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University digital media co-occurrence networks reveal structure and dynamics of brand visibility in the attention economy

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As universities compete for visibility to attract student enrollment and build scientific reputation, the management of institution of higher education (IHE) brand has emerged as an important strategic endeavor. Yet our understanding of the factors that condition the structure and dynamics of brand stratification within regional IHE ecosystems is limited. Instead, our best approximation for brand equity derives from widespread IHE rankings, which lack contextual and relational features for understanding the patterns of engagement in the fast-moving attention economy, and in particular how institutional partnerships can generate brand equity by leveraging ecosystem network effects. To this end, here we develop a framework for measuring two dimensions of brand equity, namely visibility, and association, according to the frequency of digital media articles featuring a university's official name. We demonstrate this approach for 29 universities in California and Texas based upon 2 million media articles published between 2000 and 2020 and validate our approach by correlating university digital media visibility with ARWU Shanghai rankings and freshman enrollment growth. As roughly 10% of the article sample features >1 university, longitudinal analysis of institutional co-occurrence reveals the extent to which brand association stratifies according to regional proximity, institutional specialization, and prestige. Interestingly, despite the shared value generated from media co-visibility, the frequency of multi-university media articles has declined over time, which we attribute to paradigm shifts in media content production following the 2007–08 financial crisis and the COVID-19 infodemic, in addition to increased competitiveness of the attention economy. Topic classification of media article titles shows how specialized institutions may strategically manage their brand equity by aligning content production with dominant media topics to reinforce brand visibility with broader social, technological, and environmental narratives.

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Introduction

The modern research university is situated at the intersection of education, research, public service and public investment (Kenney and Mowery, 2014; Kirp, 2003; Owen-Smith, 2018; Petersen and Montaño Ramirez, 2025; Rouse, 2016), which requires the brand management of institutions of higher education (IHE) to extend across multiple sectors (e.g., research, athletics, real estate). Consequently, IHE brand management generates commensurate operational costs associated with student, faculty, and donor recruitment, along with the management of accumulated human, intellectual, and infrastructure capital, which together manifest as premiums in faculty salary and student enrollment costs, among others (Altbach, 2012; Rouse, 2016; Rouse et al., 2018; Stephan, 2012).

In this way, institutional brand is an increasingly fundamental pillar of the academic enterprise (Kirp, 2003), placing increased focus on brand visibility and co-visibility (Aaker, 1991; Newmeyer et al., 2018; Ramadan, 2019) within the broader attention economy (Brossard, 2013; Brynjolfsson and Oh, 2012; Ciampaglia et al., 2015; Drèze and Zufryden, 2004; Goldhaber, 1997; Simon et al., 1971; Smithson et al., 2011). As such, in addition to securing students, star faculty, scientific achievement, public and private funding, real estate development, sports achievement, and alumni support (Marginson, 2006, 2013; Rouse, 2016; Rouse et al., 2018), the competitiveness of IHE increasingly depends on producing digital web-based content and tracking the attention it receives across the vast media ecosystem.

The importance of brand visibility has proliferated in the attention economy emerging across both the internet and social media platforms, which are invaluable resources for identifying IHE mission and values, for showcasing student achievements and research outcomes, and for highlighting the differentiating factors vis-a-vis competitors (Ballantyne et al., 2006; Smithson et al., 2011). Yet there is scant literature analyzing the brand equity derived from the total print visibility of an institution's official name. While there is substantial research activity in the field of webometrics (Barnett et al., 2017; Park and Park, 2024; Thelwall, 2009) utilizing the network of hyperlinks between official institutional websites to explore the emergence of regional and global university networks (Park and Thelwall, 2006; Thelwall, 2002), we are aware of just a single study where the number of university name mentions constitutes the measure of institutional visibility (Lee and Park, 2012). Instead, an alternative proxy for IHE brand equity employed in webometrics, scientometrics, and organizational studies literature streams are global university rankings, in particular those produced by the ARWU "Shanghai", Times Higher Education, and US News & World Report (Barnett et al., 2014; Lee and Park, 2012; Marginson, 2006; Rouse, 2016).

However, there are a number of documented limitations to IHE rankings. By and large, rankings generate a flattened oversimplification of the complex ecosystem of entities and their interrelationships. Another limitation of the ranking approach is the compression of multiple attribute variables into a single composite rank, which discards substantial latent information. As such, rankings sacrifice precision for clarity, as two entities with successive rank may differ greatly, or incrementally, in their underlying score. In the present case, IHE rankings also lack consistency and transparency, as they each tend to focus on different dimensions of the IHE mission (e.g., education, research, or combinations thereof) and employ different model inputs with different weights that are not typically specified (Hazelkorn, 2009, 2015; Rouse, 2016). Several IHE rankings incorporate survey instruments that are susceptible to traditional experimental biases, including reputation bias manifesting as a reinforcement effect derived from other rankings and prestige mechanisms that inform IHE rankings (Safón, 2019; Safón and Docampo, 2020). Moreover, in the absence of comprehensive historical data on every attribute of every institution, then these approaches are susceptible to omitted variable bias and thus may miss miss critical "X" factors that explain nuanced aspects of brand equity (Safón, 2013).

To address these issues, it is essential to develop brand equity metrics that are comprehensive across institutions, and retain contextual and relational features that are useful for identifying ecosystem network effects. A candidate metric employed in the webometrics literature is the centrality of an IHE within the global network of hyperlinks that comprise the internet (Barnett et al., 2014; Lee and Park, 2012; Ortega and Aguillo, 2009). However, two large-scale studies analyzing hyperlinking between IHE across Europe conclude that the degree of hyperlinking to and from a university largely reflects institutional size, and fails to capture more nuanced aspects of reputation signaling and subjective perspective (Lepori et al., 2014; Seeber et al., 2012), which are nevertheless relevant dimensions for brand equity analytics. Moreover, the methodology to quantify the number of hyperlinks from institutional website A to institutional website B does not permit cross-temporal studies, as hyperlinks do not generally have time-stamps, and so hyperlink counts capture time-aggregated tallies thru the sampling date.

An alternative data source that does permit inter-temporal (dynamical) analysis of brand equity and association are the vast quantities of digital footprints in web-based communication and other new media sources (Ding et al., 2020; Nuortimo and Harkonen, 2019; Oh et al., 2020), which are also endowed with readily identifiable time-stamps and other contextual information (e.g., media source and background/narrative topics). To this end, we develop a framework for IHE altmetrics, analogue to those developed for research and researchers (Cronin and Sugimoto, 2014; Sugimoto et al., 2017), by analyzing the frequency and co-occurrence of IHE featured by name in digital media articles – Fig. 1a shows an example.

We apply this framework across a corpus of roughly 2 million articles published between 2000 and 2020 collected from the Media Cloud (MC) database (MC-Consortium 2024)—see the *Supplementary Information* (SI) Figs. S1 and S2. Our methodology leverages the comprehensive breadth and depth of MC data that have advanced our understanding of 'new media' content production paradigm (Roberts et al., 2021; Waisbord, 2018), the diversity of media sources and messages relating to specific topics and events (Chuang et al., 2014; Faris et al., 2017), and the structure and dynamics of media ecosystems comprised of distinct identifiable entities (Arroyave et al., 2024; Petersen et al., 2025, 2019; Wells et al., 2020). As in the latter approach, we employ exact string matching to identify individual media articles featuring official university names. This method generates a consistent measure of brand visibility, over time and across institutions. Moreover, the roughly 1 in 10 media articles that mention two or more IHE simultaneously provide novel inroads to analyzing the structure and dynamics of brand association generated within and across the two regional IHE ecosystems in California (CA) and Texas (TX) that we focus upon.

The structure and dynamics of media co-visibility networks are eluded by other metrics used to proxy IHE brand equity. As such, the framework developed in what follows can enhance our understanding of institutional hierarchies and stratification in the digital media attention economy. In particular, IHE co-occurrences in digital media supports the combination of network analytics (Barabasi, 2016) and topic-classification methods for quantifying the relational and contextual basis of brand association and alliances at high resolution. To this end, we

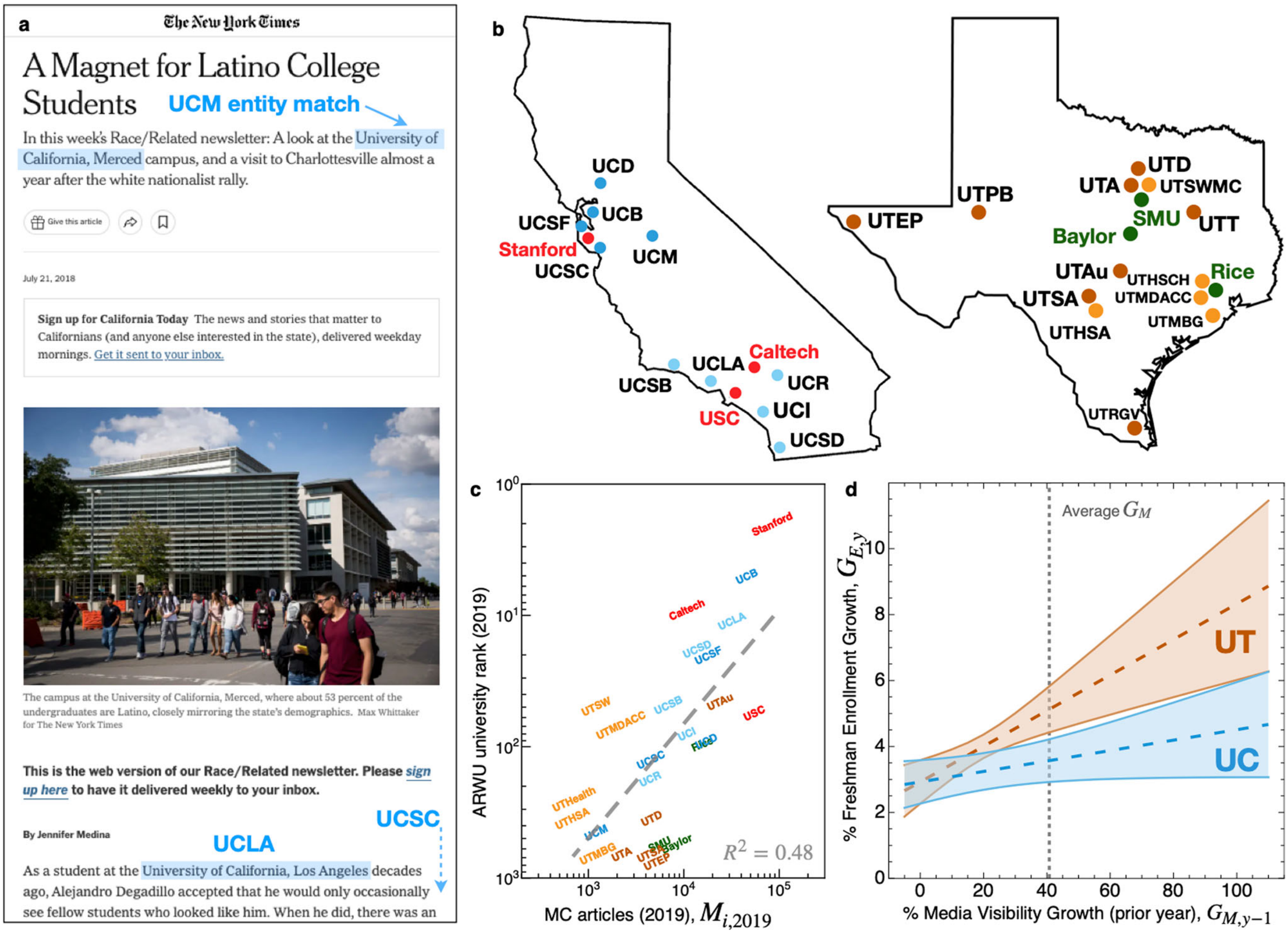

Fig. 1 Framework for institutional media visibility analytics: schematic of the data collection process and validity assessment. a Media articles obtained from Media Cloud (MC-Consortium, 2024) are identified by full-text string matches of official university name and also common abbreviations (e.g., UCLA). Shown is an example article highlighting UCM that also features UCLA and UCSC. **b** Geographic distribution University of California System: 10 universities, northern (southern) colored blue (light blue); University of Texas System: 8 research universities (brown) and 5 affiliated medical centers (yellow); regional counterparts: 6 private Carnegie R1/R2 research universities: green (Texas-TX), red (California-CA). **c** Media visibility M_i provides a consistent and granular proxy for brand equity, and is moderately correlated with extant brand equity metrics, such as the international Academic Ranking of World Universities (ARWU). **d** Marginal effects of media visibility growth on freshman enrollment growth, by multi-campus university system, as estimated using a 1-year lagged regression model implemented with institutional fixed effects specified in Eq. (2). On the aggregate, a 1% increase in media visibility correlates with a $\beta_{GM} = 0.034\%$ increase in freshman enrollment.

orient our framework analysis around the following 3 research questions (RQs):

(RQ1) Digital media altmetrics (institutional level): How do they correlate with traditional institutional metrics – namely, ARWU rankings and student enrollment trends – and what advantages do they entail?

