Supplementary Materials for

Quantifying reputation and success in art

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Supplementary Information

S1   Data Description

Our dataset was collected by Magnus, a company operating in the art world. It combines information on artists exhibits, auction sales, and primary market quotes, extending the information available on websites such as ArtFacts or Artprice.

S1.1   Data on Art Exhibits

To collect data on art exhibits, Magnus first identified institutions worldwide, using: i) online aggregators, such as `www.artforum.com`, `www.index-berlin.de`, and `www.chelseagallerymap.com`, ii) art institutions associations websites, like `www.artdealers.org`, and iii) art fairs websites, such as `www.artbasel.com`, identifying 7,568 museums and 16,002 galleries. For each institution, they then collected the information listed on their websites on all past exhibits, allowing them to identify 787,473 art exhibits. For each exhibit, they recorded the name of all exhibited artists, the date at which it occurred, and the geographic location where it took place, allowing them to reconstruct the exhibition history of 496,354 artists since 1980 and across 143 countries (Figs. S1, b to d). They also collected information on artists birth date, city of origin, as well as death date in case of non-living artists. The birth date is available for a subset of 140,925 artists, and the city of origin for 64,971 artists.

To independently validate that this procedure allows to reconstruct the exhibition history of a particular artist, we used information from the personal websites of a random sample of 678 artists in the dataset born after 1950 and with more than ten exhibits in our dataset. We find that on average 71% of an artist's exhibits listed on their website were present in our dataset. This number goes up to 80% for artists with more than 20 exhibits; 83% for artists in the top decile of prestige, and 91% for artists born after 1970.

Naturally, less information is available for low ranked galleries. This is an inherent problem with data collection, where entities with low prestige are often less documented. Therefore, we may overestimate the initial reputation of some artists simply because their early exhibits at low prestige institutions was not recorded. Yet, as the data collection was institution-based, not artist centered, we do not believe this bias affects our main results. Indeed, the missing data on exhibits

will disproportionately include less prestigious artists.

S1.2   Data on Art Auctions

Magnus also compiled a dataset containing information on art auctions, by collecting all past transactions listed by the largest auction houses, such as Sotheby's, Christie's, or Phillips, as well as auction price aggregators. It documents 3,257,886 sales that occurred at 127,208 auctions since 1970 (Figs. S1, e to g). Each sale is characterized by its date, its realized price (converted to 2013 USD), the name of the artist, the name of the auction house, and the artwork media (paintings, photographs, sculptures, etc...). Sales prices do not include transactions occurring in private sales.

To account for the increasing price paid for artworks over time, we normalize each sale price by the annual average auction sales price ("relative price"), allowing us to compare artworks across artists and time. For instance, the $179,365,000 sales price of "Les Femmes d'Alger" corresponds to a 3,660 multiplier relative to the average 2015 market price.

S1.3   Institutional Setting

An exhibit in our dataset corresponds to an event in which one or several artworks by one or several artists are being shown to the public in a gallery or a museum. The dataset only resolves whether an artist's work has been exhibited in an institution, not the mechanism or process that led to this exhibition. In practice, institutions often exhibit the artworks of artists that they hold in their inventory, or whose work their curator appreciates. Galleries also regularly exhibit the work of artists they represent, in an effort to bring more attention to these artists. Artists can also be invited to participate in an exhibit, and in a few cases, artists can apply and are selected by a jury.

Note that galleries typically offer the work of an artist for purchase, whereas museums do not. All exhibits occurred at galleries and museums, and all sales come from auctions. We have access to prices quoted in the primary market (galleries) used in Fig. 2h, however the actual sales prices are subject to negotiation.

Art exhibits in our dataset are only characterized by the exhibited artists and not by the artworks being exhibited. Hence, we cannot distinguish between exhibits including artworks that have recently been produced from those including artworks lent by other institutions.

S2 Art Institutions

In the main text, we have defined an order τ co-exhibition network, whose nodes are museums and galleries, connected by weighted directed links (i,j) representing the number of artists who first exhibited in i then in j within a window of τ exhibits (Fig. S2, a and b), using eigenvector centrality to quantify an institution's prestige.

In the following, we: (i) characterize the order $\tau = \infty$ co-exhibition network, (ii) describe the procedure used to extract the network's backbone, allowing us to show a graphical representation which preserves the main elements of the network structure, (iii) offer additional details on the community structure, and (iv) discuss the relationship between alternative rankings of nodes prestige.

S2.1 Randomizing the Art Network

In the main text, we have defined the order $\tau = \infty$ co-exhibition network, connecting 16,002 galleries and 7,568 museums as nodes via 19,031,332 links, and incorporating all art movements in our dataset.

To characterize the order $\tau = \infty$ co-exhibition network, we compare it to a network constructed using randomized artists' trajectories. Taking an artist's number of exhibits as given, we sample the art institutions in which she exhibits by drawing randomly from the set of all possible institutions, the probability of sampling an institution being proportional to the institutions' total number of exhibits. We perform this operation for all artists in the dataset, hence getting a set of synthetic careers with the same number of exhibits per artist as in the original dataset, but where we destroyed all temporal and artist-institution correlations. We then compare the number of movements between each pair of institutions in the observed network and in the randomized network.

As discussed in the main text, the art movements between large institutions in the observed network is much higher than what would be expected by chance. For example, 12,260 institutions have links to MoMA, meaning that over 30 years, about half of the institutions in the network have never exhibited an artist who eventually made it to MoMA. If artists trajectories were random, we would expect 19,423 institutions to have links to MoMA (Fig. S2c). In addition, the link weight between MoMA and Guggenheim is 33 times higher than expected if artworks would move randomly between institutions (Fig. S2d).

S2.2 Visualizing the Art Network

To visualize the order $\tau = \infty$ co-exhibition network, we first select the 12,238 institutions with more than 10 exhibits in our dataset, that is 53% of the total number of institutions, hosting 96% of the total number of exhibits. We then follow the procedure described in (20) to compute a significance criterion for each link, allowing us to extract the network's backbone. We apply a log transform to the links weights, and keep the 4,000 most significant links. As some of the 12,238 institutions are disconnected from the rest of the network at the pruning stage, we connect them back to the giant component through their most significant outlink, resulting in a network that has 14,994 links.

S2.3 Community Structure

We implemented community detection on the backbone network (21), identifying 122 communities of art institutions (Fig. S3). We find that most of the art movement takes place within these communities, so that 94.2% of the art movements between communities are characterized by links that are not significant (Fig. S4). The correlation between the link weights in the backbone and full network is 49.6%, indicating that pruning the network preserved key aspects of the underlying network and community structure.

S2.4 Ranking Art Institutions

To select our preferred network-based ranking of art institutions, we use external measures of institutional prestige. First, prior to the study, a team of experts at Magnus independently assigned grades from A to D to $N = 9,392$ institutions ("experts grade"), based on criteria including longevity, quality of the artists exhibited, size and quality of its exhibition space, and art fair participation. Second, for each institution, we computed the maximum relative price of the auctioned artworks for all the exhibited artists, restricting the computation to sales that occurred in the year prior to an artist's exhibit. To be consistent, institutional prestige is computed using the order $\tau = \infty$ network that includes all the links up to 2016. In Fig. 2a, the network-based ranks are compared to the expert grades that were allocated in 2016. In Fig. 2b, the network-based ranks are compared to the sales-based ranks computed using all the auction sales prices up to 2016.

