Connected Audiences in Digital Media Markets: The Dynamics of University Online Video Impact

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Abstract

This paper analyses whether the audience dynamics of one content provider can explain the audience dynamics of a different content provider, and the resulting network of connections among providers. The type of connections in this network determines whether the audience of one creator influences or is susceptible to other creators' audience. Granger causality networks are applied to prestigious universities that provide online videos on YouTube and the structure of the Audience Dynamics Network is described. This network presents an unbalanced degree distribution and a core-periphery structure. The centrality of the universities in the network is discussed and universities with influential and susceptible roles are identified. We find that audience connection is determined by the differences in the online video impact between each pair of universities. Centrality in the network is associated with university prestige, but this relation is mediated by online video impact.

Keywords: Digital media markets, online video, Granger causality networks, world-class universities, time series

JEL codes: A20, I20, L14

1. Introduction

Production and consumption of contents have changed dramatically in the last years due to the emergence of new forms of content provision. Creators have started to release their creations directly, thanks to a flourishing market of platforms that has made it easy for a wide spectrum of producers to provide different types of content (Luca, 2015). This has paved the way for the consumption and production of multimedia content directed to a "long tail" of very small niches (Anderson, 2004). Among these platforms, YouTube, which was devised to allow for low budget broadcasting (Kim, 2012), is one of the most successful. Such an environment has led audiences to behave very differently. Possibly, the most striking fact is the success of small producers who cater to new tastes, thus attracting a huge number of viewers. Some of these *youtubers* are able to challenge mass media, making their content available to several million subscribers (Gaenssle and Budzinski, 2020). Traditional content providers have reacted to this process by adopting a multi-channel strategy, trying to capture part of the new market (Cunningham et al., 2016). As a result, many media companies now provide their products via multiple platforms, including YouTube (Telkmann, 2021). Currently, this platform has become a place where traditional media producers, independent creators, companies and institutions broadcast their own videos (Kim, 2012), which are disseminated and viewed by a global audience.

The behaviour of audiences in this new environment has become an important object of research. One of the most studied phenomena is how some of these videos are able to reach an extremely large audience, in a diffusion process known as "virality" (Khan and Vong, 2014). However, despite increasing research on how contents are widely disseminated **(see, for instance, Al-Rawi, 2019)**, to the best of our knowledge, the question as to how audiences move from one particular producer to another has not yet been explored. The study of these relations should reveal the existence of influential producers, agents who exert an effect on the audience of others -susceptibles-. In this paper we explore the existence of the system of audiences in this new broadcasting market and propose an analytical framework, that we call the Audience Dynamics Network. To this end, we apply Granger causality networks to identify the connections among the YouTube audiences of prestigious universities, which are actively participating in video provision via the Internet. Universities devote more and more resources to the dissemination of their activities through different social media. Most of the research regarding academic online videos has been devoted to the study of the characteristics of such videos (Shoufan, 2019b), but evidence as to how universities disseminate their contents and obtain an answer from their audience is scarce (Arroyo-Barrigüete, 2019; Ros-Gálvez et al., 2021). In this line, the centrality of the Audience Dynamics Network is analysed. Centrality in networks refers to a measure of the relevance of a given agent in the network structure (Bonacich, 1987; Borgatti, 2005). We draw on this concept to identify the most relevant universities, which tend to occupy central positions in the network i.e., those universities playing influential roles in the dissemination of content.

The objective of our research is, therefore, to propose an analytical framework for studying the relationships among the audiences of content creators and to apply this framework to analyse audiences of highly prestigious universities. Thus, we try to answer the following research questions:

RQ1: Are YouTube audiences connected? If so, what is the structure of the Audience Dynamics Network?

RQ2: Which factors determine connections among audiences on YouTube?

RQ3: Is centrality in the Audience Dynamics Network associated with observable characteristics of the content creators?

Herewith, we contribute to the extant research on digital media markets and on universities on YouTube. In the next section, we review the literature regarding universities and online video, and on Granger causality networks. In section 3 we present our hypotheses and the methods; section 4 includes the results of our empirical application; and in section 5 we discuss the implications of our results, limitations of our approach and identify further research lines.