(RQ2) Media co-visibility network structure (systems level): To what degree do brand association networks reflect assortative factors (prestige, geographic proximity and topical narrative)?

(RQ3) Topical dynamics (event-history level): How robust are brand association networks over time, and to what degree are they augmented by exogenous systemic shocks to the attention economy?

Results provide inroads for the institutional assessment of media visibility, and can inform marketing strategies for student enrollment and retention from the perspectives of brand trust and loyalty (Rasoolimanesh et al., 2024; Vander Schee, 2010). Co-occurrence analysis further advances our understanding of brand equity that is co-produced by association when two or more institutions are co-mentioned (Newmeyer et al., 2018; Ramadan, 2019), which is relevant to measuring the value of 'brand alliances' within the context of multi-campus university systems (MUS) (Petersen and Montaño Ramirez, 2025).

Background and motivation

The IHE attention economy – what's in a name? As the cost of media content production and distribution decreased with the advent of the web, institutions have become steeped in competition for the attention of the masses (Goldhaber, 1997; Simon et al., 1971). However, the associated attention and brand equity deriving from institutional signatures have traditionally been challenging to quantify.

Prior work in the field of webometrics has elucidated the structure of institutional affiliations by analyzing hyperlink networks (Lee and Park, 2012; Ortega et al., 2008; Ortega and Aguillo, 2009; Park and Thelwall, 2006; Thelwall, 2002; Thelwall and Zuccala, 2008), associated variants such as URL and web citations (Barnett et al., 2014; Kretschmer et al., 2007), and individual IHE name mentions occurring in web text (Lee and Park, 2012) (which is the most similar to the methodology employed here). Together, these complementary methodologies have supported the application of network science methods (Barabasi, 2016) to elucidate the structure of international networks of IHE, as well as identify the relative strengh of geographic, institutional, academic, and other social factors that contribute to the overall connectivity between webpages hosted by official IHE web domains (Kretschmer et al., 2007; Lepori et al., 2014; Seeber et al., 2012).

Yet advances in Web 2.0 (Brynjolfsson and Oh, 2012) and text analysis methods in marketing research (Berger et al., 2022; Büschken and Allenby, 2016; ElKattan et al., 2023; Mathew, 2024) have fostered new opportunities for mapping both the demand and supply side of the attention economy emerging around the deluge of web-based new media (Ciampaglia et al., 2015; Drèze and Zufryden, 2004; Lazer et al., 2009; Smithson et al., 2011). In this regard, we leverage the precise publication timestamps, the diversity of independent media sources, and the broad range of narrative topics inferred from digital media article titles. These data features facilitate analyzing the evolution of the IHE ecosystem, and correlating the dynamical structure of brand co-visibility with the dynamic undercurrent of media narratives. As such, our framework supports simultaneously analyzing two distinct dimensions of brand equity that are promoted in media communications – namely, institutional visibility and association.

A related paradigm is how institutions increasingly seek data-driven opportunities for holistic self-assessment to guide strategic decision making. The development of consistent and highly generalizable measures of brand equity may offer new ways for IHE (here encompassing traditional universities, as well institutions more focused on education or research) to compete for valuable resources that are auxiliary to the core education and research missions, thereby conferring dynamic capabilities for maneuvering in turbulent environments (Eisenhardt and Martin, 2000; Teece, 2007). For this reason, IHE invest substantial resources into external relations departments (e.g., https://www.ucop.edu/external-relations-communications/index.html) to manage the ecosystem of interacting yet distinct enterprises (education, research, public service and public/private investment, health care provision, government relations, and legislative lobbying) that constitute the broad scope of the modern IHE (Kirp, 2003; Rouse, 2016).

Widespread university ranking systems – such as the ARWU "Shanghai", Times Higher Education, and US News & World Report—represent distinct arenas where IHE brand, values, and achievements are distilled into a summary score and rank associated with the official institutional name. Such rankings reinforce perceptions of relative brand equity because individuals naturally associate institutions of similar rank. Consequently, IHE rankings promote university names, along with derivative and abbreviated forms, as distinct brand entities. By way of example, consider the University of California Los Angeles, which specifically encourages their abbreviation UCLA to promote their trademarked brand name (UCLA Brand website); and the University of Texas MD Anderson Center, which employs a strikethrough in official brand logos to emphasize its core mission.

In this way, universities along with medical centers and other specialized research institutes represent an institutional sector that features high levels of brand recognition associated with their official name. For this reason, journalistic standards support using the official institutional name in reporting, either because the IHE is the article's focal context, or as a reputation signal conferred upon the expert affiliate being interviewed. This brand name visibility framework readily generalizes to other organizational systems where the use of official names are normalized and can be readily disambiguated, such as US National Parks (Arroyave et al., 2024; Petersen et al., 2025).

As such, the official name of a given institution is the focal entity identified by our media visibility framework. Take for example the New York Times article titled "A Magnet for Latino College Students" (Medina, 2018) featured in Fig. 1a, which mentions three particular University of California campuses associated with the overarching context of student demographics. While the article title connotes institutional mission and values associated with a principal customer base (students), the media source connotes cultural and topical significance. Moreover, the co-mention of three universities establishes the basis for signaling similarity and differentiation that are essential inputs to student information-gathering and decision-making, while also connoting institutional membership in an overarching university system, which connotes a brand alliance in and of itself (Newmeyer et al., 2018; Ramadan, 2019).

Theoretical motivation. This work contributes to literature streams developing an organizational theory of the modern research university (Kirp, 2003; Rouse, 2016), as well as the marketing and strategy literature regarding institutional brand, identity and reputation (Aaker, 1991; Ballantyne et al., 2006). Considering the common service objectives of universities (knowledge transfer, workforce training and auxiliary experience delivery) and related destination-amenity industries, research from tourism & hospitality management on digital branding and marketing provide translatable insights (Pike and Page, 2014).

The first theoretical construct that we seek to measure is brand visibility. Prior research on small and medium-sized tourism accommodation enterprises found that online visibility correlates positively with overall competitiveness (Smithson et al., 2011). In the present context, their results suggests that democratization of new media content production has enhanced the competitiveness of smaller IHE, while extending the geographic basin of attraction for student enrollment across the entire IHE ecosystem, independent of institutional size.

Our second theoretical construct focuses on brand association, a relational concept that relies on consistently identifying instances of brand co-visibility. Explicit brand connections offer a clear strategy for promoting brand alliances that enhance and reinforce perceptions of common reputation and quality. Likewise, such alliances foster distinct opportunities for product differentiation. From the consumer perspective, brand association has the added advantage of narrowing the range of choices, thereby reducing the cognitive effort required to compare and sort competing brands when detailed information, such as product quality or pricing, is unavailable. In the present setting, these considerations predict relatively stronger brand associations within MUS, as these multi-institutions inherently connote shared educational standards, institutional mission, and values. Considering the extent to which IHE brand loyalty is promoted by college sports, legacy enrollment preferences, and alumni networks, brand association among MUS campuses fosters differentiation between campuses, while at the same time reinforces shared identity across the university system (Kato, 2021; Mills et al., 2022).

Methods

Digital media dataset construction. We developed large-scale sample of media articles produced in the news media ecosystem mentioning a specific set of universities using methods of computational social science (Ahonen, 2015; Ding et al., 2020; Lazer et al., 2009; Oh et al., 2020) applied to the science of science

(Fortunato et al., 2018). Primary source data were collected from the Media Cloud (MC) project (MC-Consortium, 2024) open application programming interface (API), which provides access to a database of digital media articles accessible via the web (representing news articles, blog posts and other web content). Since its inception in 2008, this valuable open resource has supported over 88 published studies—see https://www.mediacloud.org/research.

The breadth of the MC project is vast, web-crawling at a rate of roughly 1 million stories per day and reaching a size of > 1.7 billion searchable items as of 2021 (Roberts et al., 2021). As such, MC provides a comprehensive supply-side representation of the digital media attention economy. Notably, due to copyright restrictions, MC does not supply full article text, but instead provides granular article-level metadata. As such, we collected university-specific records by querying the MC API using each institution's official name, e.g., "University of California Los Angeles"; moreover, for the most prominent institutions, we also merged records obtained using their official abbreviations (e.g., UCLA, Cal Berkeley, MD Anderson Cancer Center). Our final data sample is comprised of roughly 2 million articles published by roughly 58 thousand media source providers (e.g., New York Times, LA Times, etc.)—see Fig. 2.

Figure 1b shows the geographic distribution of universities in our sample, which focuses upon two specific regional innovation systems (RIS) in California and Texas. These IHE were selected based upon their geographic proximity, institutional similarity and the alignment of research and education missions; see (Petersen and Montaño Ramirez, 2025) for further details regarding IHE sample selection. The 29 IHE belong to three subgroups (including two MUS): the University of California (UC; comprised of 10 public campuses); the University of Texas (UT; comprised of 13 public campuses and affiliated health science centers); and 6 prestigious private universities (3 in CA and 3 in TX). Notably, the UT is comprised of a 8-campus multi-disciplinary university system alongside a 5-campus system of specialized biomedical and health science centers.

Metrics for brand visibility & brand association. The total number of media articles from year y that feature IHE i provides a consistent and granular measure of brand visibility, which we denote by $M_{i,y}$. In what follows, we leverage four types of primary source metadata available for each MC article (denoted by the index a):

1. the article title, T_a;
2. the publication date (defining the year y_a and month m_a);
3. the media source s_a publishing the article (e.g., New York Times, Washington Post);
4. article-level tags (e_a) useful for identifying granular article entities ("Obama", "Supreme Court") and themes (e.g., "medicine and health", "research"); note that these tags are not uniformly provided (only 18% of articles in our sample have tags).

To exhibit the variation in media source audience and orientation, we manually separated the set of s into three non-overlapping subsets corresponding to: (a) large regional and national mainstream media (MM30); (b) local mainstream media associated with specific cities and metropolitan areas; (c) and other, corresponding to new media sources associated with websites, blogs and content aggregators. Notably, sources belonging to the MM30 and other sources are the most prominent content producers, characteristic of the modern web-based news media ecosystem designed for scale via the democratization of content production and the reduction of editorial oversight (Petersen et al., 2019). Figure 2c indicates relatively small variation in the fraction f_i^{MM} of an institution's total media visibility that is featured in the MM30, and for this reason we aggregate all media sources in what follows.

Each instance of an identifiable brand name represents a salient pointer that information consumers can instantaneously follow or bookmark for follow-up (Drèze and Zufryden, 2004; Smithson et al., 2011). On the aggregate, these instances represent the total number of pointers to the brand. Compared to alternative web-presence metrics such as hyperlink counts, IHE name visibility shares certain features. In particular, both approaches rely on unique non-ambiguous identifiers that can be readily tabulated by web search algorithms and web-crawlers (Ortega and Aguillo, 2009; Thelwall, 2002; Thelwall and Zuccala, 2008). However, by construction, the actual hyperlink is often obscured by the HTML anchor text, such that the IHE affiliated with the hyperlink is not obvious to a human reader. Moreover, even if the human reader inspects the specific domain name associated with the hyperlink, the particular IHE may not be inferable. For example, the domain www.mdanderson.org does not specifically connote the parent UT affiliation, whereas https://uthscsa.edu/ does.