We find that measures of nodes centrality based on inlinks, such as nodes eigenvector centrality

(Fig. S5a, column 1), nodes instrength (Fig. S5a, column 2), and nodes Pagerank (Fig. S5a, column 3), are more correlated with the experts grades (Fig. S5a, columns 7) and the sales-based ranks (Fig. S5a, columns 8) than measures of nodes centrality based on outlinks, such as nodes eigenvector centrality on the reverse network (Fig. S5a, column 4), nodes outstrength (Fig. S5a, column 5), and nodes Pagerank on the reverse network (Fig. S5a, column 6), suggesting to select a network-based ranking based on inlinks. The correlations between measures of nodes centrality based on inlinks are high ($\rho_S \geq 0.82$), yet nodes eigenvector centrality has the highest correlation with the sales-based ranks ($\rho_S = 0.88$), compared to nodes instrength ($\rho_S = 0.83$), and nodes Pagerank ($\rho_S = 0.72$). The correlation between nodes eigenvector centrality and the experts grades ($\rho_S = 0.47$) is slightly lower than that of nodes instrength ($\rho_S = 0.49$), and nodes Pagerank ($\rho_S = 0.51$). Yet these differences in correlation with the experts grades are small and driven by institutions in the lower tail of the prestige distribution. As shown in Fig. 2a, institutions rated A by experts are in a narrow top band based on their centrality-based network ranks, indicating that experts are quite good at identifying top institutions. It is those rated lower that have more uncertainty. The overlap in the ranking of institutions which are only one grade apart reflects the subjective judgment of institutions of comparable prestige, likely biaised by the perception of recent exhibits (*23*). Overall, sales data is a far more objective information on the perceived value and prestige. In addition, age is not necessarily a good measure of institutions prestige, as some new galleries start out with high prestige, indicating that their owners/curators have access to successful artists (Fig. S5a, column 9).

In principle, we could construct a prestige measure from the co-exhibition network at any window τ: we find that nodes strengths are highly correlated across co-exhibition networks of different windows ($\rho_S \geq 0.88$, Fig. S5b). Yet, the correlations between the network-based and the sales-based ranks or, to a lesser extent, the expert grades, are monotonically increasing with τ (Fig. S5c), indicating that the order $\tau = \infty$ co-exhibition network is the most suitable to characterize the relative prestige of art institutions. The predictive power of the order $\tau = \infty$ network suggests that there is a tremendous amount of information in the full history of the art movement – reinforcing the fact that art and its appreciation relies on cumulative history, rather than momentary information.

Finally, we find that institutional prestige remains stable over time (Fig. S5d), allowing us to use the network ranks computed while relying on all the links (order $\tau = \infty$ network) to rank exhibition

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prestige over time. Although the ranking stability slightly deteriorates over time, it affects exhibits which occurred more than two decades ago and represents only a small fraction of the exhibits in our dataset. In a robustness check, we also find that using time-varying network ranks has no effect on our main results.

A minority of institutions, like Galerie Boisserée, specialize in low value productions by highly regarded artists. A weakness of constructing a ranking of art institutions relying only on exhibited artists characteristics is that the rank of such institutions will be biased upward (Fig. S6). One could address this caveat by constructing medium-specific rankings.

S3 Art Careers

S3.1 Measuring Artists' Reputation

As mentioned in S2.4, the rank of an institution can change over time as the number of institutions in the entire network increases. Hence, to compare institutions prestige over time, we convert annual institutions' ranks into percentiles, so the most prestigious institution in a given year has prestige $\pi = 1$ and the least prestigious one has prestige $\pi = 0$.

We tried several choices to group artists based on their initial average reputation. We varied the number of groups and the cutoff values, finding that these choices did not impact our results. We used a larger range of average initial reputation for artists who started at low prestige institutions given that their dropout rate is higher than that of artists with high average initial reputation.

S3.2 Estimating the Model's Components

To simulate the random walk model, we estimate the probability of exhibiting at institution i' after exhibiting at institution i in a given year t. $T_{i,i'}^{a,t}$ be the number of times an artist a is successively exhibited at institution i and at institution i' prior to year t. The probability of exhibiting at institution i' after exhibiting at institution i in year t is

$$p_t[i'|i] = \frac{\sum_{\{a\}} T_{i,i'}^{a,t}}{\sum_{\{i'\}} \sum_{\{a\}} T_{i,i'}^{a,t}}. \tag{S1}$$

In other words, to simulate artists' trajectories, we use the transition probabilities estimated from the $\tau = 1$ network recomputed each year using all the links up to the previous year.

To simulate the memory model, we additionally need to estimate the memory component $\mu[\pi'; m]$. Let $N_{\pi'}^a$ be the number of exhibitions of prestige π' an artist a has, and let $N_{m,\pi'}^a$ be the number of exhibitions of prestige π' an artist a has when the average past prestige of his past τ exhibits is equal to m. We can estimate the memory component by

$$\mu[\pi'; m] = \frac{p[\pi'|m]}{p[\pi']}, \tag{S2}$$

where

$$p[\pi'|m] = \frac{\sum_{\{a\}} N_{m,\pi'}^a}{\sum_{\{\pi'\}} \sum_{\{a\}} N_{m,\pi'}^a}, \tag{S3}$$

and

$$p[\pi'] = \frac{\sum_{\{a\}} N_{\pi'}^a}{\sum_{\{\pi'\}} \sum_{\{a\}} N_{\pi'}^a}. \tag{S4}$$

We estimate $\mu[\pi'; m]$ on a random sample consisting of 70% of the selected 31,794 artists, only keeping exhibitions occurring after an artist's fifth exhibits. In principle, the memory component could also be time-varying. However, simulating the model using a time-varying estimate of the memory component does not improve its fit to the real data, so we assume that the memory remains constant over time.

S3.3 Model Selection

To simulate the memory model, we fit a second order polynomial interpolation to the estimated memory component. We compute the root mean square error between the observed and the simulated exhibitions prestige trajectory for each of the remaining 30% of artists as we vary the memory length. We find that the model's fit improves until a memory length of $n_\tau = 12$ exhibits, after which there is no more improvement (Fig. S8a).

The proposed modeling framework does not predict the specific institutions that exhibit an artist during his career, only their level of prestige. This limitation is independent of the number of