2. Literature Review

2.1. Universities and online video

YouTube allows the online broadcasting of user-generated videos, which can be shared, commented on, liked/disliked, etc. Around 1 billion hours ($1e10^9$) are consumed on a daily basis on YouTube (http://www.youtube.com/intl/en-US/about/press/), which is currently the second most popular website in the world (after Google) and the largest video sharing site (Schwemmer and Ziewiecki, 2018). Audio-visual content on YouTube is easily accessible to all kinds of users around the world. Therefore, it can go viral (Khan and Vong, 2014), based on features such as the characteristics of the content creator, the contents that creators share or even the interactions between them (Han et al., 2020), as well as others such as to which extent the content creator holds an influential role on its subscribers and to which extent subscribers are likely to share the creator´s contents -i.e. susceptible role- (Susarla et al., 2016). These online videos have been shown to play a key role in purchasing and behavioural decisions (Oh et al., 2017; Tseng and Huang, 2016). Hence, ever since its creation in 2005, YouTube has gained importance for the promotion of product and services and, as a result, today it has become a key marketing tool (Schwemmer and Ziewiecki, 2018). University managers soon identified the opportunities that YouTube offers, as a free-access broadcast channel, to promote themselves globally in a context of increasing competition. Thus, by means of extensive use of online video (Sugimoto et al., 2017), universities draw on YouTube to consolidate their image and to activate communication with their academic community (Guzmán-Duque and del Moral-Pérez, 2014), to globally promote their academic prospectus (Mwenda et al., 2019), as well as to disseminate knowledge, increase visibility and generate a brand image (Martín-González and Santamaría Llarena, 2017). This is reflected by the fact that, of the 500 most prestigious universities ranked by ARWU (2018), 433 have institutional accounts on YouTube (Meseguer-Martínez et al., 2019b). Technical aspects and cognitive features have been identified as significant correlates of success in academic videos (Meseguer-Martínez et al., 2017; Shoufan, 2019a, 2019b). Institutional characteristics of the universities have been shown to be associated with their impact on YouTube, with a significant relation between university prestige and online video impact for world class universities, which seems to be no longer apparent when a wide spectrum of universities is under consideration (Meseguer-Martínez et al., 2019a, 2019b). The dynamics of audiences in online video have been modelled through different approaches (Borghol et al., 2011; Figueiredo, 2013; Trzciński and Rokita, 2017), with virality being a case of particular interest (Figueiredo et al., 2011; Jiang et al., 2014; Khan and Vong, 2014). For educational videos, Saurabh and Gautham (2019), and Arroyo-Barrigüete et al. (2019) have shown that audiences of academic online videos move according to the academic calendar, with an increasing number of views during exam periods. Regarding university online videos, the dynamics of university audience on YouTube has also been analysed and compared to that of educational channels with results suggesting similar behaviours across both types of channels (Ros-Gálvez et al., 2021).

2.2. Granger causality networks

Granger causality networks have been widely used in recent years to analyse whether the dynamics of a time series associated with one agent is related to others. In this type of model, direct relationships among time series are established using Granger causality tests (Granger, 1969). If the time series x_t i.e., the values taken by a variable for agent x over a period of time $t=1,\dots,T$, causes the time series y_t in the Granger sense, it implies that variations in the time series associated with x influence the time series associated with y. This is evaluated through a significant test of the parameters relating past values of x_t with current values of y_t. If these parameters are statistically different from zero it can be said that x_t Granger-causes y_t. In this case, past values of x_t have an influence on y_t and y_t is susceptible to past values of x_t. Thus, the number of connections in a Granger causality network allows one to measure how influential or susceptible each agent (or node) in the network is (Výrost et al., 2015). Influential and susceptible agents in online social networks are key issues. For instance, in word-of-mouth studies, it has been consistently shown that central positions in the social structure are associated with how influential or susceptible the agent is. A natural question then is to identify the characteristics that are associated with each type of agent (Aral and Walker, 2012; Susarla et al., 2016).