Thus, explicit instances of the IHE name in legible digital media are more relevant to brand marketing analytics, as they offer granular instances of how the brand is situated, perceived, and associated. Because official brand names are promoted and reinforced by the parent institution, they can be automatically identified, and are thus countable. As such, similar to hyperlink metrics, they reinforce web-search algorithms that sort and recommend results according to perceived relevance and salience of the brand entity. Compared to the information codified by hyperlinks between institutional websites, brand associations formed through digital media co-visibility differ in two additional aspects. First, digital media are likely to span a broader contextual background, as their production is not limited by institutional guidelines on content relevance, sentiment, or timeliness; and also, digital media are generated by diverse sources, whereas hyperlinks embedded in institutional websites are generated by select institutional representatives. Second, digital media articles include a publication timestamp, often at the daily time resolution, whereas hyperlinks lack this precision. This difference emerges because web page metadata tends to record when the page was first created or last updated, making it challenging to determine precisely when a hyperlink was added. In light of these distinctions, we analyze the total number of media articles from year y that feature the official name of IHE i, which provides a consistent and granular measure of a brand's media visibility, denoted by $M_{i,y}$.

Similarly, it follows that brand association can be proxied by the co-visibility of two brand names, such that one brand entity reinforces the pointer to a coincident brand entity. We explored the feasibility of this definition by analyzing the frequency of media articles featuring N_u universities. Results indicate that the probability distribution $P(N_u)$ follows an extremely right-skewed Zipf distribution: 89% of articles feature just one university; 8.5% feature 2 universities; and 2.1% featuring 3 or more universities. Interestingly, while the nominal rate of multi-university articles featuring $N_u \geq 2$ has grown exponentially over the sample period, the percentage of articles that are multi-university has fallen roughly in half from 20% in 2000 to 10% in 2020—see Fig. S3.

Given that the majority of articles with $N_u \geq 2$ feature $N_u = 2$ institutions, we employ a pairwise (dyadic) measure of brand association. Specifically, we use the Jaccard similarity index given by

$$J_{ij,y} = \frac{C_{ij,y}}{M_{i,y} + M_{j,y} - C_{ij,y}} \in [0, 1]. \quad (1)$$

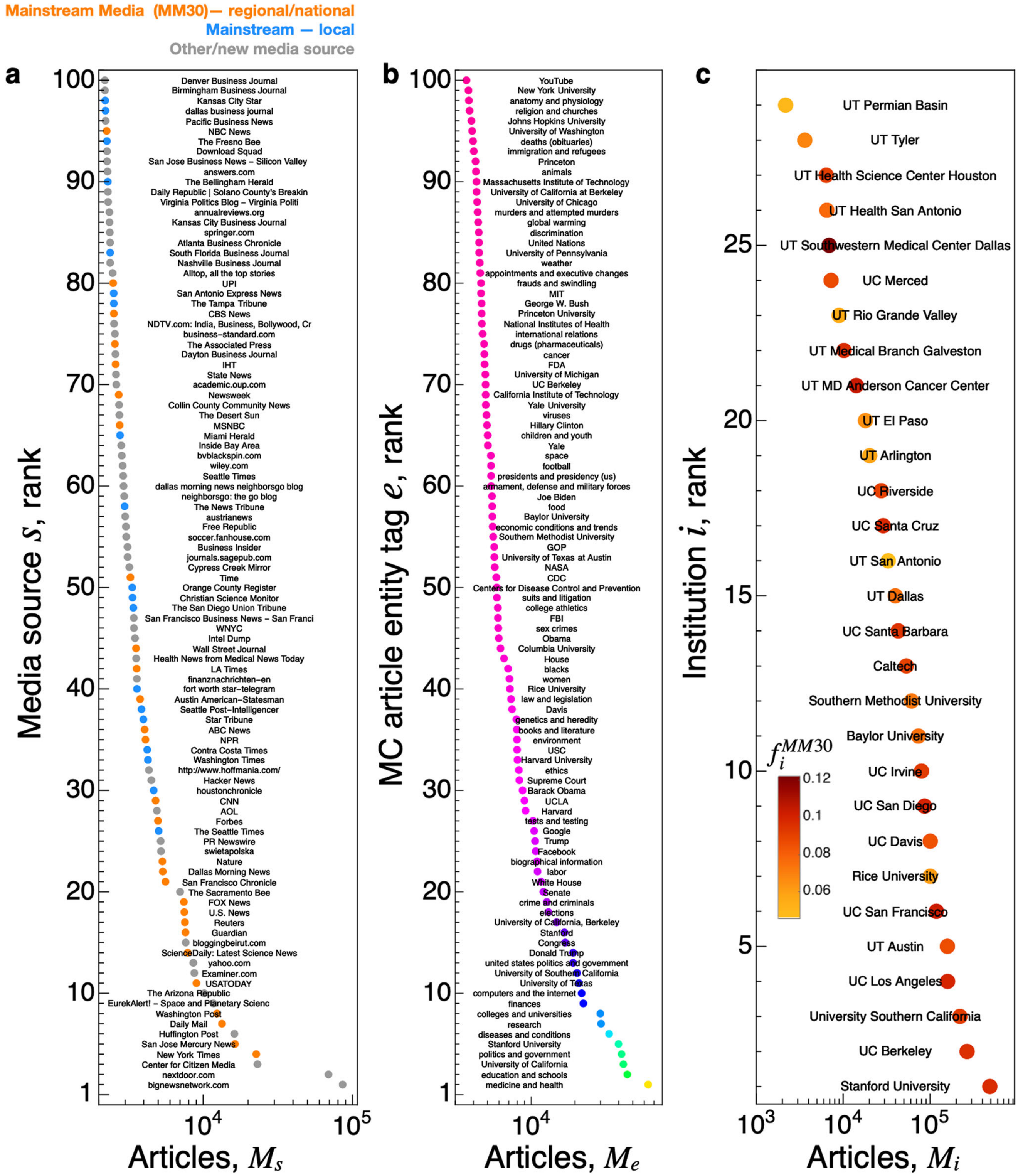

Fig. 2 Institutional and contextual distribution of IHE media visibility. Descriptive statistics including media source, Media Cloud entity tags, and total IHE media visibility. **a** The top-100 media sources ranked according to article count, M_s. Colors indicate media source group: 30 select regional/national mainstream media sources (MM30, orange); local mainstream media (blue); other (gray). **b** Media Cloud annotates articles by entity tags identifying distinct entities and topic categories. Shown are the top-100 entities ranked according to the article count, M_e. **c** Institutions ranked according to the total number of media articles M_i featuring each institution i over 2000–2020. Each data point is shaded according to the fraction f_i^{MM30} of the M_i articles that were published by mainstream MM30 sources indicated in (**a**).

where $C_{ij,y}$ is the number of media articles where institutions i and j are co-visible in a given time period y. Importantly, J_{ij} is bounded and intensive, as it accounts for both secular growth in news media content production over time, as well as the wide variation in M_i across IHE – see Figs. S1 and S2, respectively. The standardization of the metric serves as a critical methodological safeguard, particularly in intertemporal studies spanning significant time periods (Petersen et al., 2018); see (Montaño Ramirez and Petersen, 2025; Petersen et al., 2025; Petersen and Montaño Ramirez, 2025) for similar systems integration analyses implementing the Jaccard index to address co-production inflation. We further validate this choice of pairwise metric by way of unsupervised network clustering algorithm that reproduces the expected institutional stratification within and across regions. For example, the maximum $C_{ij,y}$ observed between two institutions over our entire sample period is between Stanford University and UC Berkeley, featured together in $C_{ij,2000-2020} =$ 25, 747 media articles corresponding to $100 \times J_{ij,2000-2020} = 3.5\%$ of their combined media visibility – see Fig. S2.

Validity assessment: enrollment growth and media visibility regression model. To demonstrate the validity of $M_{i,y}$ as a measure of brand equity in relevant use case setting, we analyzed its relation to freshman enrollment, $E_{i,y}$, at each of the 17 undergraduate-serving campuses in the UC and UT systems using publicly-available enrollment data provided by each system over the period 2013–2021. To avoid confounding effects of secular growth, we estimate the relationship between media visibility growth $G_{M,i,y} = 100(M_{i,y} - M_{i,y-1})/M_{i,y-1}$ and undergraduate enrollment growth, $G_{E,i,y} = 100(E_{i,y} - E_{i,y-1})/E_{i,y-1}$, while also accounting for other university and system-level covariates by way of a hierarchical model specification implemented with institutional fixed effects. Our model specification is as follows,

$$G_{E,i,y} = \beta_i + \beta_{GM} G_{M,i,y-1} + \beta_E \ln E_{i,y-1} + \gamma_y + \epsilon_i \tag{2}$$

which employs a 1-year lag between dependent and independent variables.

Topic classification of media article titles. To identify a consistent set of narrative contexts that correlate with brand co-visibility, we applied a pre-trained machine learning text classifier to each article title, T_a. The topic classifier is available in *Mathematica* software, and was trained on a corpus of Facebook posts, which are of similar length and contextual density as article titles and other abbreviated text sources used in marketing, such as customer reviews (Berger et al., 2022; Büschken and Allenby, 2016). By applying this classifier to each T_a, we consistently identify broad topic categories associated with each article.

See the SI Appendix *Extended Methods* and Fig. S4 for more details regarding: the data collection process using the Media Cloud API; Media article disambiguation, in effect to merge articles with the same title from the same media source that have multiple instances with distinct web addresses; the topic classification of article titles.

Results

Validity of media visibility as a proxy for brand equity. It is reasonable to expect that different measures of brand equity, such as visibility and institutional rankings reflect common sortings (Drèze and Zufryden, 2004; Rouse, 2016; Smithson et al., 2011). Hence, as a first consistency check, Fig. 1c correlates the media visibility in 2019 with university rankings from the same year. Results show that media visibility explains 48% of the variation in the research-oriented ARWU ranking of international universities.

To further demonstrate the informational value of $M_{i,y}$ across a longer time horizon, we estimated the impact of a 1% increase in media visibility in a given year on the enrollment growth in the following academic year. This analysis is based upon a panel of the seventeen UC and UT campuses that focus on undergraduate education over the period 2013–2021. Results indicate a statistically significant and positive relationship on the aggregate, $\beta_{GM} = 0.034$, ($p = 0.026$; 95% CI $= [0.005, 0.063]$). Disaggregating the effect size by university system reveals a substantially larger coefficient for campuses belonging to the UT system—see Fig. 1d and Table S1 for the full table of regression model parameter estimates.

To summarize, for a university increasing its media visibility by the average value of $\overline{G}_M$=40.8% (which is nearly the same for each MUS), we estimate corresponding enrollment growth of 3.5% for UC campuses and 5% for UT campuses. These effect sizes highlight the significant impact that shifts in brand visibility can have on attracting visibility, student applications, and ultimately, student enrollment.

Digital media co-visibility networks reveal institutional stratification. Building on the granularity and consistency of J_{ij} as a measure of brand association, the ensemble of J_{ij} values enables a systematic analysis of the structure and stability of brand associations over time. The prominence and stability of institutional linkages are signatures of brand alliance (Newmeyer et al., 2018; Ramadan, 2019). As such, we posit that if a measure of brand association is appropriately calibrated, then system-level communities emerging from the structure of J_{ij} will reflect ground-truth associations (institutional and regional). Hence, we expect that MUS membership—a form of institutional homophily reflecting shared mission, values, resources and other characteristics – to emerge naturally from our network community analysis.