exhibits used to initialize the model (Fig. S8b): after two years, the fraction of correctly predicted institutions drops to zero. Note that the fraction of correctly predicted institutions slightly increases at long time horizons, driven by elite artists oscillating between high prestige institutions.
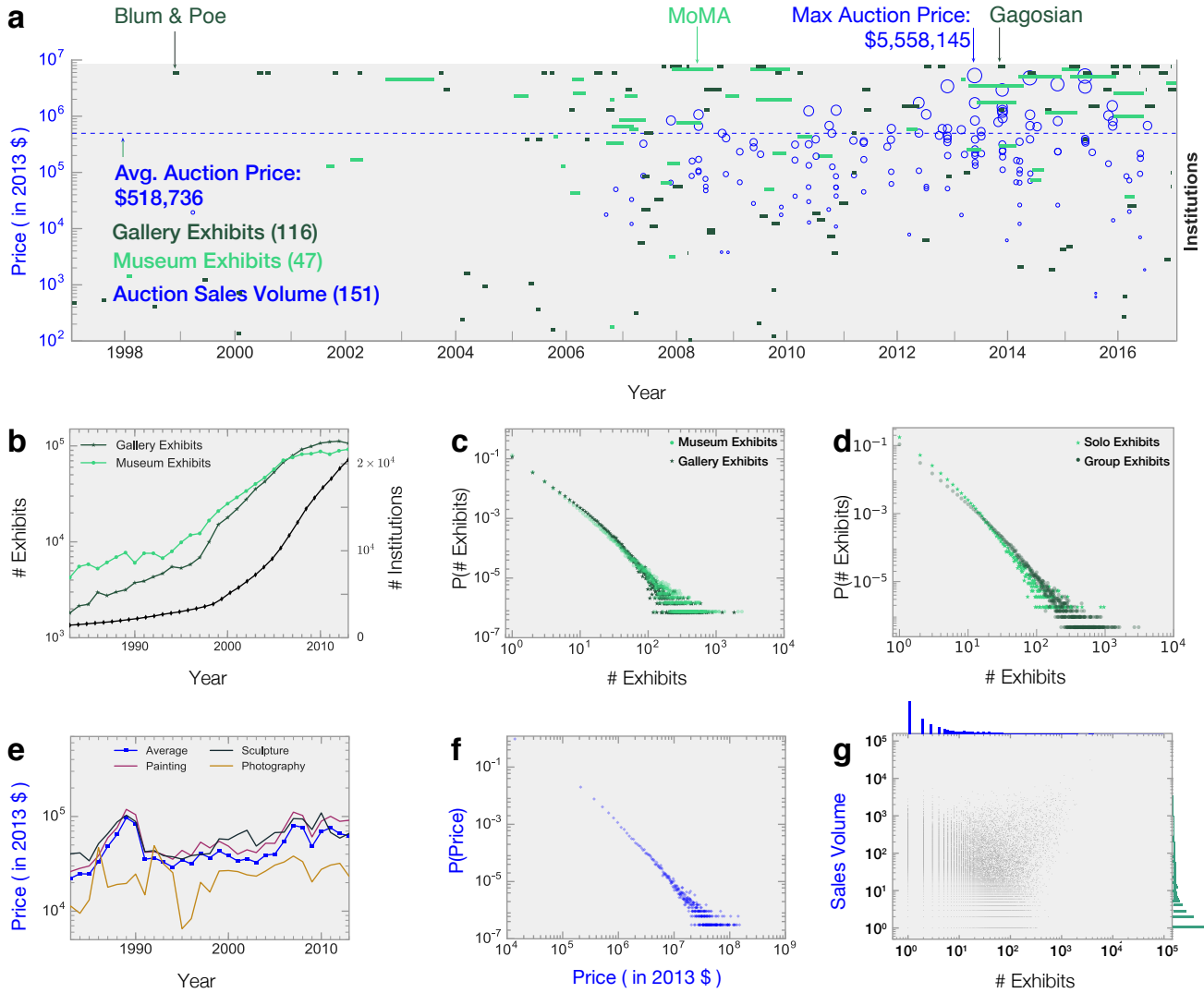
Mark Grotjahn (1968 -)

