captures the memory of the system about artists' reputation, written as

$$\mu\left[\pi_{i_{\tau+1}};m_\tau\right] = \frac{p\left[\pi_{i_{\tau+1}}\middle|m_\tau\right]}{p\left[\pi_{i_{\tau+1}}\right]} \quad (2)$$

where

$$m_\tau = \frac{1}{\tau}\sum_{k=1}^{n_\tau}\pi_{i_{\tau-k+1}} \quad (3)$$

is the average reputation, representing the average prestige of the artist's past n_τ exhibitions. In other words, memory acts as a multiplicative weight that depends on the average past reputation of the artist and the prestige of the target institution. This allows us to measure the memory term $\mu\left[\pi_{i_{\tau+1}};m_\tau\right]$ directly from the data, helping us document strong reputation effect for all artists (supplementary text S3.2 and Fig. 3, D to F). Consider an artist whose previous exhibitions conferred an average reputation in the bottom decile, e.g., m = 0.1 (Fig. 3D). His chances of exhibiting next at an institution whose prestige π is in the bottom decile was 3.4 times higher than expected by chance, and his probability of moving to a top-decile institution was only one-fifth of that expected by chance. The monotonically decreasing $\mu\left[\pi_{i_{\tau+1}};m_\tau\right]$ with prestige π indicates that an artist with low previous reputation had a 17 times higher chance of moving next to a low-prestige institution than to a high-prestige one. We observe the opposite trend for an artist whose previous reputation was in the top decile, e.g., m = 0.9 (Fig. 3F): Her relative chances of exhibiting once again at a high-prestige institution were 42 times higher than moving to a low-prestige institution.

To test the role of reputation, we simulated the career of each artist in our sample, using as input only their first five exhibits and the universal (artist-independent) $\mu\left[\pi_{i_{\tau+1}};m_\tau\right]$ functions to decide where they would exhibit next. The model accurately captured the lock-in effect observed in real careers (Fig. 3C). The forecast error saturated beyond n_τ = 12 (supplementary text 3.3 and fig. S8a), indicating that the past 12 exhibitions offered an optimal memory to capture the role of reputation in artistic careers. The modeling framework did not predict the specific institutions that exhibit an artist, but only their level of prestige (figs. S8, b to h, and S9). This is partly because there are many institutions within each community, with comparable prestige.

As Fig. 2F illustrates, 240 artists who began their career in low-prestige institutions did break through, having the average prestige of their last five recorded exhibits in high-prestige institutions. We find that those who do break through do so within the first 10 years of their careers (fig. S10a). We also find that among their first five exhibits, breakout artists exhibit in institutions with a wider range of rankings, their initial prestige standard deviation being 18.6%, compared to 10.3% for those who did not break through (p = 10^{-22}, fig. S10b); they exhibit in more distinct institutions, their initial fraction of exhibitions in distinct institutions being 70.3%, compared to 49.3% (p = 10^{-21}, fig. S10c); have higher maximum exhibition prestige (0.60 compared to 0.41, p = 10^{-25}, fig. S10d); and their network distance to MoMA is equal to 0.48, compared to 0.60 (p = 10^{-26}, fig. S10e). In other words, later access to high-prestige institutions is improved by an intensive early "shopping around."

Although talent is difficult to measure, we expect an artist's talent to be uncorrelated with their country of origin, implying that the distribution of initial reputation should not vary across artists of different origin. However, initial reputation was not equally distributed across artists of different country of origin (Fig. 3G). In many countries, artists start and end their career in low-prestige institutions (Fig. 3H); those, however, born in countries with better access to the art network have a higher chance of starting and ending their career at the top.

Our analysis focused on art surveyed by galleries, museums, or auction houses, so non-object–based art, like performance art, was underrepresented. We also focused on success measures tied to institutional access, ignoring multiple dimensions through which art and artists enrich our society (*18*). Yet, even with this limited focus, our results codify the stratification of the art world, which limits access of artists to institutions that would be beneficial to their career. Quantifying these barriers and the mechanism of access could help establish policies to level the playing field. For example, the art world could benefit from the implementation of lottery systems that offer some underrepresented artists access to high-prestige venues, or blind selection procedures, successfully implemented in classical music (*19*), enhancing the inclusion of neglected works and artists.