This expectation is grounded in prior literature based upon analysis of networks formed by hyper-links between webpages hosted by the IHE domain (Park and Thelwall, 2006; Thelwall, 2002; Thelwall and Zuccala, 2008). Within this context, several studies have identified geographic proximity and language as important factors explaining institutional centrality within IHE hyperlink networks (Lee and Park, 2012; Ortega et al., 2008; Ortega and Aguillo, 2009). Yet a dominant factor explaining IHE hyperlink connectivity is institutional size, which is positively moderated by institutional prestige (Barnett et al., 2014; Lepori et al., 2014; Seeber et al., 2012). Instead, our chosen relational measure, J_{ij}, mitigates biases associated with the large size variations (encountered in our sample as well as the IHE ecosystem at large) according to its very definition as an intensive quantity (a size-normalized fraction). Accordingly, this co-visibility measure is well suited to elucidate the roles of geographic proximity, institutional homophily and prestige as they manifest within and across the CA and TX regional IHE ecosystems over time.

Figure 3a exhibits the structure of the $J_{ij,2010-2020}$ matrix calculated for the 11-year period 2010–2020. The structure as well as the extreme values are highly correlated with regional proximity, as there is significant within-state co-visibility, but relatively little across-state co-visibility. This is in contradistinction to analogous research co-publication frequencies tabulated for the same set of universities, which features significant integration across the CA and TX regional innovation systems (Petersen and Montaño Ramirez, 2025). The differing rates and aggregate structure indicate that institutional competitiveness in the attention economy is largely intra-regional. This insight is further supported by our results

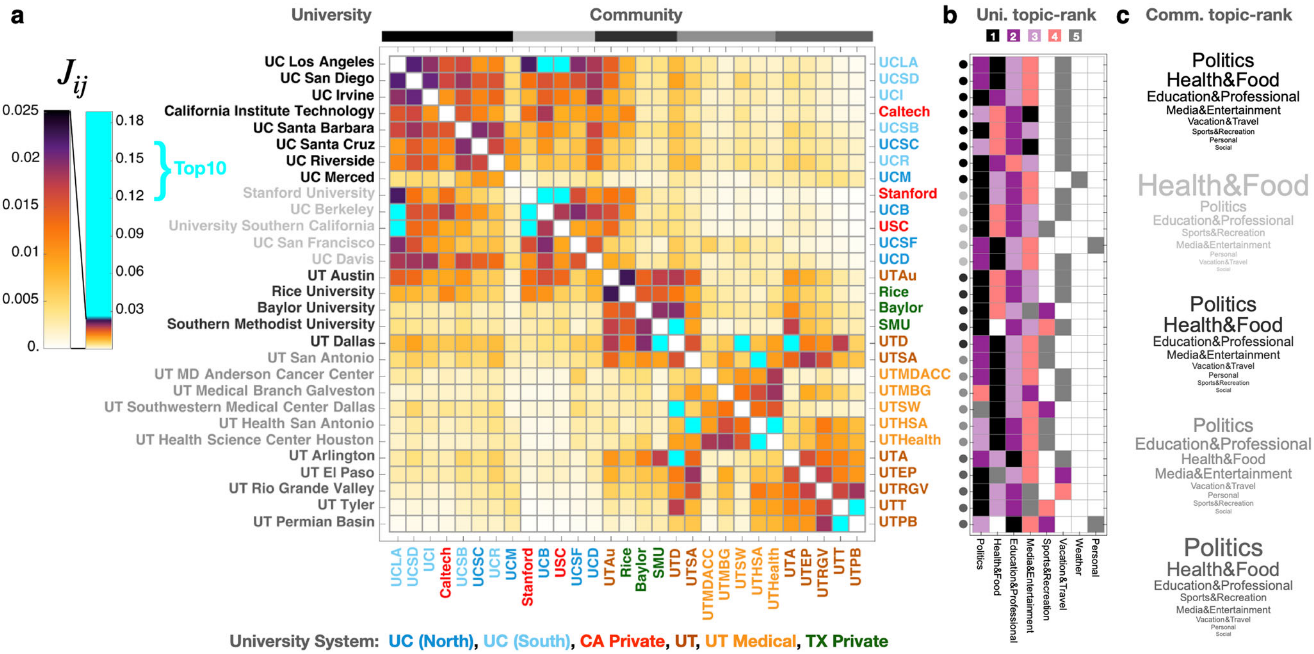

Fig. 3 Media co-visibility provides a granular proxy for brand association. The Jaccard similarity index, denoted by $J_{ij,y}$, is a quantity that measures the fraction of media articles featuring institutions *i* and *j*—see Eq. (1). **a** Shown is the full ensemble of $J_{ij,y}$ values, calculated over the period 2010–2020 and represented as a sorted matrix. Institutions are grouped according to communities identified using the Louvain modularity maximizing algorithm (Blondel et al., 2008), as indicated by the gray-scale border segments along the upper border; within each community, institutions are ordered according to their total media visibility, M_i. Community members are largely correlated according to regional proximity, institutional specialization and prestige. See the *SI Appendix* GIF for a dynamic visualization of Jaccard co-occurrence matrices at the 1-year resolution from 2000 to 2020. **b** Institution-topic matrix identifying the top-5 media article topic categories; circles on left margin indicate the community. **c** Rank-ordered topic categories for each community; each topic is sized proportional to the log frequency across all media articles associated with that university community.

showing that national and local media sources tend to feature smaller numbers of IHE in the same article—see Fig. S3.

The structure of $J_{ij,2010-2020}$ also exhibits stratification according to institutional prestige. By way of example, consider the relatively large $J_{ij,2010-2020}$ values that do extend across state lines. Those extreme values are exclusively between Rice University (and UT Austin) and other premier universities in CA. Prestige stratification is further reflected by the emergent community-level structure, which we identified by analyzing the entire ensemble of pairs in the $J_{ij,y}$ matrix. To be specific, we identified IHE communities by applying an unsupervised network clustering algorithm that identifies groups of nodes featuring statistically higher strengths of within-community links versus those that extend beyond the community (Blondel et al., 2008). The ordering of rows (columns) for $J_{ij,2010-2020}$ thereby encodes the community structure, as denoted by the gray-scale bar across the top of Fig. 3a. Also note that institutions are sorted within community according to decreasing media visibility M_i.

As such, it is notable that the strongest $J_{ij,2010-2020}$ values tend to occur in the upper-left corner of each community. This pattern is indicative of prestige sorting between the most prominent institutions, i.e., those featuring the largest media visibility, M_i. Taken together, the reproduction of geographic and institutional hierarchies captured by the $J_{ij,y}$ community structure provides a consistency check that media co-visibility is a valid measure of brand association. Results indicate that prestige and geographic proximity are important factors in California, as there is a rough split between northern and southern IHE. Similarly, role of institutional specialization appears to be dominant factors in Texas, with the UT Medical institutions forming their own community.

Institutional specialization mediates brand association. To what degree does $J_{ij,y}$ capture the alignment of specialized institutions? To address this question, we applied NLP text classification to identify the media topics associated with brand visibility and co-visibility. Figure 3b shows the 5 most common topics associated with media articles featuring each IHE. By and large, the topics are concentrated upon the *Politics*, *Health&Food* and *Education&Professional* categories. The *Health&Food* category is consistently top-ranked among the medical and health science oriented institutions.

There is also considerable variation in top-ranked categories across IHE, and even notable variation among members of the same co-visibility community. Interestingly, the first community (including UCLA) is the only community featuring a mixture of principal topics, whereas the remaining communities are highly aligned according to their principal topics. This correlation indicates that specialized institutions (i.e., IHE that are biomedical and health science oriented, including UCSF and the UT health science centers) are primed for brand co-visibility.

Co-visibility dynamics indicate paradigm shifts in media production. The volume and diversity of content produced in the attention economy has grown by over two orders of magnitude over our 21-year sample period, both at the aggregate and for individual universities. Yet at the same time, the co-production of brand equity has decreased on a per-article basis, as indicated by the average value of the co-visibility matrix, denoted by $\overline{J}_y$. Plotted in Fig. 4a, the characteristic pairwise frequency of any two universities being featured in the same media article has decreased from 2.6% in the period 2000–2008 to 0.9% from 2009 to 2020. Similarly, the variation in co-visibility calculated as the standard

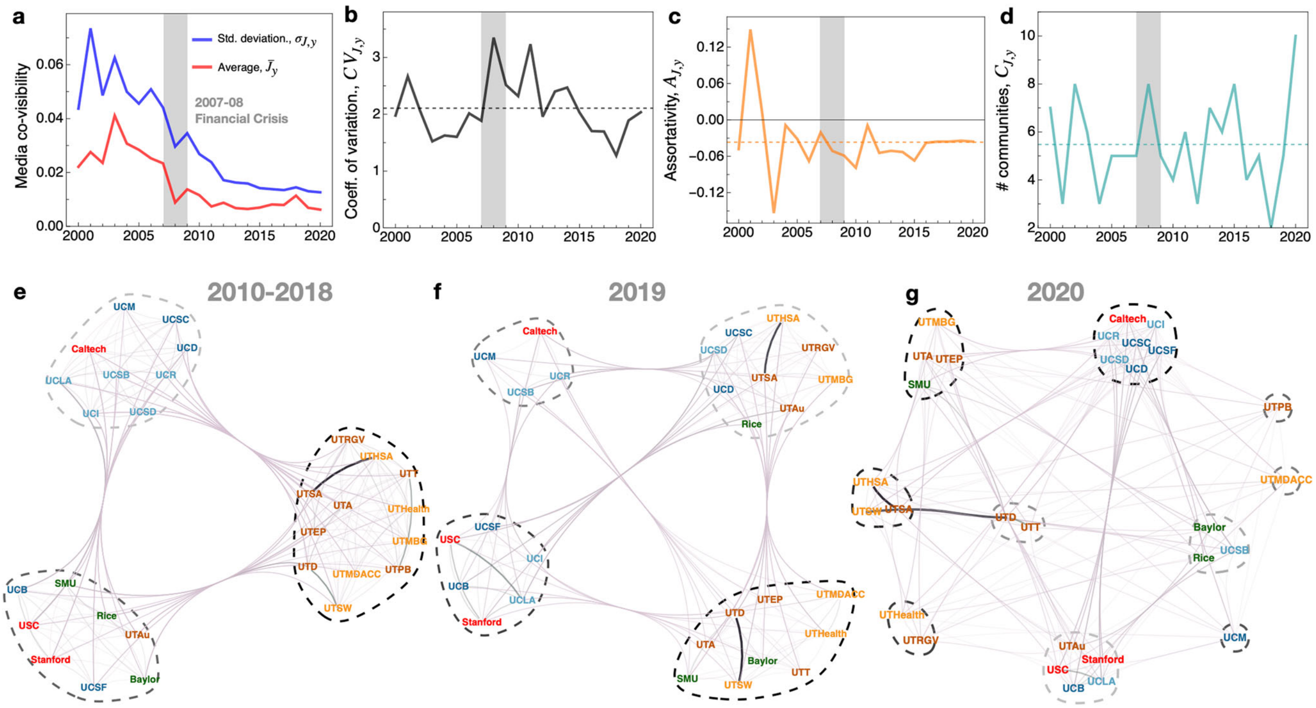

Fig. 4 Dynamics of brand co-visibility exhibit sensitivity of attention economy to exogenous shocks. Characteristic values for the $J_{ij,y}$ matrix calculated at the annual level: **a** the average $\bar{J}_y$ and standard deviation, $\sigma_{J,y}$; **b** the coefficient of variation, CV_y, which is a measure of inequality; **c** the assortativity, $A_{J,y}$, which quantifies sorting of IHE in $J_{ij,y}$, with negative values indicating disassortativity; **d** the number of communities, $C_{J,y}$. Dashed lines indicate the mean value calculated over 2000–2020. See the *SI Appendix* GIF for a dynamic visualization of $J_{ij,y}$ at the 1-year resolution from 2000 to 2020. Geography and prestige condition the **e** long-term and **f** short-term stratification of media co-visibility networks. **g** Extreme fragmentation of IHE communities during the first year of the COVID-19 pandemic.

deviation of the matrix values, denoted by $\sigma_{J,y}$, also features a steady decline.