Figure S1: **Data Description**: (a) Timeline of Mark Grotjahn's career, showing all auction sales (blue), museum exhibitions (light green) and gallery exhibitions (dark green) documented in our database. The length of each rectangle marks the duration of each exhibit. Prices do not include transactions occurring in private sales. (b) Number of artists' exhibitions (left) and number of existing institutions (right) over time, showing that the number of recorded exhibits increased at an increasing rate during the second half of the 1990's, reflecting both the growth of the art-related establishment, as well as the fact that an increasing number of art institutions started to keep digitized records of their exhibits. The precise factors explaining the variations in the aggregate number of art exhibits over time are left for future research. (c) Empirical probability density function of the number of exhibitions per artist, separating museum and gallery exhibits. (d) Empirical probability density function of the number of exhibitions per artist, separating solo and group exhibits. (e) Annual average auction prices (in 2013 USD) across all artistic media (blue), paintings (brown), sculptures (black) and photographs (yellow). (f) Empirical probability density function of auction sales prices (in 2013 USD). (g) Sales volume vs. number of exhibits, as well as their marginal distributions.
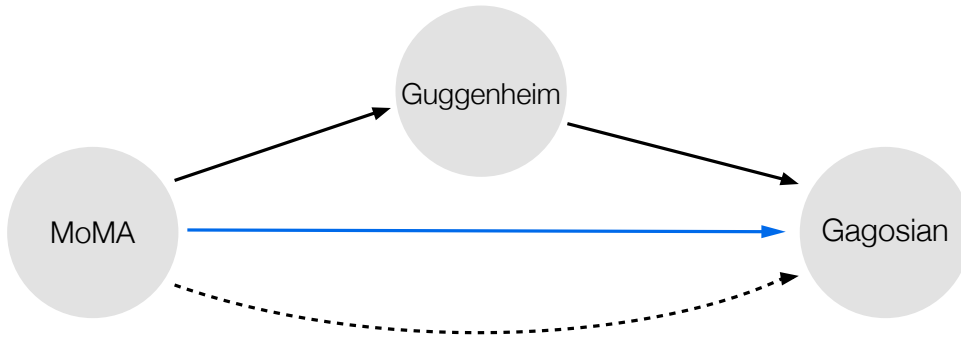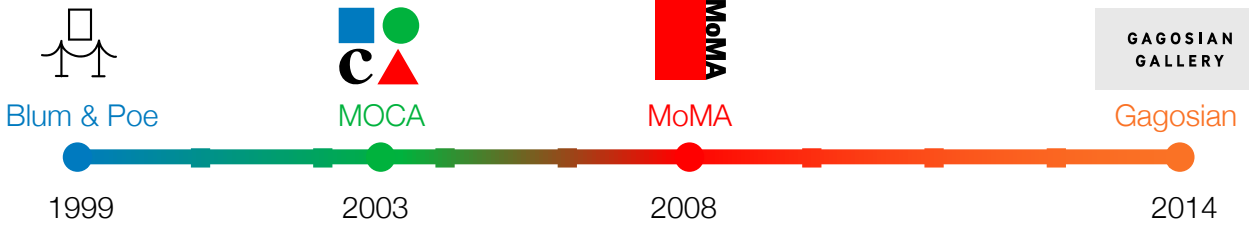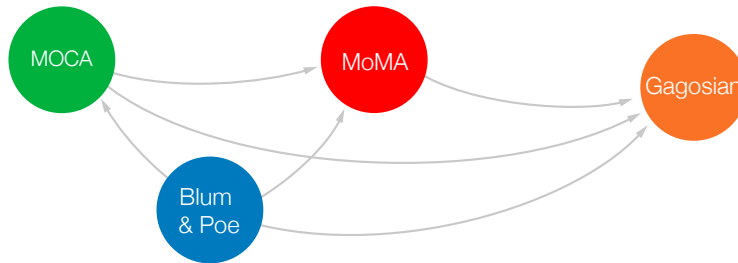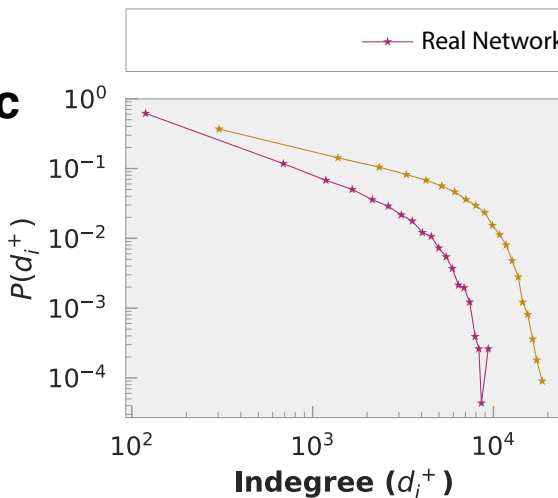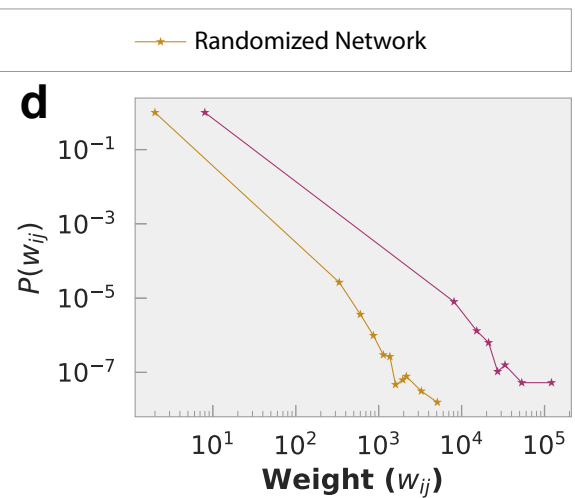
Figure S2: **Constructing the Co-exhibition Network:** (a) An artist with two exhibits at (MoMA, Gagosian) contributes a value of one to the link MoMA → Gagosian in the order $\tau = 1$ network (blue). An artists with three exhibits (MoMA, Guggenheim, Gagosian) contributes a value of one to the links MoMA → Guggenheim and Guggenheim → Gagosian in the order $\tau = 1$ network (black), and to the link MoMA → Gagosian in the order $\tau = 2$ network (dotted black). (b) Schematic representation showing how the career of an artist who had four exhibits contributes four nodes and six links to the order $\tau = \infty$ network. (c) Empirical probability density function of the order $\tau = \infty$ network indegree (purple), and after the randomization procedure described in S2.1 (yellow). (d) Empirical probability density function of the order $\tau = \infty$ network link weights (purple), and after the randomization procedure described in S2.1 (yellow). These distributions show that the art movement involves heavily large institutions.