Granger causality networks have been used extensively in finance since the seminal paper by Billio et al. (2012). In that paper, the authors construct a Granger causality network among monthly returns of hedge funds, banks, broker/dealers, and insurance companies. More precisely, they estimate the network of relations and their directionality among the most important financial institutions in these sectors via pairwise Granger causality tests. These authors find the fraction of causal relations over all the possible pairs, the number of institutions Granger-caused by each element as well as the number of institutions causing each element in their system. With this information, they identify the most central institutions based on how connected they are to the rest of the elements in the network. In addition, they analyse whether the characteristics of these financial institutions might explain their influence and position in the network. These points have been also developed in later literature. For instance, Výrost et al. (2015) estimated a Granger causality network to identify the relationships among 20 developed stock markets. In their study, they identified determinants of the binary existence or absence of a connection in such a network, by means of different Logit models. They find that the temporal proximity of the closing times of the markets significantly explain the existence of nodes. In this line, Hué et al. (2019) analyse the network of Granger connections among the largest worldwide banks and find that their size, business model and profitability are significant determinants when explaining the relevance/centrality of each bank in the network.

Previously, these networks had been used extensively in neuroscience (Bullmore and Sporns 2009), or, more recently, to identify system properties in more and more environments. For instance, Caraiani (2013) studies Granger causality networks in business cycles, Du et al. (2018) apply them to analyse the propagation of airport flight delays, Papaioannou et al. (2020) in electricity markets, Park et al. (2020) in currency markets and Huang et al. (2020) in the companies in the Chinese A-share market. However, as far as we know, Granger causality networks have not been applied either to online video interactions or to online social media. Nevertheless, Ver Steeg and Galstyan (2012) do follow a related approach to study behaviour on Twitter. These authors study whether the time series of agents posting on Twitter causes the time series of other agents in the same social network. However, they draw on transfer entropy, a nonlinear generalization of Granger causality, to identify such relations. They find that the extent to which an agent is influential in the network is associated with the relevance of the agent measured by number of followers.

3. Hypotheses and Methodology

3.1. Hypotheses

Granger causality relations among time series has unveiled the existence of connected systems in different types of markets, where the time series associated with different nodes are causally related (e.g., Billio et al., 2012; Papaioannou et al., 2020; Park et al., 2020). Such causal relations have also been identified among content creators in social media (Ver Steeg and Galstyan, 2012), in line with the body of literature on the interdependence of agents in social media (Aral and Walker, 2012; Susarla et al., 2016). Universities have become content producers of online video through their presence on YouTube (Meseguer-Martinez et al., 2019; Mwenda et al., 2019). We consider that the audiences of YouTube are good candidates for causal relations with each other. Therefore, firstly, we hypothesize the existence of an Audience Dynamics Network:

H1: There are universities whose audience dynamics cause the audience dynamics of other universities, creating an Audience Dynamics Network.

A central question in the study of social networks is why one agent influences another (see for instance, Aral and Walker, 2012). In a Granger causality network, it is common to study the existence of a connection between any two nodes according to their observable characteristics (Billio et al., 2012; Výrost et al., 2015; Hué et al., 2019). Along these lines, it has been found that the features of content creators play a key role in the diffusion of content in social media (Han et al., 2020). In particular, institutional characteristics of universities such as geographical location, prestige or specialization have been considered in assessing their impact on social media (Lovari and Giglieto, 2012; Brech et al., 2017; Lund, 2019). Based on this, when considering the relationship between audiences of two universities, university characteristics are natural candidates to determine the existence of a relation of influence. Given our research framework, we consider online video impact to be a reasonable candidate to explain influence relations on YouTube. This leads us to establish our second hypothesis:

H2: The influence of one audience dynamic on another depends on the online video impact and the institutional characteristics of both universities.

Finally, nodes with a central position play an influential role in social networks (Ilyas and Radha, 2011), and as mentioned, the characteristics of content creators have an effect on their influence in the network (Han et al., 2020). Thus, the prestige of the content creator results in increased influence in the network (Rutz et al., 2012). In this vein, university prestige has been found to be associated with online video impact on YouTube (Meseguer-Martinez et al., 2019a). As prestige and leadership trigger connections in a social media network (Susarla et al., 2016), we consider that university prestige should be related to the centrality of the audience of the university in the network. Thus, we propose our last hypothesis:

H3: University prestige is associated with centrality in the Audience Dynamics Network of universities.

3.2. The Audience Dynamics Network

We analyse the existence of a network of audience dynamics among content providers in digital media markets. Let N= {1, 2, …, n} be a set of content providers. We define an Audience Dynamics Network Γ as a collection of pairs *xy* such that if *xy* belongs to Γ then the audience dynamics of *y* is caused by the audience dynamics of *x*, with $x, y \in$ N. More precisely, if the link *xy* exists, it means that variations in the audience dynamics of *x* are followed by variations in the audience dynamics of *y* i.e., audience rises and falls of content provider *x* anticipate audience rises and falls of content provider *y*.