These trends indicate that media articles increasingly tend to focus on a single university, with roughly 90% of articles in 2020 being mono-university ($N_u = 1$)—see S3e. Hence, brand equity production has become more singular over time – which is opposite of trends observed for multi-university research co-production (Petersen and Montaño Ramirez, 2025). As the frequency distribution $P(N_u)$ shifts towards smaller N_u values over time, we find this pattern to be stronger among the national and regional mainstream media sources—see Fig. S3c. This result aligns with the dynamics of an increasingly competitive attention economy, where the advantages of exclusive attention outweigh the benefits of extending reach by sharing co-visibility.

The inequality across the matrix component values also exhibits the sensitivity of the attention economy to exogenous shock. To identify variability across the IHE ecosystem, we measure structural inequality by way of the coefficient of variation $CV_{J,y} \equiv \sigma_{J,y}/\bar{J}_y$. Interestingly, we observe heightened levels of co-visibility inequality immediately following the onset of the 2007–2008 global financial crisis—see Fig. 4b. The recovery from this broad crisis extended into the long term as institutions implemented cost-savings measures well into the early 2010s. As a rapid cost-savings measure, institutions reduce marketing expenditures during significant market downturns. Consequently, many university communications departments, and legacy news reporting at large, underwent significant staff reductions (Deuze et al., 2010). In addition to workforce decline, other negative impacts include the loss of professional and institutional memory, and a diminished capacity to sustain brand value over the long term (Quelch and Jocz, 2009). Alongside this industry transformation came a surge of new media sources within the digital news ecosystem (Mitchell and Holcomb, 2016; Picard, 2014). A relatively long recovery period followed, as indicated by the $CV_{J,y}$ time series taking until 2012 to return to the full 21-year average value.

To what degree did this pervasive shock to the news media industry affect the micro-level structure of brand associations among IHE? To address this question, we calculate the assortativity of $J_{ij,y}$, denoted by $A_{J,y}$ – see Fig. 4c. This metric was designed to measure homophily among neighbors in social networks (Newman, 2002). If IHE with relatively high (low) average co-visibility tend to pair with other IHE featuring relatively high (low) co-visibility, then the $J_{ij,y}$ configuration would be characterized as assortative (corresponding to $A_{J,y} > 0$). Conversely, if IHE with relatively high (low) average co-visibility tend to pair with other IHE featuring relatively low (high) co-visibility, then the $J_{ij,y}$ configuration would be characterized as dis-assortative ($A_{J,y} < 0$).

By and large we observe robust dis-assortative sorting ($A_{J,y} < 0$), which is consistent with a separate analysis of research co-production among the same IHE (Petersen and Montaño Ramirez, 2025). In this way, IHE share micro-level structural similarities with other biological and technological systems featuring featuring $A < 0$, which are attributed to resource constraints and zero-sum interactions (Newman, 2002). Accordingly, the negative shift in assortativity after the 2007–08 crisis suggests that IHE adjusted to short-term financial constraints by prioritizing co-visibility with regional institutions.

Just as a system's structural response to exogenous shocks can be revealing, so too is the long-term structure that emerges according to more stable sorting factors. To illustrate this, Fig. 4e shows the long-term community structure that emerged during the financial crisis recovery period (2010–2018). The composition and relative stability of macro-level communities in the $J_{ij,y}$ matrix highlight the dominant influence of more time-independent factors—namely, geographic proximity, institutional homophily, and prestige. In particular, two of the three long-term communities are composed of IHE from a single region. Institutions within these communities are almost exclusively part of the region's MUS, with Caltech being the exception. The single mixed community features several of the most prestigious universities from each region, along with nearly all of the private universities. This sorting appears to be reinforced by institutional homophily, which generally reflects how shared backgrounds, attributes, values, and experiences promotes the formation of lasting in-group propensities (McPherson et al., 2001). In the present context, UC and UT multi-institutions promote institutional homophily via several channels, including employment opportunities, student admissions, and research collaboration (Petersen and Montaño Ramirez, 2025).

Yet the 3-community structure identified for $J_{ij,2010-2018}$ is not entirely representative of the inter-temporal structure, which is more fragmented. Instead, the number of communities identified per year varies around the 21-year mean (std. dev.) of 5.5 (±2.0) communities—see Fig. 4d. At this annual time resolution, we observe relatively higher levels of mixing across geographic proximity and prestige groups. Interestingly, the peak in $CV_{J,y}$ during the 2007–2008 crisis coincides with a local maxima in $C_{J,y}$, which suggests that the fragmentation of the community structure is an indicator of systemic stress. Consistent with this observation, we also observe notable fragmentation during the first year of the COVID-19 pandemic – see Fig. 4g. Unlike the 2007–2009 crisis characterized by fast reductions in financial resources available for university media communications, it is possible that fragmentation during 2020 followed altogether different mechanisms deriving from the 'infodemic' of pandemic-related content production (Gallotti et al., 2020; Gruzd et al., 2021).

Topical shifts and brand alignment during systemic crisis. Results from the previous section point to a relevant question – to what degree did the COVID-19 infodemic affect brand co-visibility? To address this question, we focus on a group of 9 IHE in CA with the largest media prominence. Figure 5 illustrates the 20 strongest links (i.e., the highest J_{ij} values, corresponding to those above the 75th percentile) as well as the topical profile for each link among this group. We show the topical profile of media articles represented by each link with a pie chart comprised of 11 article title topic categories, denoting the frequency of category c in period y by $P_{ij,y,c}$.

Comparing the non-overlapping periods 2010–2015, 2016–2019 and 2020, we note consistency in terms of the identification of the strongest 20 links, which facilitates comparative deduction. For example, visual inspection of the topical profiles between the 2010–2015 and 2016–2019 periods indicates a remarkable level of stability, with most $P_{ij,y,c}$ dominated by the *Politics*, *Health&Food* and *Education&Professional* categories, consistent with Fig. 3b, c.

The co-visibility network for 2020, however, contains systematic shifts in the topical frequencies aligning with dominant health crisis themes. To illustrate the changes, Fig. 5d conveys the percent change between the co-visibility data aggregated over the period 2016–2019 and 2020. By coloring each link according to the sign of the change, roughly half of the links feature a relative reduction in co-visibility (red), reflecting the system-level fragmentation discussed in the previous section. The topic categories responsible for this reduction were *Weather*, *Sports&Recreation* and most notably, *Education&Professional*, which experienced a −23% reduction. Contrariwise, the topics that increased their share the most were *Politics* (increasing by 20%), *Health&Food*, *Vacation&Travel* and *Personal*. Shifts in topic categories are sensitive to particularly notable research outcomes receiving widespread press. Hence, crises tend to promote institutional synergies that were primed to align with the dominant narratives of the information deluge.

Discussion

We developed a framework for representing the production-side of the attention economy, enabling the consistent and granular measurement of brand equity associated with an institution's name. Our approach leverages the distinct nature of official institutional names as readily identifiable text entities to operationalize an analysis of two aspects of brand equity – namely, *visibility* and *association*. While this work is based upon a case study of 29 universities from two select US states, our methodology readily generalizes to other IHE, regions and brand sectors. To be specific, the application of this approach relies upon: (a) unique name identifiers to avoid identification ambiguities while also supporting consistent and granular identification; and (b) data availability, consisting of a comprehensive representation of the system where the entities are mentioned, which further facilitates the robust identification of brand co-occurrences.

A principal advantage of this framework is how it can be applied to IHE independent of their prominence, thereby including both small and large universities. Accordingly, this comprehensive approach may temper a brand equity advantage for elite universities, which receive a vast majority of attention according to their status, thereby supporting self-reinforcing 'Matthew effect' competitive dynamics (Petersen et al., 2011). A more holistic approach that distinguishes educational visibility from research visibility may provide a more representative appreciation for the net impact of public universities (Oreskes, 2023), especially when considering multi-campus university systems at large (Petersen and Montaño Ramirez, 2025).

The breadth and depth of the media data also facilitates adopting a systems science perspective for understanding and comparing institutional brand equity, and thereby provides institutions a data-driven resource for evaluating and strategizing brand management (Ahonen, 2015; Amaral and Uzzi, 2007; Axelrod and Cohen, 2008; Eisenhardt and Martin, 2000; Madhavan et al. 2020; Teece 2007). Moreover, this approach opens avenues for better understanding how universities are contextualized and perceived by the public, which complements research-oriented altmetrics (Cronin and Sugimoto 2014; Sugimoto et al., 2017), hyperlink-oriented webometrics approaches (Kretschmer et al., 2007; Lee and Park, 2012; Lepori et al., 2014; Ortega et al., 2008; Ortega and Aguillo, 2009; Park and Thelwall, 2006; Seeber et al., 2012; Thelwall, 2002; Thelwall and Zuccala, 2008), and science communication studies (Brossard, 2013; Brossard and Scheufele, 2013).

This framework is subject to certain limitations. First, official institutional names can nevertheless be ambiguous (e.g., University of Miami in Florida and Miami University in Ohio), and the sampling method must be extended in notable cases to include articles using formal abbreviations (e.g., UCLA, Cal Berkeley, USC). Another limitation of the Media Cloud project is the concentration on English-based content. Nevertheless, because we are analyzing U.S. institutes of higher education, this language bias should not significantly affect our sample and analysis, but does limit extending this framework to the measurement of international brand equity. A final limitation regards the contextualization of the media articles, which is limited to inferences based upon the article title since MC does not host the full article text due to legal copyright restrictions.

In summary, our analysis provides several insights on the structure and dynamics of university brand equity (co-)