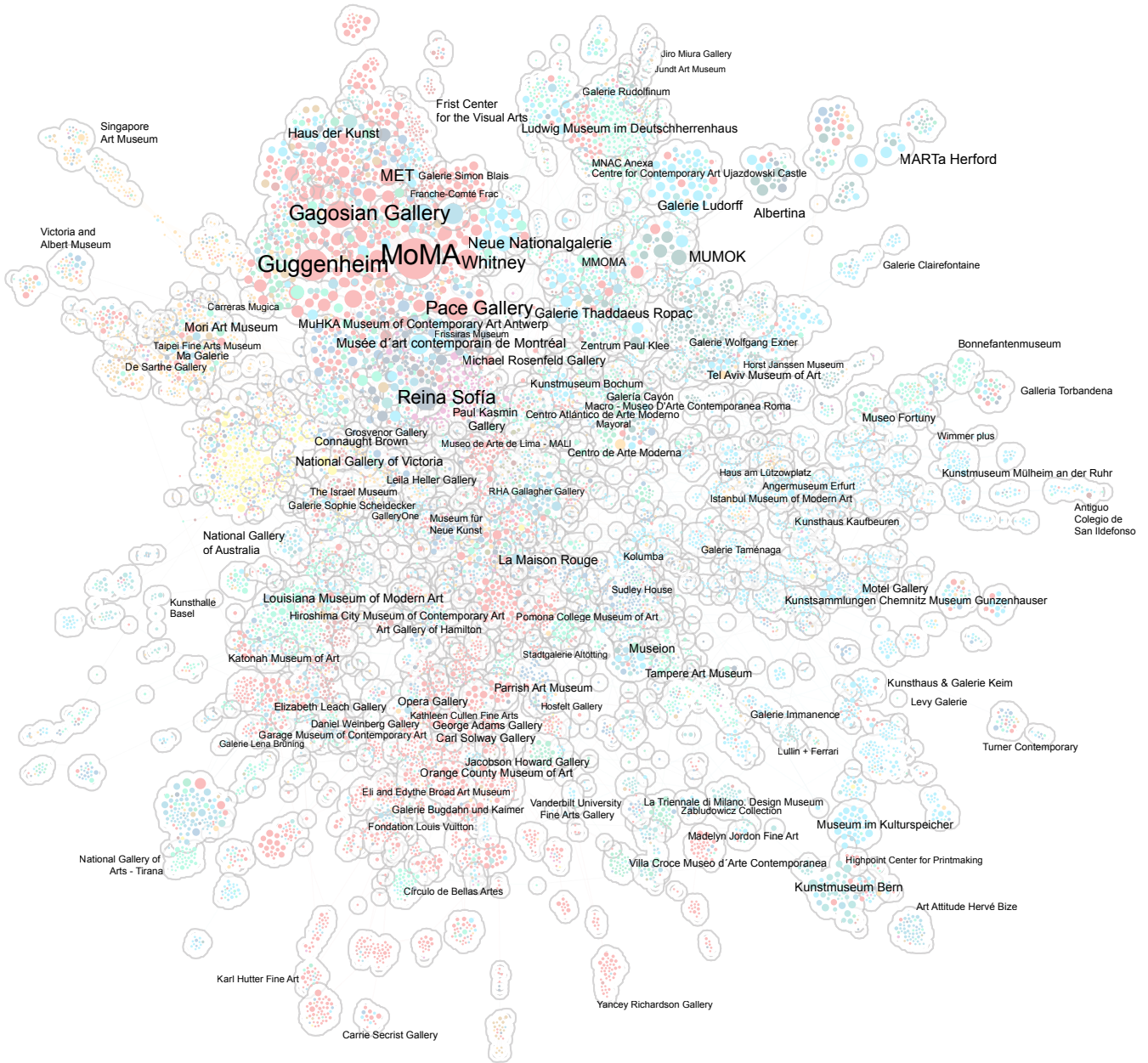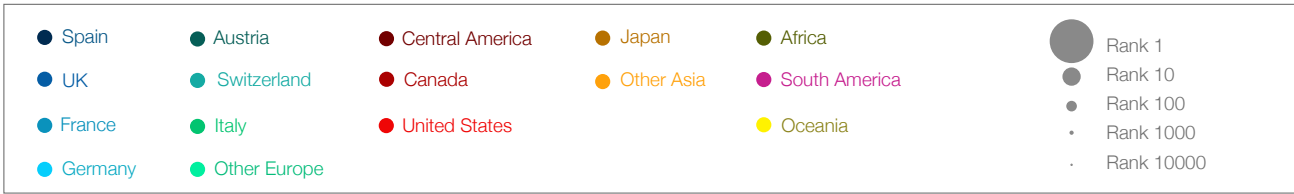
Figure S3: **Co-exhibition Network**: Reproduction of Fig. 1 in which we highlighted all of the 122 identified communities. A community consists of institutions that tend to be more interconnected to each other than to institutions outside of their own community.
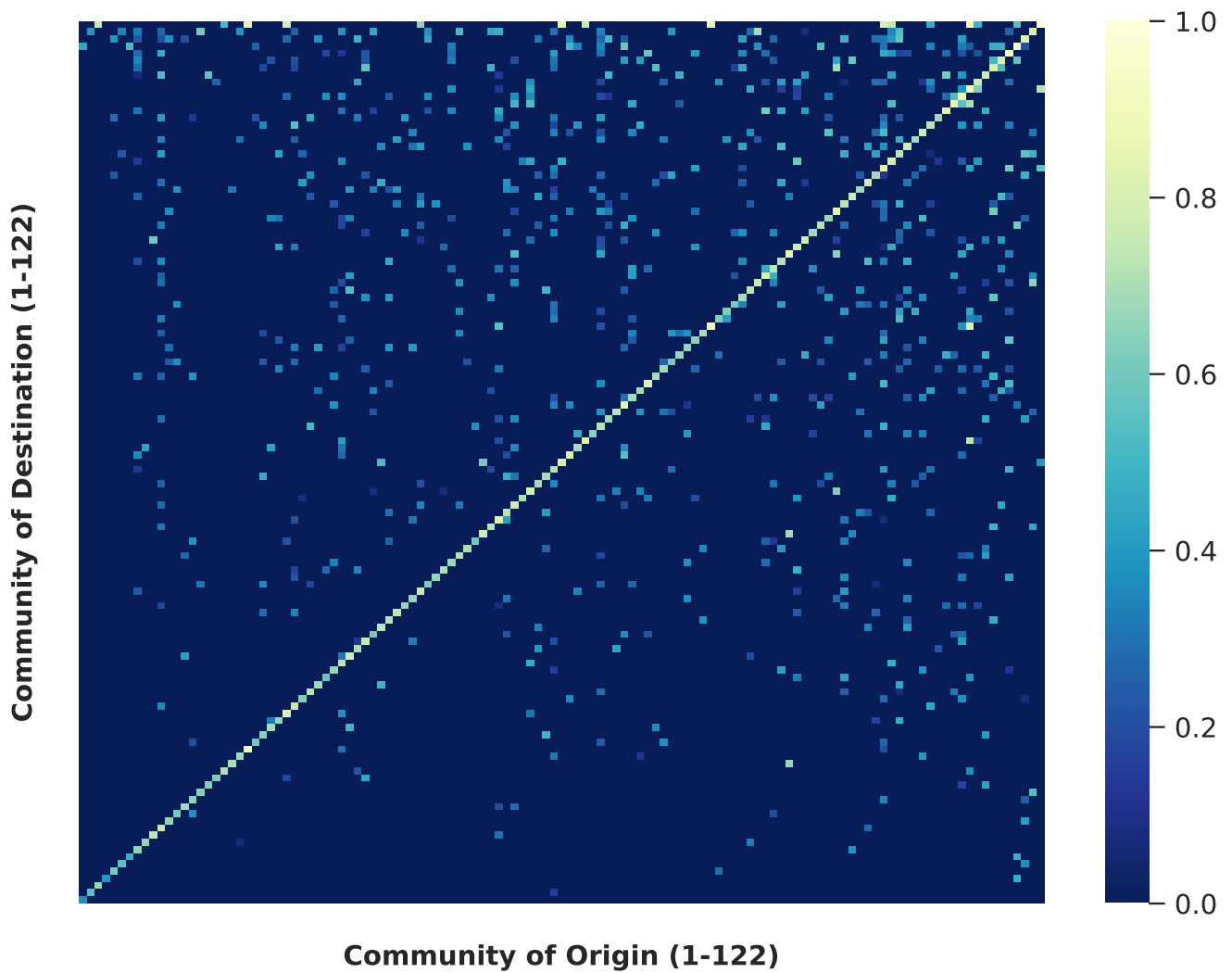
Figure S4: **Movements Between Communities**: The log weights of the links between communities in the backbone network, normalized between 0 and 1. Communities are identified using community detection on the backbone network (*21*), and ranked by the total weight of their outlinks.
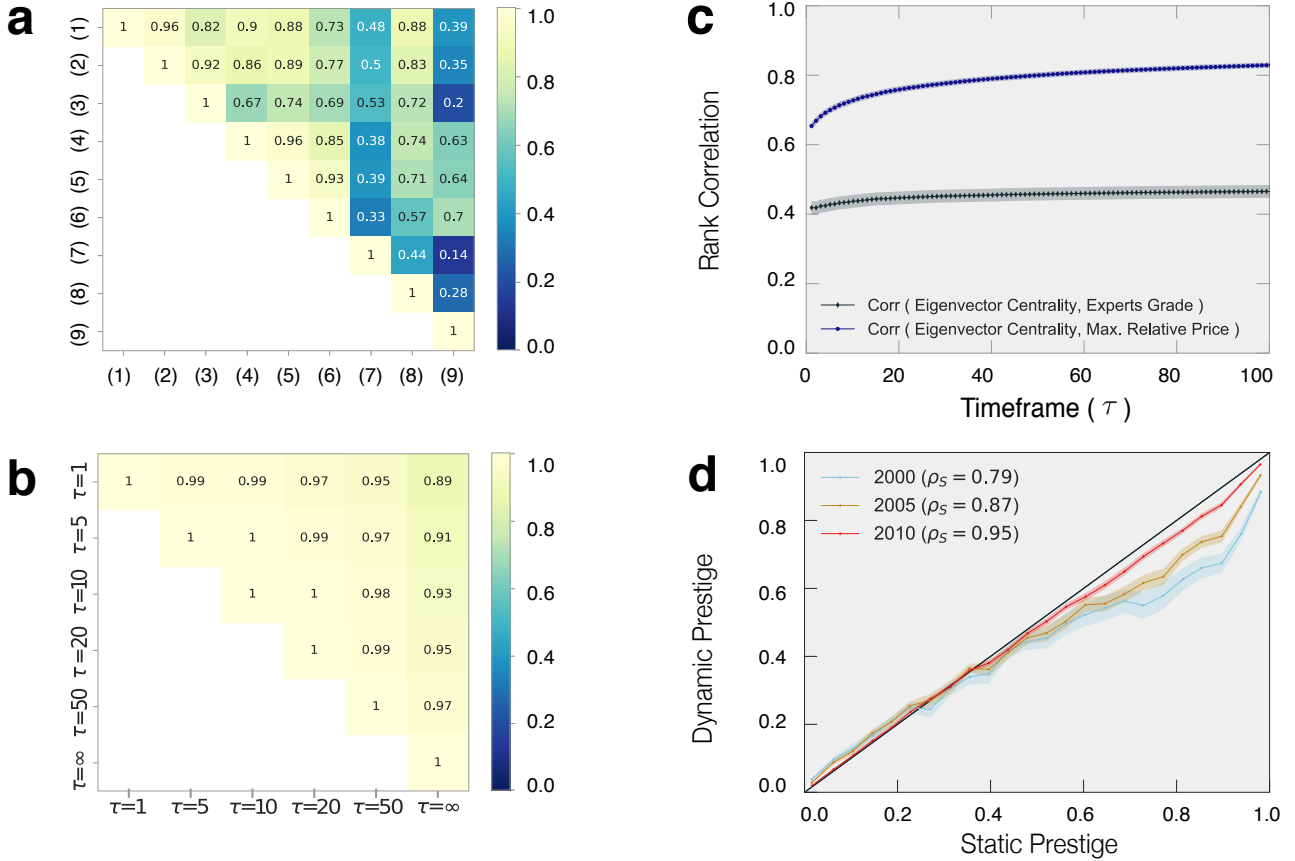
Figure S5: **Validating the Ranking of Art Institutions**: (a) Spearman correlations between alternative network-based measures of prestige calculated on the order $\tau = \infty$ network: (1) nodes eigenvector centrality (our baseline ranking), (2) nodes instrength (3) nodes Pagerank, (4) nodes eigenvector centrality computed on the reversed network, (5) nodes outstrength (6) nodes Pagerank computed on the reversed network. These network-based rankings are also compared to known measures of prestige: (7) experts grades, (8) our sales-based ranking, and (9) institutions age, showing that eigenvector centrality has the highest correlation overall. (b) Rank correlation between nodes strength, when $\tau = \{1, 5, 10, 20, 50, \infty\}$, showing high correlations across co-exhibition networks constructed at different window. (c) As a function of the network window τ, we show the rank correlation between the network ranks, the sales-based ranks (blue) and the experts grades (black), demonstrating that the order $\tau = \infty$ co-exhibition network is the best choice to compute network-based measures of prestige, as it maximizes the correlations between the network-based ranks and external prestige measures. (d) Relationship between the nodes eigenvector centrality computed using all the links of the order $\tau = \infty$ network up to 2016 ("Static Prestige"), and those computed using all the links up to a given year T={2000,2005,2010} ("Dynamic Prestige"), converting nodes eigenvector centrality into percentile. We only included institutions that had been active for at least five years at the time of ranking, showing that the prestige of institutions remains stable over time.