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SUPPLEMENTARY MATERIALS

www.sciencemag.org/cgi/content/full/science.aau7224/DC1
Materials and Methods
Supplementary Text
Figs. S1 to S10
References (*23*)

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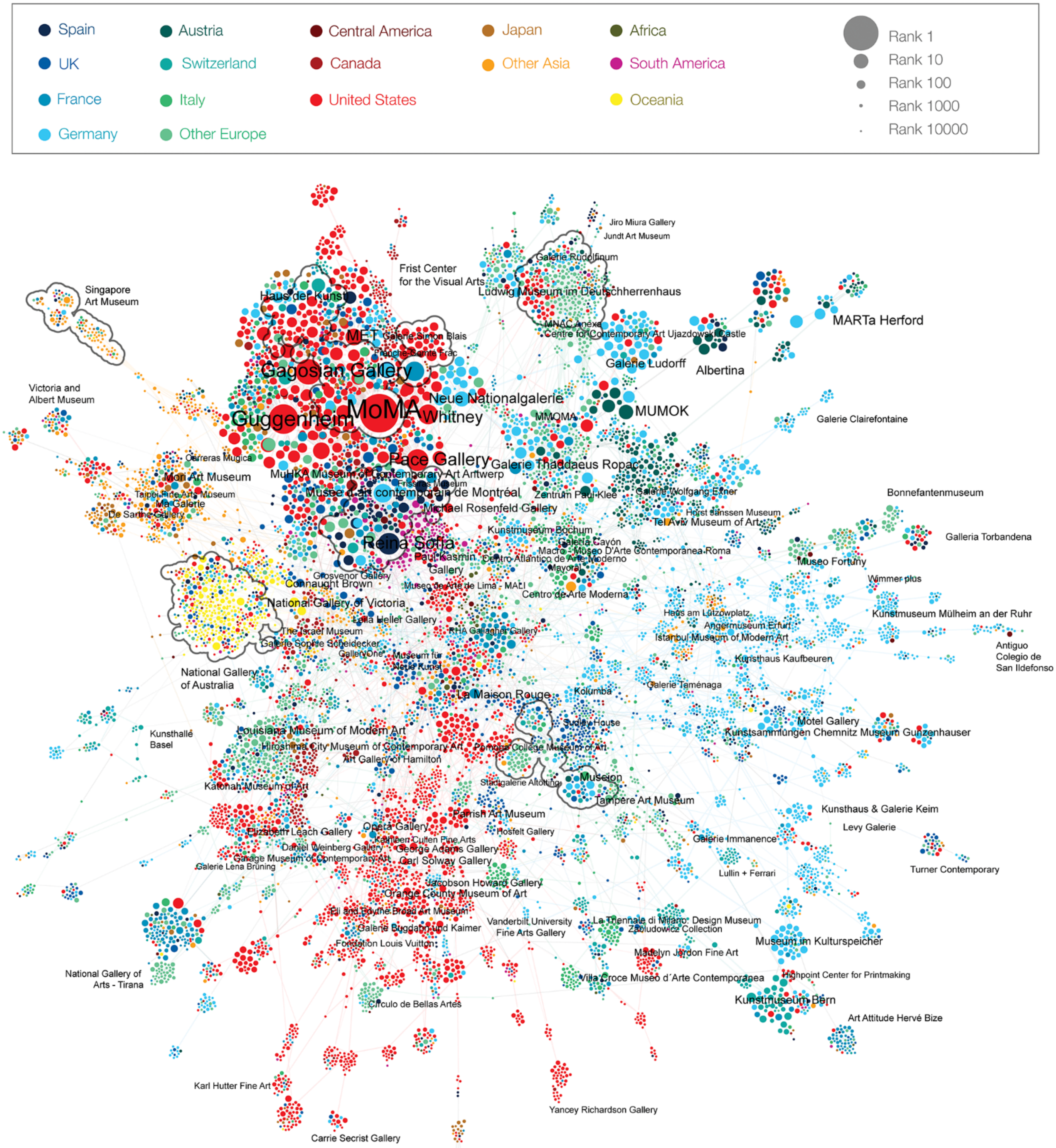

Fig. 1. Coexhibition network. Force-directed layout of the order $\tau = \infty$ coexhibition network, whose nodes are institutions (galleries, museums). Node size is proportional to each institution's eigenvector centrality. Nodes are connected if they both exhibited the same artist, with link weights being equal to the number of artists' coexhibitions. Node colors encode the region in which institutions are located. Links are of the same colors as their end nodes, or gray when end nodes have different colors. For visualization purposes, we only show the 12,238 nodes corresponding to institutions with more than 10 exhibits; we pruned the links by keeping the most statistically significant links (*20*) (supplementary text S2.2). We implemented community detection on the pruned network (*21*), identifying 122 communities (supplementary text S2.3). We highlighted five of them, the full community breakdown being shown in fig. S3. We also show the names of the most prestigious institution for each community.