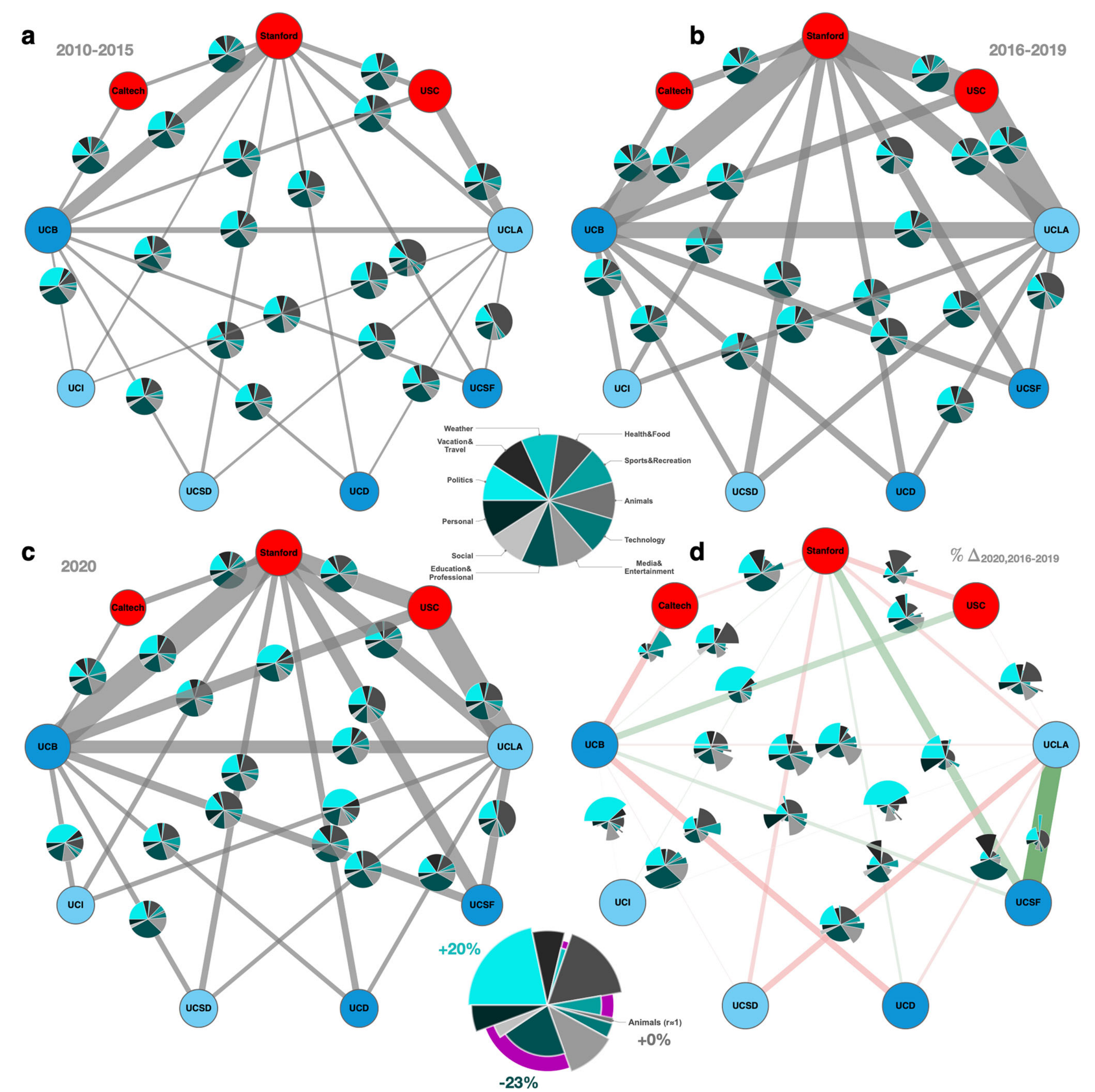

Fig. 5 Topical contextualization of media co-visibility. Each network shows a core set of 9 highly co-visible universities in CA, connected by links with thickness proportional to $J_{ij,y}$. Each link contains a pie-chart showing the article title topic category distribution $P_{ij,y,c}$ calculated for the $C_{ij,y}$ co-occurring articles that feature both university *i* and *j*. Shown are networks representing three sequential periods: **a** $y :=$ 2010–2015; **b** 2016–2019; **c** 2020. **d** Visualizing the structural shifts between the co-occurrence networks shown in (**b**, **c**). Each link has thickness proportional to the percent change % $\Delta = 100(J_{ij,2020} - J_{ij,2016-2019})/J_{ij,2016-2019}$, and shaded green (red) if the change is positive (negative). Each link also contains a pie-chart showing the same proportions as in (**c**), but with variable radii encoding the relative changes $P_{2020,c}/P_{2016-2019,c}$. The large pie-chart at the bottom shows the average across the entire sample, indicating a 20% increase in *Politics* media articles and a−23% decrease in *Education& Professional* articles during the first year of the COVID-19 pandemic; the purple background indicates the baseline radius for visual comparison. The most notable increased frequencies are for *c* associated with the pandemic -- *Politics*, *Vacation& Travel* and *Health& Food* -- and universities with prominent biomedical and health research focus and medical schools -- Stanford, UCLA, UCSF.

production, and identifies various avenues for future development to foster dynamic marketing capabilities tailored to individual institutions (Ding et al., 2020; Soykoth et al., 2024; Teece, 2007). As a start, results from our analysis of undergraduate enrollment across 17 different UC and UT campuses from 2013 to 2021 suggests that moderate investments in campus communications that stimulate media visibility growth could translate into consequential increases in competitiveness for freshman enrollment growth.

According to a regional systems approach, our analysis provides valuable historical perspective on the integration and stratification of universities in the attention economy. An increasing frequency of digital media featuring just a single institution reflects the increasing competitiveness within the attention economy. At the same time, the co-occurrence of multiple institutions in digital media is largely correlated with regional proximity, both in regard to both the universities themselves, as well as the media sources that promote them.

Our results also point to the strategic alignment of institutional content production with dominant media topics as they arise, which reinforces brand visibility and association according to broader social, technological and environmental narratives. To this end, we applied machine learning methods to classify article titles according to a consistent topic space, which affords analyzing narrative alignment between entities. The juxtaposition of media co-visibility with narrative topic co-variability facilitates analyzing the sensitivity of the attention economy to exogenous shocks such as the 2007–08 global financial crisis and the COVID-19 pandemic, which are representative of paradigm shifts affecting digital media production and consumption. In order to navigate periodic socio-economic 'storms', institutions can capitalize on the strengths of regional systems by investing in strategic synergies for brand visibility co-production. This approach enhances brand equity associations and boosts the visibility of the entire university system—key aspects of advancing the multifaceted mission of modern higher education institutions.

Data availability

All primary source data are openly available from Media Cloud (MC-Consortium 2024). Parsed data and code for reproducing figures and regression model parameter estimates are available on the Dryad open data publishing platform (10.5061/dryad.2rbnzs7zc).

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Author contributions

AMP performed the research, wrote the manuscript, collected, analysed, and visualized the data.

Competing interests

The author declares no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve collecting data from human participants.

Informed consent

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Additional information

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Supplementary Information – Appendix Text, Figures S1-S6 and Table S1

University digital media co-occurrence networks reveal structure and dynamics of brand visibility in the attention economy

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Extended Methods

Data collection from Media Cloud. Building on prior work quantifying the co-visibility of entities ranging from specific individuals (Petersen et al. 2019) to systems of systems (Arroyave et al. 2024; Petersen et al. 2025; Petersen and Montaño Ramirez 2025), here we assembled a dataset of 1,947,349 unique media articles mentioning at least one of the 29 IHE analyzed. We collected these data from the Media Cloud project (MC) database (MC-Consortium 2024).

The entry point for the analysis are collections of media articles specifically mentioning each university by official name. The procedure for obtaining metadata for a particular IHE is as follows. Starting with a specific set of words (i.e., the official IHE name), we query the MC API using Apache Solr syntax to identify exact text matches while at the same time accommodating slight wording variations, which returns metadata on a corresponding set of media articles. For example, the Apache Solr text query *"University California Merced"∼7* identifies matches within 7 tokens of each other, which accommodates a number of written variants, including "University of California at Merced" and "University of California, Merced", as well as even "University of California Merced and Santa Cruz".

Data were obtained by querying MC for records featuring each institution's official name "University of California Los Angeles" or alternative abbreviation (e.g., UCLA). Media articles indexed by the MC database are characterized as content accessible via the web (representing news articles, blog posts and other web content). Results of our query were produced by 57,947 distinct media sources (2554 of which produced $\geq$ 100 articles).

Media article disambiguation. We applied a media article disambiguation method developed in (Petersen et al. 2019) to refine the set of media article data downloaded from MC. This article disambiguation addresses the issue that a single article (inferred by its title, publication date and media source) may nevertheless have multiple different URLs, representing different hyperlinks from different facets of the host website to a common media article, e.g. blog section, RSS feed section, and front page. The PI developed a computationally-intensive method to addressed this redundancy by merging articles with the same MC media source, similar publication date, and similar title into a single article instance so that article counts are not systematically inflated. Article title similarity is assessed by calculating the Damerau-Levenshtein edit distance D_{jk} between the title T_j and T_k, applied to all article pairs within the dataset. This reduced the sample size from 2.24 million to 1.94 million, representing a 13% compression.

Topic classification of article titles. We used the built-in text classifier available via the function *Classify[ ]* included in Mathematica v12 software to identify topics reflected in the title of each article. The topic classifier is trained on a corpus of Facebook posts, which are structurally similar to article titles in terms of length and specificity. The Mathematica classifier maps a provided text string onto a normalized vector of topic likelihoods spanning 25 different categories: "Books", "CareerAndMoney", "SocialMedia", "FamilyAndFriends", "Fashion", "Fitness", "FoodAndDrink", "Health", "Technology", "Leisure", "QuotesAndLifePhilosophy", "Relationships", "Movies", "Music", "PersonalMood", "PetsAndAnimals", "Politics", "SchoolAndUniversity", "SpecialOccasions", "Sports", "Television", "Transport", "Travel", "VideoGames", "Weather". See the classifier's description page for more details.

To validate the accuracy of the topic classifier within our sample of media article titles, we used the internal set of MC article-level entity tags – for the 100 most frequent tags, see **Fig. 2**(b). The rank-ordered correspondence between each classifier topics and the 10 most frequent entity tags is shown in **Fig. S4**, which exhibits a high degree of correspondence such that most categories feature the same MC label in the 1st or 2nd rank of labels for that category. To reduce the dimensionality in order to facilitate visual representation, we then merged estimated topics and their corresponding likelihoods onto a refined set of 11 topic categories employed in **Figs. 3** and **5**.

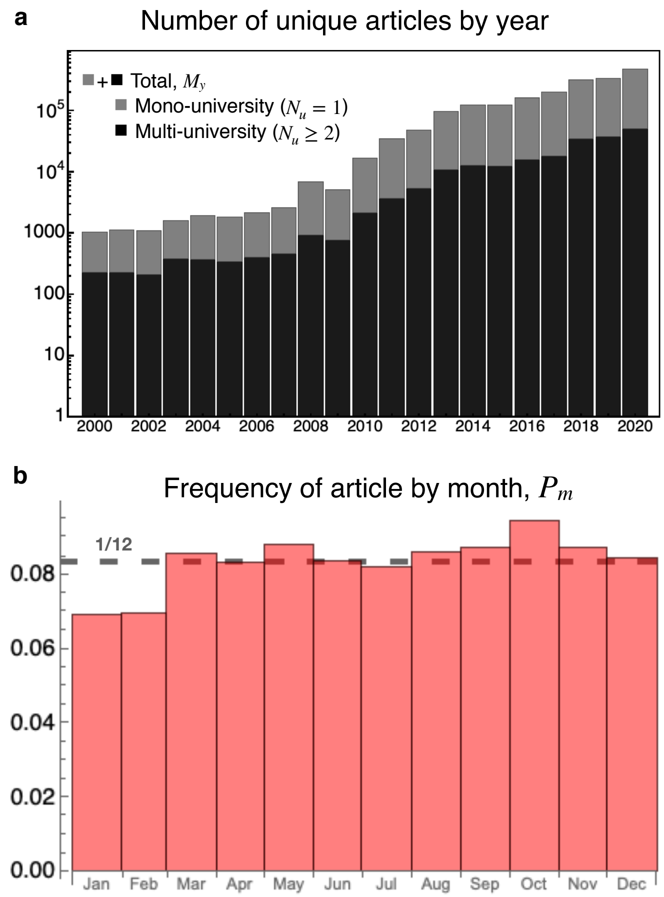


FIG. S1. **Temporal distribution of IHE media visibility.** Descriptive statistics including sample size by publication year and month. **(a)** The height of each bar indicates the total number of unique media articles by year, M_y. Complementary mono-university and multi-university (mentioning two or more institutions) article subsets are indicated by the stacked bars heights. **(b)** Frequency $f(m_a)$ of unique media articles by month.