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1 MoMA - Museum of Modern Art
2 Guggenheim
3 Gagosian Gallery
4 Pace Gallery
5 Museo Nacional Centro de Arte Reina Sofía
6 Whitney Museum of American Art
7 Galerie Boisserée
8 Centre Pompidou
9 MET - Metropolitan Museum of Art
10 The Art Institute of Chicago
11 Fondation Beyeler
12 Richard Gray Gallery
13 Neue Nationalgalerie
14 Galerie Thaddaeus Ropac
15 MUMOK
16 The National Gallery of Art
17 LACMA - Los Angeles County Museum of Art
18 Galerie Thomas
19 Leo Castelli
20 ZKM Museum of Contemporary Art
21 David Zwirner
22 Galerie Ludorff
23 Kunsthaus Zürich
24 MOCA
25 Kunstmuseum Liechtenstein
26 Hauser & Wirth
27 Galerie St. Etienne
28 Kunstmuseum Basel
29 Museum der Moderne Rupertinum
30 MARTa Herford
31 Mnuchin Gallery
32 Berggruen Gallery
33 Walker Art Center
34 Barcelona Museum of Contemporary Art
35 Museo Thyssen-Bornemisza
36 Skarstedt Gallery
37 Paula Cooper Gallery
38 The Menil Collection
39 Houston MFAH
40 Galerie Gmurzynska
41 Hamburger Kunsthalle
42 MoMA PS1
43 Acquavella Galleries
44 Martin-Gropius-Bau
45 Marlborough Gallery
46 Haus der Kunst
47 MCA Chicago
48 Staatsgalerie Stuttgart
49 Philadelphia Museum of Art
50 Lévy Gorvy
51 Musée d'art contemporain de Montréal
52 Stedelijk Museum
53 Matthew Marks Gallery
54 Kunst- und Ausstellungshalle der Bundesrepublik Deutschland
55 Hamburger Bahnhof
56 Albertina
57 MART- Museo d'Arte Moderna e Contemporanea di Trento e Rovereto
58 Museum of Fine Arts Boston
59 Museum of Contemporary Art (MCA)
60 Fondation Maeght
61 Galerie Lelong
62 Marian Goodman Gallery
63 Moderna Museet
64 Albright-Knox Art Gallery
65 Sprengel Museum Hannover
66 The Getty Center
67 Lentos Kunstmuseum Linz
68 Indianapolis Museum of Art
69 Tate Modern
70 Fundación Joan Miró
71 La Maison Rouge
72 Kunstsammlung NRW
73 Museo Picasso Malaga
74 Serralves Museum
75 Contemporary Arts Museum Houston
76 Michael Rosenfeld Gallery
77 Waddington Custot Galleries
78 National Museum of Modern Art Tokyo
79 Paul Kasmin Gallery
80 Museum Folkwang
81 Dickinson
82 Pinakothek der Moderne
83 Dallas Museum of Art
84 CAPC - Musée d'art contemporain
85 Hammer Museum
86 Museum Kunstpalast
87 Schirn Kunsthalle
88 Museum Ludwig
89 Van Abbemuseum
90 Louisiana Museum of Modern Art
91 Gallerie Karstern Greve
92 Andrea Rosen Gallery
93 Royal Academy of Arts
94 White Cube
95 Cheim & Read
96 Grand Palais
97 Sperone Westwater
98 Kunsthalle Duesseldorf
99 Francois Pinault Foundation
100 Whitechapel Gallery