We now introduce some convenient definitions from graph theory (Bollobás, 2001) that will be applied to the study of the Audience Dynamics Network. A *path* is a sequence of links that connects two content providers (for instance, {13, 34, 54, 57} is a path between content provider 1 and content provider 7). A *directed path* is a path where the end node of a link is the initial node of the following link (for instance, {13, 34, 45, 57} is a directed path between content provider 1 and content provider 7). A weakly connected component C is a subset of N such that for any two content providers in C, there is a path that connects them, and there is no other content provider connected to any element in C. A strongly connected component C’ is a subset of N such that, for any two content providers in C’, there is a directed path starting in each of them and finishing in the other. Let *A* be the adjacency matrix of Γ, i.e., the *nxn* matrix such that element *xy* in A equals 1 if $xy \in \Gamma$ and 0 if $xy \notin \Gamma$. Let $N_{x.} \in N\colon \left\{\forall y\colon y \in N_{x.} \Leftrightarrow xy \in \Gamma\right\}$ be the set of *susceptibles* of *x* and $N_{.x} \in N\colon \left\{\forall y\colon y \in N_{.x} \Leftrightarrow yx \in \Gamma\right\}$ the set of *influentials* of *x*. Susceptibles of *x* are all those content providers whose audience dynamics are caused by the audience dynamics of *x*, while influentials of *x* cause the audience dynamics of *x*. We call *In-degree* of *x* the number of influential content providers of *x*, $\#\{N_{.x}\}$, and we call *Out-degree* of *x* the number of susceptible content providers of *x*, $\#\{N_{x.}\}$. *PageRank* is the centrality measure that was originally used by Google in order to classify web pages in its search engine, and that was widely used later. In our case, we define the *PageRank* of a university x in the Audience Dynamics Network as[1]

$$PR_x = 0.15 + 0.85 \sum_{y:yx\in\Gamma'} \frac{PR_y}{\#\{N'_y\}}$$

The *PageRank* of a university *x* in the Audience Dynamics Network can be understood as an alternative measure of influence, such that the influence of a university is quantified as the number of audience dynamics that are caused by *x*, weighted by the *PageRank* of those universities, obtained in a recursive way.

3.3. Sample and measures

For the empirical analysis, we selected the 30 most prestigious universities according to the list of world-class universities from the 2018 edition of the ARWU ranking. The official YouTube channel of each university was identified by means of a manual search in university homepages. Daily views data from each channel was retrieved for the period between 26th December 2016 and 2nd October 2018 for each university channel from the historical data stored on Social Blade (2020), which provides the total accumulated views of YouTube channels on a daily basis.

We drew on the total accumulated views at the beginning of the period of analysis (*initial impact*) as a measure of online video impact. We define the *audience dynamics* of the university channel on YouTube as the time series of daily views for all the videos released by the channel. The daily views are computed as the differences of the *total (accumulated) views* series. Thus, in our sample, each *audience dynamics* accounts for 646 observations for each channel. The *total views* series retrieved from Social Blade had some missing or repeated values that were linearly interpolated to preserve the trending behaviour of the data. During this process, we eliminated from the sample four universities with more than seven consecutive missing values: Princeton University, the University of Pennsylvania, the University of Toronto and the University of North Carolina at Chapel Hill. Thus, the final data base

[1] Following Brin and Page (1998), we consider for the computation of *PageRank* that dangling nodes, i.e., nodes with *In-degree* = 0, cause everyone else in the network, and thus Γ' includes the same links that Γ plus all the links zx, such that z is a dangling node. In the same vein, $\#\{N'_{y.}\}$ is Indegree of y under network Γ'. For simplicity we also follow original parameters, which includes 0.85 as the *damping parameter*.

comprises 26 world-class universities. In addition, the *total views* series presented some non-increasing values that could be due to the removal of some videos from the YouTube channel or changes in the algorithm to compute the total amount of views. These were also linearly interpolated to mirror the general evolution of the series around these observations. During this process, an average of 75.4 out of 646 daily data were interpolated in each university channel.