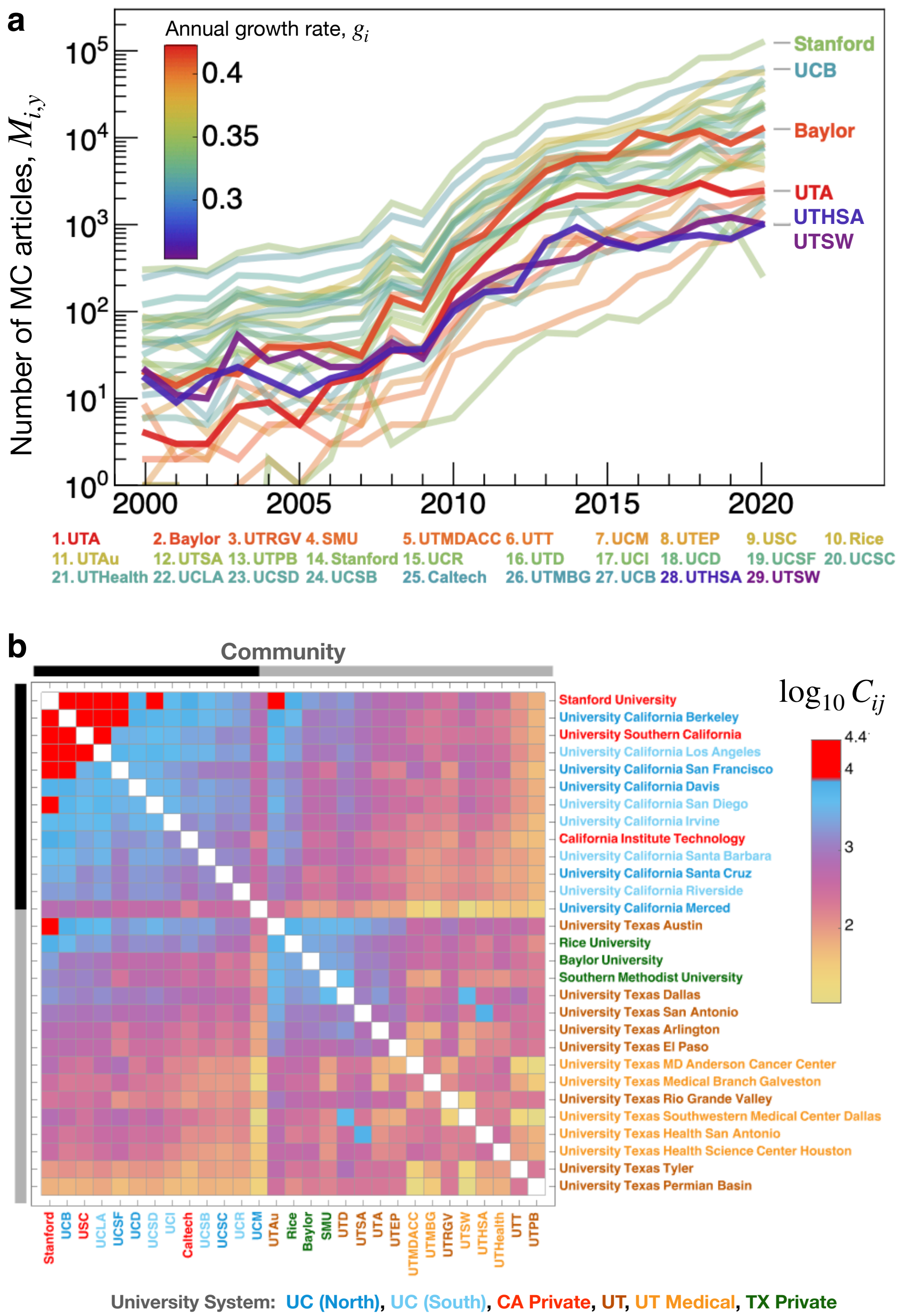


FIG. S2. **University-level media visibility.** **(a)** The number $M_{i,y}$ of MC articles featuring institution i in year y is a proxy for brand visibility. Each curve is colored according to its exponential growth rate g_i calculated at the 1-year resolution corresponding to the model $M_{i,y} \propto \exp[g_i y]$. Universities are listed in rank-order of g_i to illustrate the size-growth variation. **(b)** The co-occurrence count matrix C_{ij} showing the number of media articles featuring institutions i and j, aggregated over 2000-2020. Institutions are grouped according to clusters identified using the Louvain modularity maximizing algorithm (Blondel et al. 2008), as indicated by the gray-scale border segments along the upper border; within each cluster, institutions are ordered according to their total media visibility, M_i. The two communities entirely coincide with the two regions analyzed, CA and TX. The top 10 C_{ij} values are indicated by red; the color index is shown in log scale, with the maximum value corresponding to 25,747 media articles.

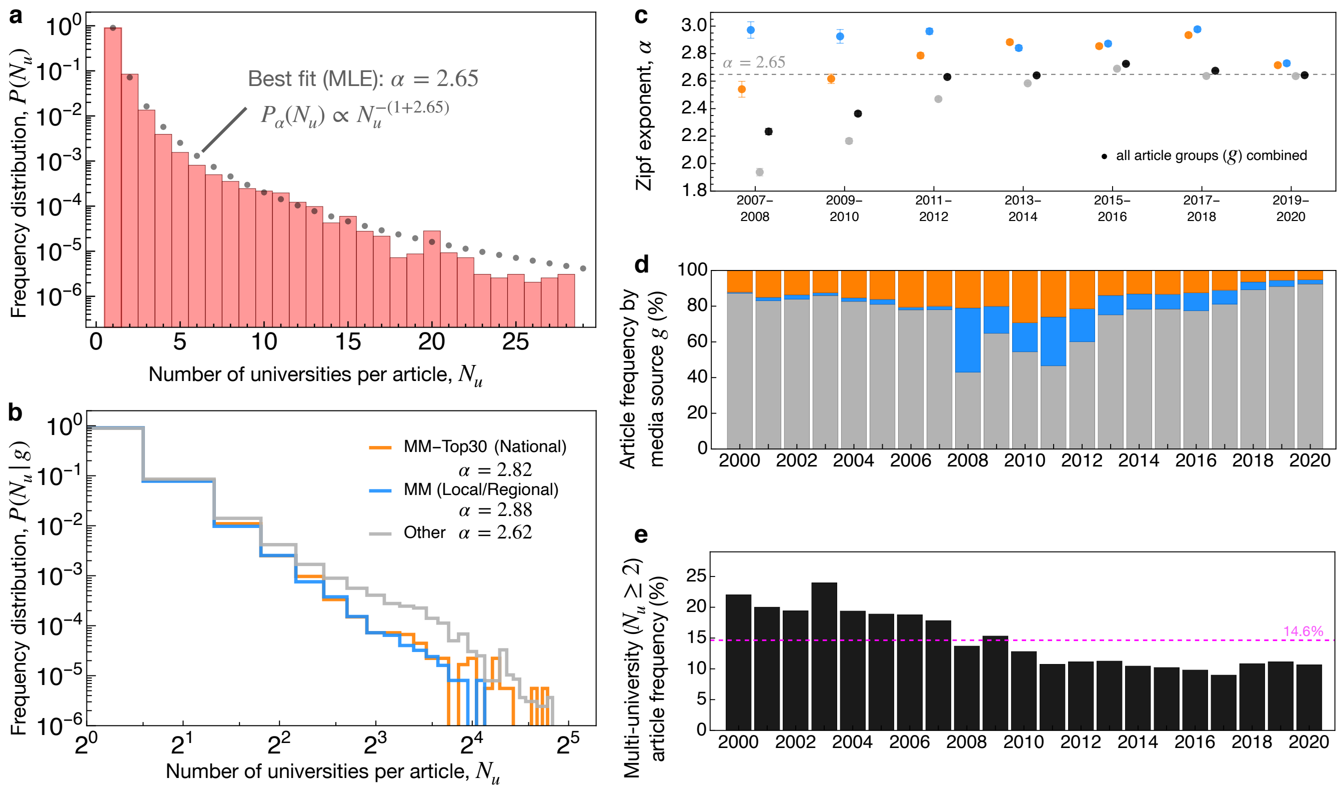
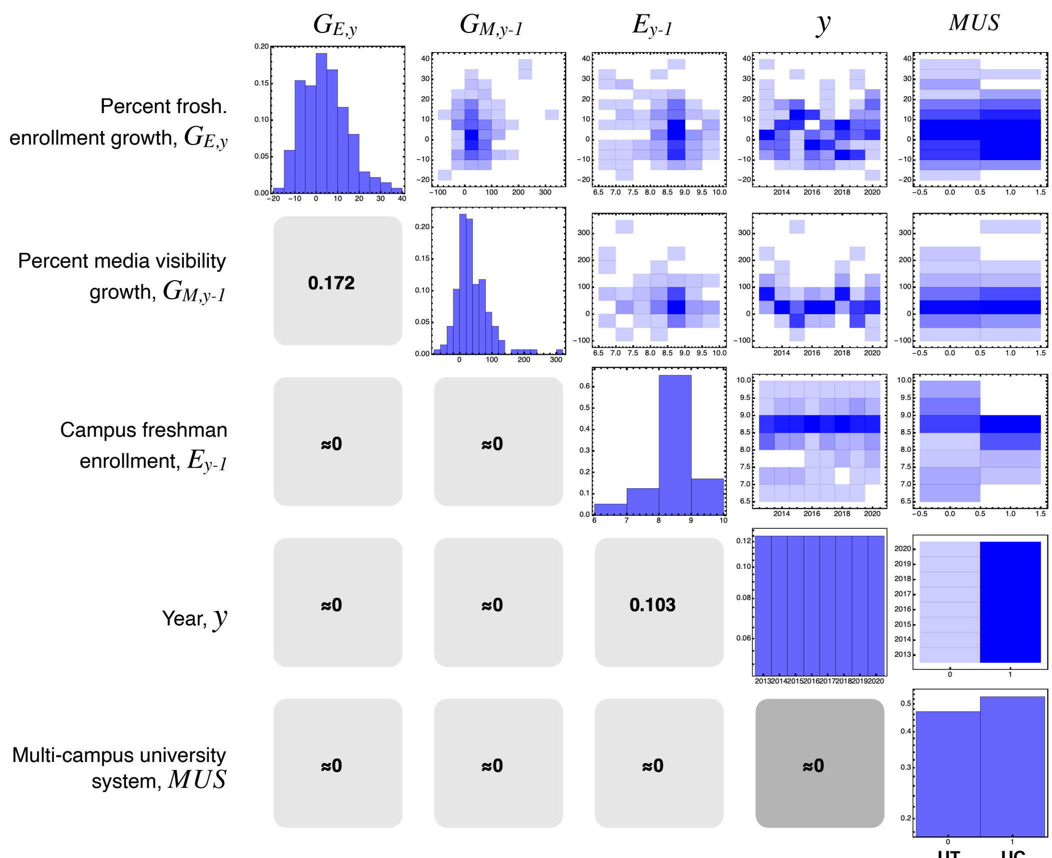


FIG. S3. **Intensity of multi-university news media visibility**. **(a)** While the average number of institutions per media article, $N_u = 1.15$, this single number does not readily convey the rich higher-order information contained in the full frequency distribution, $P_\alpha(N_u)$ – which is well-fit by the Zipf distribution $P_\alpha(N_u) \sim 1/N_u^{1+\alpha}$. This canonical Zipf count distribution is quantified by a single parameter, the scaling exponent α, which we estimate using the robust maximum likelihood estimator (MLE): the exponent calculated for the entire data sample is $\alpha_{\text{all}} = 2.65$. Larger α values signify a smaller likelihood of finding multi-university news articles with $N_u \geq 2$. **(b)** Empirical frequency distributions $P_\alpha(N_u|g)$ conditioned on media source group g. Estimated scaling exponents α_g indicated in the legend. **(c)** Evolution of α_g calculated over 2-year non-overlapping periods from 2007 to 2020. The black dots correspond to $\alpha_{\text{all},y}$ calculated independent of g for a given period. Error bars indicate the standard error in the MLE estimate. The aggregate trend for all media source groups combined (black points) is increasing, and indicates that the frequency of multi-university news is diminishing over time. Comparing results for media source groups, the national and local/regional MM media sources feature fewer multi-university news articles. **(d)** Percentage of media articles produced by a given media source group g by year, exhibiting the sudden increase in the relative share of content produced by local/regional mainstream media sources following the 2007-08 financial crisis. **(e)** Percentage of multi-university media articles (featuring $N_u \geq 2$) by year. The dashed magenta horizontal line indicates the average frequency of 14.6 over the 21-year period (unweighted); computed across all articles independent of year, 10.6% of all media articles are multi-university.