Figure S6: **Ranking of Art Institutions**: A list of the 100 most prestigious institutions according to their network ranks.
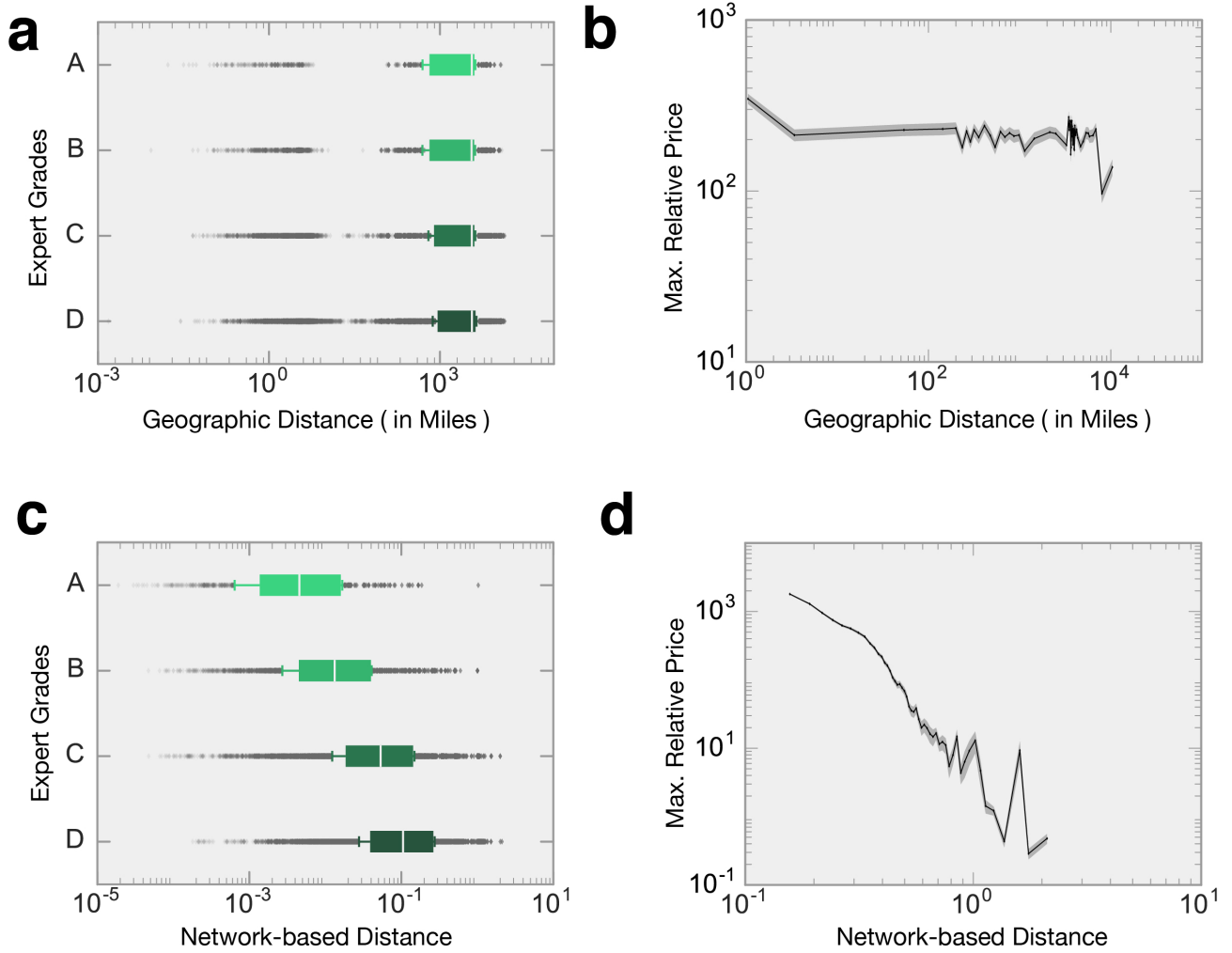
Figure S7: Network-based Distances and Geographic Distances: (a) Box-and-whisker plot showing institutions grade as a function of their geographic distance to the top ten institutions, showing no relationship. (b) Institutions maximum relative price as a function of their geographic distance to the top ten institutions, showing no relationship. (c) Box-and-whisker plot showing institutions grade as a function of their network-based distance to the top ten institutions, showing a strong relationship. (d) Institutions maximum relative price as a function of their network-based distance to the top ten institutions, showing a strong relationship. The network-based distance between two institutions is defined as the shortest path length between them, the cost of traveling on a link being equal to the inverse of the link's weight. Distance are computed on the order $\tau = \infty$ network. In the box-and-whisker plots (a) and (c), the whiskers correspond to 5% of observations below (above) and the low (high) quartiles. In the conditional mean plots (b) and (d), the shaded areas correspond to the standard error around the mean taken after binning the data in 50 intervals of equal mass.
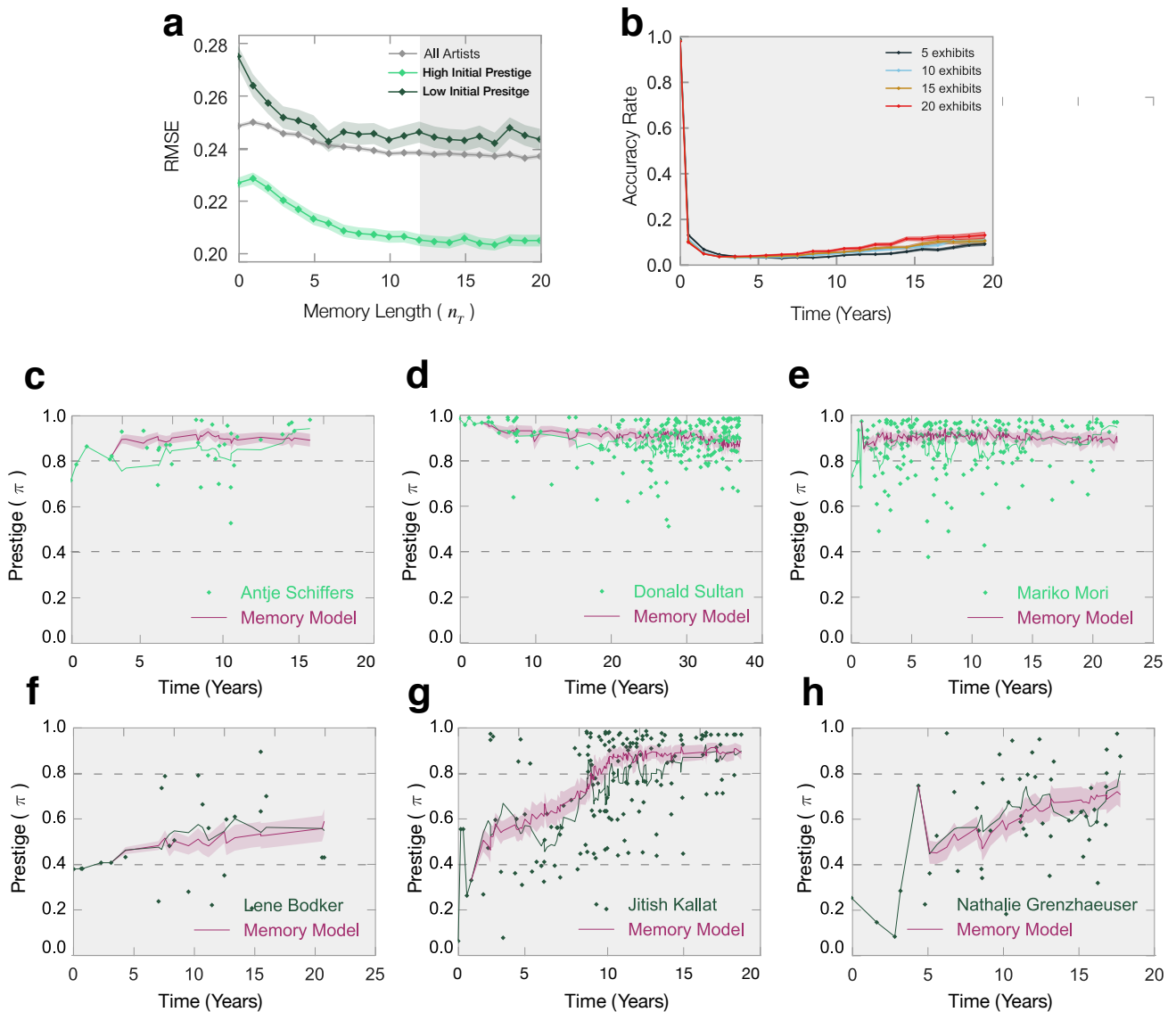
Figure S8: Measuring the Model's Fit: (a) Root Mean Square Error (RMSE) of artists exhibitions prestige as a function of the memory model's memory length n_τ. A memory length equal to zero corresponds to the memoryless case. The RMSE is computed for each artist, then averaged across artists in each group, showing that the model's fit improves until a memory length of $n_\tau = 12$ exhibits, after which there is no more improvement. (b) Fraction of institutions in which artists actually exhibited over time, when the model is initialized using $\tau = \{5, 10, 15, 20\}$ exhibits. To compare the different cases, we set time (x-axis) to start when the latest observed exhibit occurred in each case, demonstrating that the model's ability to predict the specific institutions that exhibit an artist during his career does not improve with the number of initial exhibits observed. For three high initial reputation (c-e) and three low initial reputation (f-h) artists, we