Additionally, we consider the following relations between each pair of universities. First, the *Online video impact difference* (*ID*) between university x and y is computed as $ID_{xy} = Initial\ Impact_y - Initial\ Impact_x$, in millions. Second, the *Geographical distance* (*GD*) between universities x and y, GD_{xy}, defined in thousands of kilometers. In order to know the distances, the geographical co-ordinates of each university were obtained and then the distances in kilometres calculated. Then, the *Knowledge field distance* (*KD*) between university x and y is calculated as the Euclidean distance between the vector of scores in each knowledge field for university x - f ($KF_{x,f}$) - and university y - f ($KF_{y,f}$) -. These scores were retrieved from the last ARWU-Field[2] ranking (which corresponds to year 2016). Each of those scores is a normalized variable [0,100]. The variable *Knowledge field distance* of university x and y is then calculated as follows, $KD_{xy} = \left(\sum_f \left(KF_{y,f} - KF_{x,f}\right)^2\right)^{0.5}$. Finally, the *Prestige difference* (*PD*) between university x and y, is calculated as the difference of *total score* between each pair of universities in the ARWU 2018, as follows, $PD_{xy} = Prestige_y - Prestige_x$. Note that $GD_{xy} = GD_{yx}$ and $KD_{xy} = KD_{yx}$, while $ID_{xy} = -ID_{yx}$ and $PD_{xy} = -PD_{yx}$.

3.4. Procedures

In order to empirically identify the existence of a link *xy* in the network of connected audiences, we study if the audience dynamics of *y* is caused by the audience dynamics of *x* in the Granger sense. Granger causality is a well-established procedure to identify causality relations between time series (Dutta, 2001; Diks and Panchenko, 2006). In particular, for each of the possible pairs among the 26

[2] ARWU fields are Natural Sciences and Mathematics; Engineering/Technology and Computer Sciences; Life and Agriculture Sciences; Clinical Medicine and Pharmacy; and Social Sciences.

universities, we test whether the evolution of views of *university channel x* Granger causes the views of *university channel y* using an F-statistic to assess the statistical significance of the null hypothesis $\beta_1 = \ldots = \beta_l = 0$ in:

$$y_t = \alpha_0 + \sum_{j=1}^{l} \alpha_j y_{t-j} + \sum_{j=1}^{l} \beta_j x_{t-j}$$

where y_t are the views of content provider *y* at day *t*. For the 650 possible relationships among the 26 universities, we consider that *university channel x* Granger causes *university channel y* i.e., that $xy \in \Gamma$, when we reject the null hypothesis at 0.05 level once Bonferroni-corrected. In our application, we set the number of lagged values of the variables to be included in the regression, l, as 14. This allows us to test if the audience dynamics of a university is caused by the previous dynamics of another university during the two previous weeks. This seems reasonable in terms of our daily data while keeping a specification with a reasonable number of parameters to be estimated. The pairwise comparison among this set of universities allows us to identify cases where *university channel y* is Granger caused by *university channel x*, the opposite (one-way causality) or cases where *university channels y* and *x* cause each other (two-way causality). The *Audience Dynamics Network* obtained through this process corresponds to the *Granger causality network* of the audience dynamics of the universities in our sample.

Subsequently, the causal relationships found by the Granger test are analysed by means of Social Network Analysis. The set of individual relationships between nodes characterizes the network structure, identifying the location of the agents in the network (Hanneman and Riddle, 2005). This, therefore, allows for the graphical observation of the Granger-causal relationships that bind together the evolution of the channels within the top world-class universities. Additionally, a core/periphery analysis is conducted to test whether a group of channels occupy central positions in the network. This analysis maximizes the correlation between a model of core and periphery ties, and the observations (Brusco et al., 2017). Core and periphery sub-networks are proposed by adjusting the network data in order to estimate the centrality or closeness of each member to the core of the network (Borgatti et al., 2002).

Then, nodes (channels) are allocated either in the core or in the periphery using algorithms described by Borgatti and Everett (1999).