Category (% of all articles)	Most frequent MC article tag (% of topic articles)	2	3	4	5	6	7	8	9	10
Politics (28.)	politics and government (36.)	united states politics and government (19.)	education and schools (15.)	elections (14.)	medicine and health (12.)	Congress (12.)	finances (11.)	Senate (10.)	colleges and universities (9.8)	White House (8.9)
Health (16.)	medicine and health (64.)	diseases and conditions (42.)	research (28.)	tests and testing (11.)	cancer (9.1)	drugs (pharmaceuticals) (8.7)	education and schools (8.2)	genetics and heredity (7.6)	finances (6.6)	FDA (6.0)
SchoolAndUniversity (13.)	education and schools (54.)	colleges and universities (41.)	medicine and health (17.)	finances (9.6)	computers and the internet (8.9)	research (8.6)	ethics (8.1)	crime and criminals (7.3)	diseases and conditions (7.3)	politics and government (6.0)
CareerAndMoney (5.6)	finances (28.)	education and schools (21.)	colleges and universities (16.)	medicine and health (15.)	labor (14.)	computers and the internet (12.)	politics and government (9.3)	research (5.5)	Congress (5.3)	diseases and conditions (5.2)
Sports (5.2)	football (22.)	college athletics (20.)	education and schools (15.)	NCAA (12.)	basketball (11.)	NFL (9.8)	colleges and universities (8.9)	coaches and managers (6.5)	crime and criminals (6.1)	athletics and sports (5.9)
Technology (3.6)	computers and the internet (42.)	medicine and health (17.)	Google (16.)	research (14.)	computer software (12.)	education and schools (11.)	diseases and conditions (8.2)	Facebook (7.8)	finances (7.1)	Apple (7.0)
Travel (3.0)	politics and government (21.)	medicine and health (17.)	education and schools (10.)	diseases and conditions (10.)	colleges and universities (9.1)	travel and vacations (8.1)	international relations (8.0)	united states politics and government (7.0)	computers and the internet (5.7)	finances (5.4)
FoodAndDrink (2.8)	medicine and health (21.)	food (18.)	research (14.)	diseases and conditions (9.9)	finances (7.0)	education and schools (6.2)	environment (6.1)	diet and nutrition (6.0)	beverages (5.7)	politics and government (5.4)
QuotesAndLifePhilosophy (2.3)	medicine and health (22.)	politics and government (13.)	diseases and conditions (12.)	research (11.)	education and schools (9.3)	religion and churches (7.6)	computers and the internet (6.4)	Congress (5.4)	finances (5.2)	crime and criminals (5.1)
Books (2.3)	books and literature (27.)	medicine and health (11.)	politics and government (10.)	biographical information (9.0)	education and schools (8.7)	computers and the internet (7.9)	research (7.0)	diseases and conditions (5.6)	united states politics and government (5.3)	reviews (5.0)
VideoGames (2.2)	medicine and health (18.)	computers and the internet (15.)	research (15.)	diseases and conditions (8.1)	education and schools (8.1)	politics and government (7.3)	Google (6.8)	space (5.4)	Facebook (4.7)	crime and criminals (4.5)
Movies (2.0)	motion pictures (23.)	medicine and health (11.)	research (9.1)	biographical information (8.7)	space (6.5)	computers and the internet (6.4)	Disney (6.2)	television (5.8)	books and literature (5.1)	NASA (4.7)
Weather (2.0)	weather (23.)	research (14.)	medicine and health (13.)	global warming (12.)	environment (11.)	hurricanes and tropical storms (8.2)	water (7.3)	NASA (6.9)	floods (6.7)	diseases and conditions (6.2)
Fitness (1.7)	medicine and health (29.)	research (15.)	diseases and conditions (14.)	food (9.4)	diet and nutrition (9.0)	computers and the internet (8.0)	politics and government (7.9)	weight (7.6)	finances (6.9)	education and schools (6.2)
PetsAndAnimals (1.5)	animals (29.)	medicine and health (26.)	research (25.)	fish and other marine life (12.)	diseases and conditions (11.)	environment (11.)	genetics and heredity (6.4)	food (6.0)	endangered and extinct species (4.6)	global warming (4.1)
Television (1.4)	education and schools (14.)	ethics (14.)	crime and criminals (13.)	television (13.)	colleges and universities (13.)	frauds and swindling (9.4)	medicine and health (8.8)	politics and government (7.8)	biographical information (7.0)	computers and the internet (6.6)
Transport (1.3)	roads and traffic (16.)	accidents and safety (11.)	automobiles (9.8)	medicine and health (8.5)	computers and the internet (7.8)	education and schools (6.2)	research (6.0)	environment (5.6)	space (5.0)	Google (4.9)
SocialMedia (1.3)	computers and the internet (31.)	Facebook (24.)	medicine and health (17.)	politics and government (15.)	diseases and conditions (9.9)	education and schools (9.3)	Google (8.1)	finances (7.5)	research (7.2)	Congress (6.2)
FamilyAndFriends (1.1)	medicine and health (18.)	education and schools (18.)	ethics (14.)	colleges and universities (13.)	children and youth (9.8)	politics and government (7.6)	diseases and conditions (7.5)	crime and criminals (6.1)	research (5.3)	frauds and swindling (5.2)
Music (1.1)	music (30.)	recordings (audio) (11.)	medicine and health (8.4)	reviews (8.0)	education and schools (7.7)	computers and the internet (7.6)	biographical information (6.0)	research (6.0)	politics and government (5.8)	classical music (4.9)
Fashion (0.58)	medicine and health (22.)	diseases and conditions (14.)	education and schools (9.6)	apparel (9.0)	politics and government (8.9)	computers and the internet (8.7)	research (8.3)	Facebook (8.1)	CDC (6.6)	Centers for Disease Control and Prevention (6.6)
Relationships (0.56)	computers and the internet (15.)	education and schools (14.)	colleges and universities (14.)	ethics (12.)	crime and criminals (12.)	frauds and swindling (11.)	medicine and health (10.)	google (5.6)	research (5.2)	sex crimes (4.9)
Leisure (0.49)	medicine and health (12.)	education and schools (10.)	colleges and universities (7.5)	politics and government (7.5)	music (6.8)	animals (6.4)	research (5.9)	Google (5.3)	college athletics (5.2)	biographical information (5.1)
SpecialOccasions (0.38)	medicine and health (14.)	politics and government (13.)	biographical information (10.)	education and schools (8.2)	United Nations (7.3)	computers and the internet (6.7)	reviews (6.7)	Senate (6.5)	Facebook (6.1)	blacks (5.8)
PersonalMood (0.25)	medicine and health (26.)	research (18.)	mental health and disorders (14.)	politics and government (11.)	children and youth (11.)	American Psychological Association (9.8)	earthquakes (9.8)	White House (8.8)	biographical information (8.2)	computers and the internet (6.9)

FIG. S4. **Classification validation.** Table showing 25 topic categories (listed in the first column), followed by the corresponding top-10 rank-ordered list of MC article-level topic tags (e_a). The values in parenthesis in the first column indicate the percentage of MC articles with principal classification belonging to a given category. Each row lists the top 10 e_a corresponding to that category, with percentage shown in parenthesis. By way of example, among articles classified principally by the *Health* category, the second-most frequent e_a is “diseases and conditions”, which occurred in 42% of those articles.

FIG. S5. **Dynamics of co-visibility matrix** $J_{ij,y}$. Whereas **Fig. 3**(a) shows the co-visibility matrix $J_{ij,y}$ calculated for 2010-2020, the supplementary material GIF file titled *JaccardMatrix_2000-2020_GIF.gif* (which can be opened by a standard web browser) shows $J_{ij,y}$ calculated at the 1-year resolution from 2000-2020. However, to sustain visual order, we maintain the ordering of IHE and communities, using the same ordering as in **Fig. 3**(a). We apply a semi-fixed color scale to identify the most prominent co-visible pairs: cyan values indicate $J_{ij,y} > 0.08$ for $y \in [2000, 2009]$ and $J_{ij,y} > 0.025$ for $y \in [2010, 2020]$.



Descriptive Statistics

Variable	Average	Standard Deviation	Minimum	Median	Maximum
Percent frosh. enrollment growth, $G_{E,y}$	4.3	10.7	−19.9	3.2	38.6
Percent media visibility growth, $G_{M,y\text{-}1}$	40.8	53.1	−74.5	29.5	300.0
Campus freshman enrollment, $E_{y\text{-}1}$	8.5	0.7	6.5	8.7	9.8

FIG. S6. **Descriptive statistics**: for the $N = 136$ panel regression sample analyzed in **Table S1**. Covariance matrix: Upper-diagonal elements: bivariate histogram between row and column variables. Diagonal elements: histogram for variable indicated by the row/column labels. Lower-diagonal elements: bivariate cross-correlation coefficient: light-shaded squares indicate the Pearson's correlation coefficient between two variables that are both continuous measures; dark-shaded squares indicate the Cramer's V associate between two variables that are both nominal (categorical).

TABLE S1. **Modeling the relationship between IHE media visibility and enrollment growth.** We model the percent growth in freshman enrollment at the 17 undergraduate-serving campuses in the UC system (9 total; UC data link) and UT system (8 total; UT data link) over the period 2013-2021 using publicly-available enrollment data provided by each system. To account for secular growth, the dependent variable we model is the 1-year percent growth in enrollment $E_{y,i}$ at institution i, denoted by $G_{E,y,i} = 100(E_{y,i} - E_{y-1,i})/E_{y-1,i}$. Similarly, the focal dependent variable is the 1-year percent growth in enrollment $M_{y,i}$, denoted by $G_{M,y,i} = 100(M_{y,i} - M_{y-1,i})/M_{y-1,i}$, which we include with a 1 year lag, i.e. $G_{M,y-1}$. To account for the typical size-growth relationship, whereby larger institutions tend to grow slower than smaller ones due to life-cycle effects (Riccaboni et al. 2008), we also control for the prior year enrollment size of each campus, denoted by $\log E_{y-1,i}$. We estimate the hierarchical model by clustering errors at the institutional level, implementing the model in STATA 13 using "xtreg" and incorporating both university and year fixed effects to control for time-invariant unobserved predictors associated with each variable. The first three models shown do not account for multi-campus university system factors (denoted by the dummy variable MUS_i = 1 if $i \in UC$ and 0 if $i \in UT$), with the full model (3) specified as: $G_{E,y,i} = \beta_i + \beta_{GM} G_{M,y-1,i} + \beta_E \log E_{y-1,i} + \gamma_y + \epsilon_i$. To generates an estimation of the incremental difference attributable to differential state- and system-level factors, the interaction model (4) includes the interaction $G_{E,y,i} = \beta_i + \beta_{GM} G_{M,y-1,i} + \beta_{MUS\times GM} MUS_i \times G_{M,y-1,i} + \beta_E \log E_{y-1,i} + \beta_{MUS\times E} MUS_i \times \log E_{y-1,i} + \gamma_y + \epsilon_i$. **Figure 1**(d) shows the marginal relationship between media visibility growth G_M and enrollment growth G_E using the estimation from the interaction model, with all other covariates held at their mean values. Results indicate a statistically significant and positive relationship, $\beta_{GM} > 0$, which is substantially larger for campuses belonging to the UT system. As such, the average media visibility growth $\overline{G}_M = 40.8\%$ (which is nearly the same for each MUS), corresponds to a 3.5% enrollment growth for UC campuses and a 5% enrollment growth for UT campuses. See **Fig. S6** for covariate descriptive statistics and the covariance matrix. Robust standard errors are shown in parenthesis below each point estimate. Y indicates additional fixed effects included in the regression model.

	(1)	(2)	(3)	(4)
	$G_{E,y}$	$G_{E,y}$	$G_{E,y}$	$G_{E,y}$
Media Visibility growth (MUS = Univ. Texas System), $G_{M,y-1}$	0.0377		0.0338^{*}	0.0602^{***}
	(0.134)		(0.026)	(0.001)
MUS = Univ. California System, $\delta G_{M,y-1}$				-0.0467^{*}
				(0.013)
Prior year enrollment size (MUS = Univ. Texas System), $\log E_{y-1}$		-75.22^{***}	-71.14^{***}	-62.98^{***}
		(0.000)	(0.000)	(0.000)
MUS = Univ. California System, $\delta \log E_{y-1}$				-23.21
				(0.309)
University (i) Fixed Effects	Y	Y	Y	Y
Year (y) Fixed Effects	Y	Y	Y	Y
Constant	2.782^{*}	636.1^{***}	599.0^{***}	633.0^{***}
	(0.011)	(0.000)	(0.000)	(0.000)
N	136	136	136	136
adj. R^2	0.028	0.373	0.390	0.401

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$