report the observed prestige of its exhibit (dots) and its moving average (full line). We also simulated 100 trajectories using the memory model, using as input the artist first five exhibits only. We report the mean and standard error across the 100 trajectories (purple). Each panel (c-h) illustrates that the memory model accurately predicts the trajectory trends of individual artists.
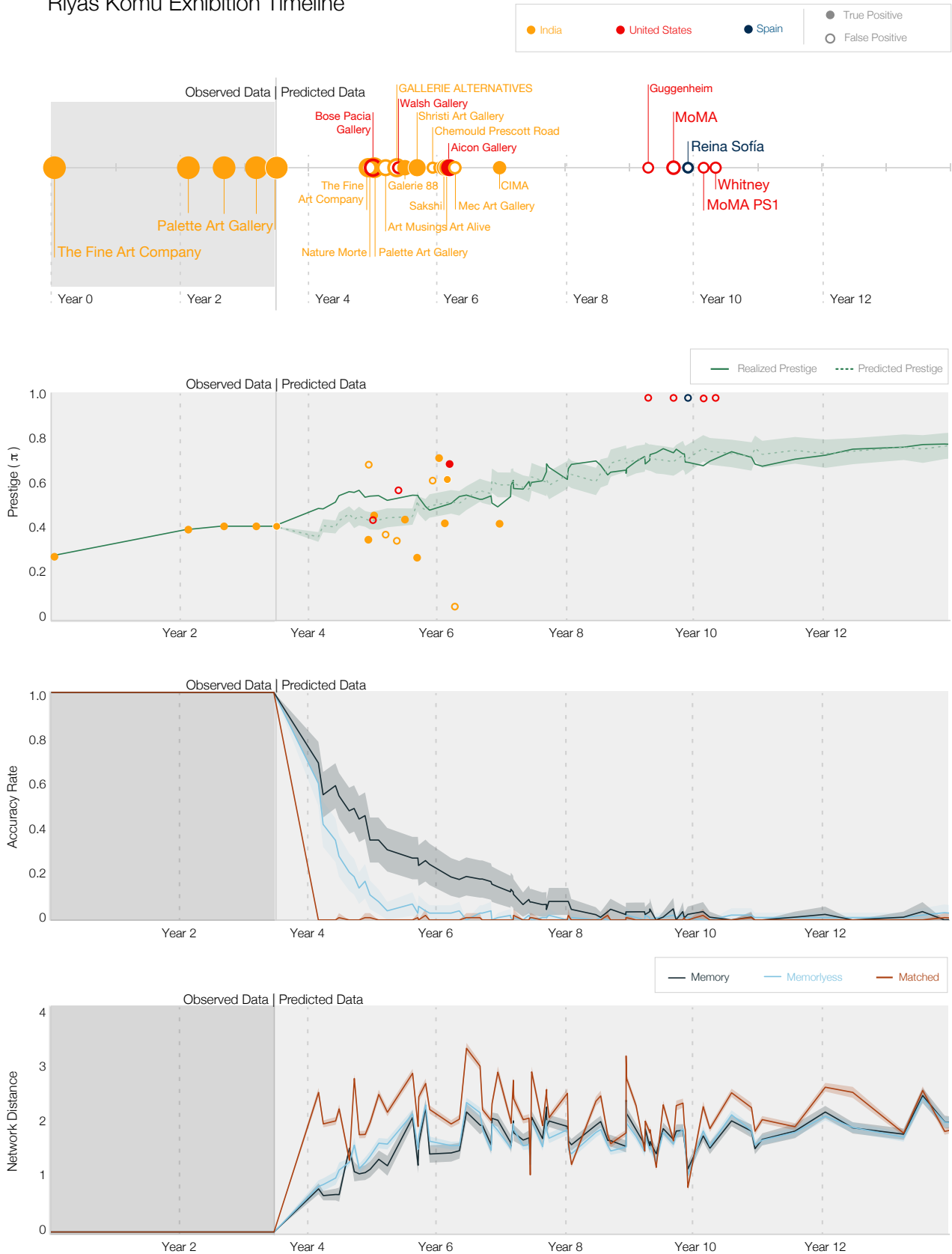
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Figure S9: **Model Mechanism**: (a) Timeline of Riyas Komu exhibits, showing the institutions occurring more than 10% of the time across simulations. Dots size is proportional to the log frequency of their occurrence across simulations. Filled dots corresponds to institutions in which the artist actually exhibited. (b) Evolution of her exhibition prestige across 100 simulations (shaded line) and in the data (full line). Dots show the subset of institutions from panel a. (c) Fraction of institutions in which the artists actually exhibited across simulations. (d) Network distance (defined as the shortest path length on the $\tau = 1$ network) between the simulated institutions and the actual ones. In the "matched" model, we simulate artists trajectory so that their prestige is within 5% of the actual prestige.
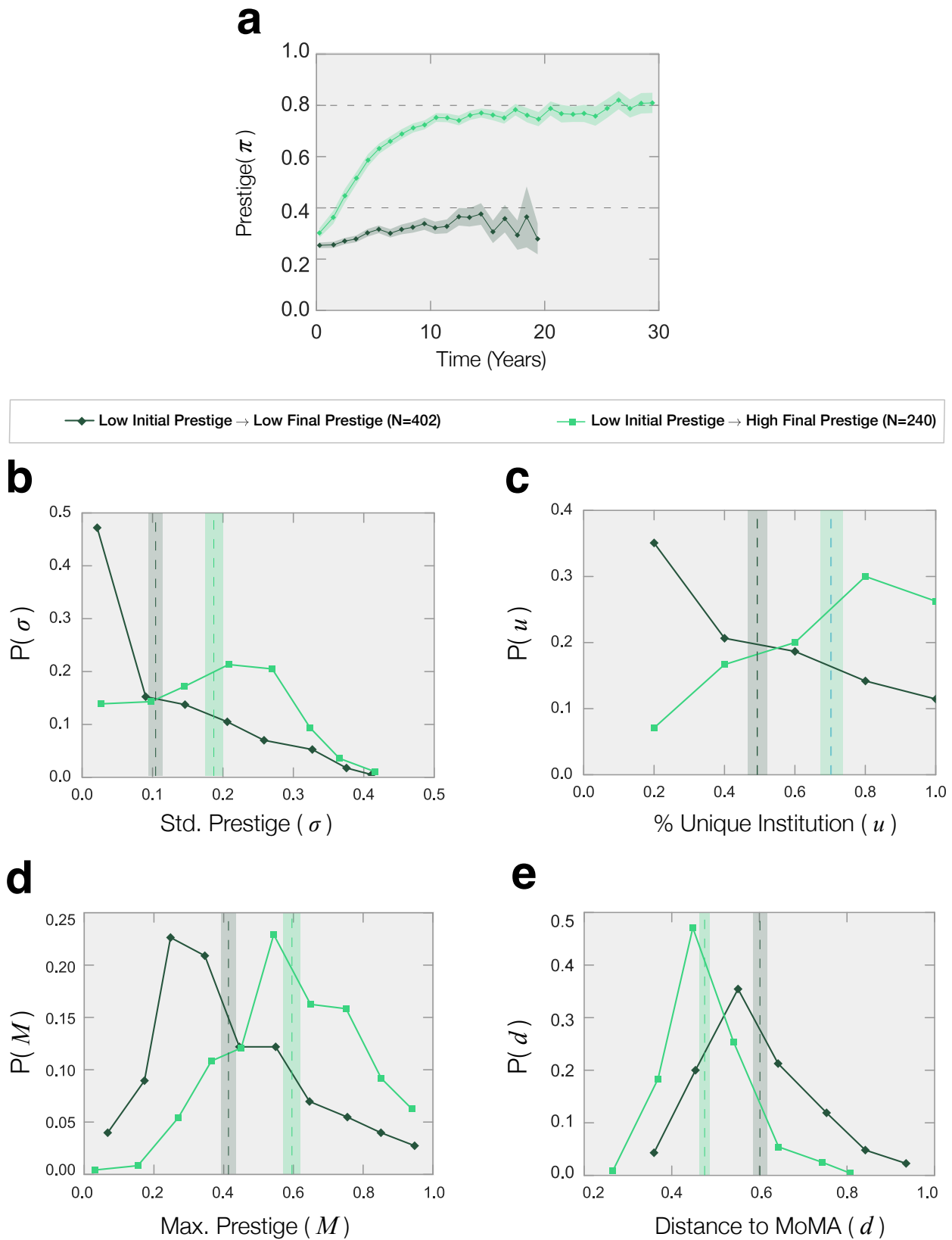
Figure S10: **Breaking Through**: We explored the career of 240 low initial reputation artists whose final exhibits are in high prestige institutions (light blue), comparing them to the 402 low initial reputation artists whose final exhibits are in low prestige institutions (dark blue). (a) Artists exhibitions prestige over time. (b) Empirical probability density function of prestige standard deviations during artists first five exhibits. (c) Empirical probability density function of the percentage of distinct institutions at which artists exhibit during their first five exhibits. (d) Empirical probability density function of the maximum exhibition prestige during artists first five exhibits. (e) Empirical probability density function of the average network distance of institutions to MoMA during artists first five exhibits. Each panel (b-e) shows factors that allow us to distinguish between low initial reputation artists who will break through from those who won't.

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