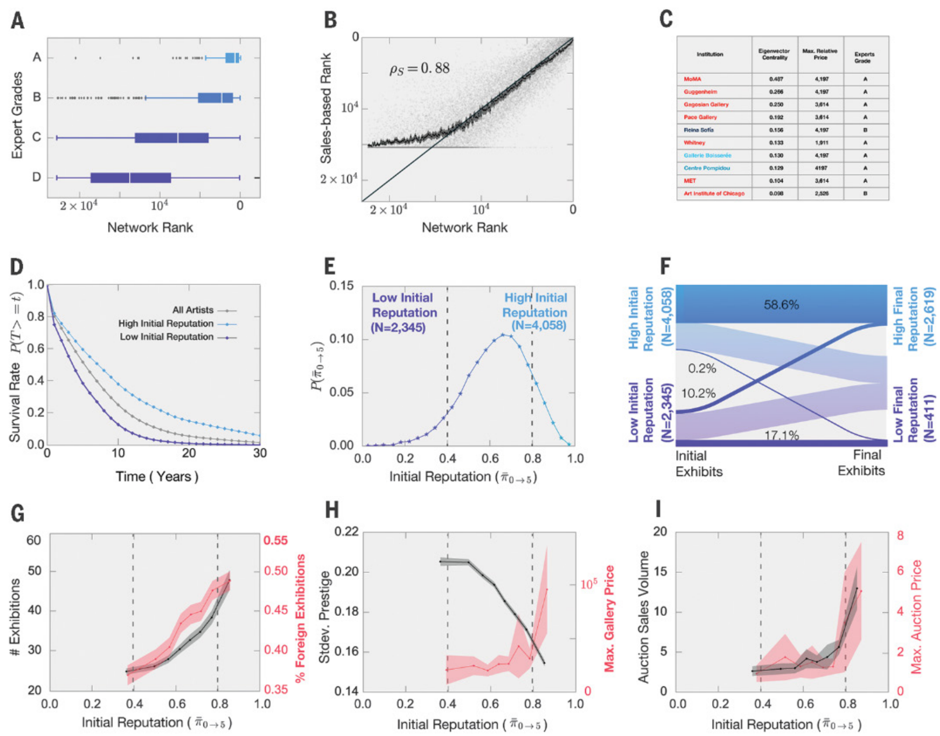

Fig. 2. Quantifying artistic careers. (**A**) Network-based prestige ranks, captured by eigenvector centrality, for institutions that were independently assigned different grades. (**B**) The relationship between sales-based ranks and eigenvector centrality-based network ranks, binned in 100 intervals, showing a high Spearman's correlation (ρ_S = 0.88). We report mean (black line) and standard error (gray shading) within each bin. (**C**) Data on top 10 institutions as predicted by the network-based ranking. Colors capture geographical location, as shown in Fig. 1. (**D**) Survival curves, showing the fraction of artists that continue to exhibit in the years following their first five exhibits based on the career of 99,265 artists with more than five exhibits. (**E**) Probability density function of average prestige during the first five exhibits for the 31,794 artists with more than 10 exhibits born between 1950 and 1990. (**F**) Diagram illustrating how the career high– and low–initial reputation artists evolves, showing the fraction of those artists whose final reputation (last five recorded exhibits) is either low or high. To show how the early career determines various success measures across a career, we consider as control variable the average prestige of the first five exhibits of an artist, and report (**G**) the total number of exhibits (left), the percentage of these exhibits outside of their home country (right), (**H**) the standard deviation of their exhibition prestige (left), the maximum price at which they are currently quoted in a gallery (in $, right), (**I**) the total number of their works that were sold in the auction market (left), and the maximum price (relative to the average market price) at which their work sold in the auction market (right). Each panel demonstrates the important role that initial reputation plays in shaping later access to institutions and financial reward.

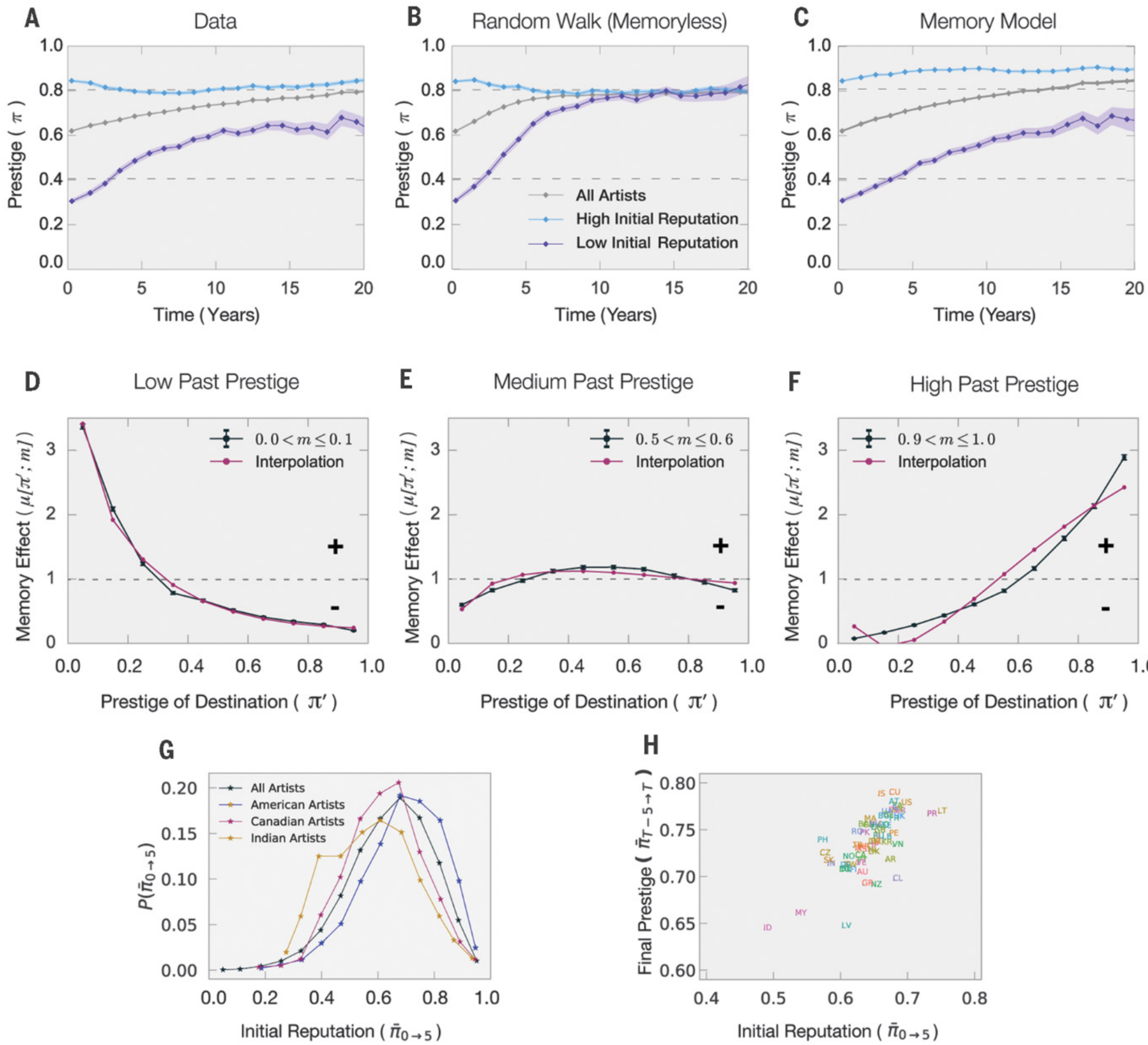

Fig. 3. Modeling the emergence of reputation. (**A**) For a random sample including 30% of the 31,794 artists with more than 10 exhibits born between 1950 and 1990, we show the evolving exhibition prestige over time. (**B**) Evolving exhibition prestige predicted by the random walk model (memoryless), documenting its failure to capture real careers. (**C**) The memory model predicts the evolution of prestige. We use the first five exhibits to initialize the models. The sequence of dates at which an artist's exhibitions occur was matched to the one we observe in the data. (**D** to **F**) Variation of the memory component with the prestige of the next exhibit π, for different ranges of values for past reputation m. π and m are reported in decile. (**G**) Probability density function of average prestige during the first five exhibits for the 31,794 artists, and the subset of those artists who were born in the United States, Canada, and India. (**H**) Final reputation versus initial reputation for artists of different country of origin.