Once the Granger connections among university channels have been identified and the Audience Dynamics Network unveiled, the next natural step is to analyse the determinants of such causation (Billio et al., 2012; Výrost et al., 2015; Hué et al., 2019). We estimate a Logit model in which the dependent variable is the probability of the audience dynamics of *y* being caused by the audience dynamics of *x*, in the Granger sense, Pr(*xy*). We propose the following specifications,

$$Pr(xy) = F\big(\alpha_0 + \alpha_i ID_{xy} + \alpha_g GD_{xy} + \alpha_k KD_{xy} + \alpha_p PD_{xy}\big) \tag{1}$$

$$Pr(xy) = F\big(\alpha_0 + \alpha_x + \alpha_y + \alpha_i ID_{xy} + \alpha_g GD_{xy} + \alpha_k KD_{xy} + \alpha_p PD_{xy}\big) \tag{2}$$

with $F(z) = \frac{e^z}{1+e^z}$

where the probability of the audience of *y* being caused by *x* depends on the *Online video impact difference* (ID_{xy}), the *Geographical distance* (GD_{xy}), the *Knowledge field distance* (KD_{xy}) and the *Prestige difference* (PD_{xy}) between both universities. Note that that ID_{xy} and PD_{xy}, as they are defined, are positive if the score of *y* is higher than the score of *x*, and negative otherwise. In the specification (2) we take into account possible intrinsic characteristics of audience dynamics of *x* as susceptible and of *y* as influential, i.e., we control the fixed effects associated with each university acting in each of the two roles.

Finally, we assess whether centrality in the network of audience dynamics is related to university prestige. A correlation and a multiple regression analysis are run among centrality, university prestige and the online video impact measures. Based on the results, we test the mediating effect of the online video impact on the relationship between university prestige and centrality (Baron and Kenny, 1986).

Table 1 summarizes the variables considered in the study.

[INSERT TABLE 1 ABOUT HERE]

4. Results

4.1. The Audience Dynamics Network of the most prestigious universities

We identify 112 significant relations among the 26 universities in our sample, out of the 650 possible ones (i.e., in 112 out of 650 possible cases, the audience dynamics of university *x* causes the audience dynamics of university *y*, in the Granger sense). This implies an average *Out-degree* (and *In-degree*) of 4.3: on average, the audience dynamics of a given university causes (and is caused by) the audience dynamics of 4.3 universities.

Result 1: The audience dynamics of the online videos of some universities are caused by the audience dynamics of other universities. Thus, there are connections among university audiences in YouTube, creating an Audience Dynamics Network. Therefore, we answer our RQ1 and, so, we accept H1.

Figure 1 depicts graphically the Audience Dynamics Network, where university channels on YouTube are represented as the nodes. Note that this is a directed network, where the arcs going out of a university point at the nodes it causes and, conversely, the arcs arriving at a university indicate the nodes causing its audience dynamics. There are 12 out of 325 potential bi-directional connections, where audience dynamics of two universities mutually influence one another. Only a group of three universities is completely connected bi-directionally (the audience dynamics of Caltech, University of Tokyo and University of Wisconsin-Maddison cause and are caused mutually). There is one strongly connected component, formed by 17 out of 26 universities. There are two weakly connected components, the biggest one with 22 universities and the smallest one with just two (audience dynamics of the University of Washington causes audience dynamics of ETH Zurich), with two other isolated universities (UC San Francisco and Johns Hopkins University), whose audiences neither cause nor are caused by the audience of any other university in the sample.

[INSERT FIGURE 1 ABOUT HERE]

The network has a core-periphery structure. In Figure 1, we depict in white the universities on the periphery and in black/grey the universities in the core sub-network. This representation groups universities depending on how integrated they are in the network i.e., universities on the periphery have an audience dynamic that has, at most, a weak relation to the rest of audience dynamics. Universities belong to the core because of their relations with other universities, but some of them play a more important role as *influential* and some others as *susceptibles*, following the literature on inter-dependence between agents in social media (Susarla et al., 2016). *Influential universities* in the core are represented in Figure 1 as black nodes and in Table 2 as *Core-out*, and have a higher *Out-degree*: their audience dynamics anticipates the audience dynamics of many other universities. *Susceptible universities* in the core are represented in Figure 1 as grey nodes and in Table 2 as *Core-in*, and have relatively higher *In-degree*: their audience dynamics are anticipated by the audience dynamics of many other universities.

High *In-degree* and *Out-degree* values of a university suggest that they play a relevant role in the network. The most influential universities according to *Out-degree* are Stanford University and MIT. The most susceptible universities according to *In-degree* are the University of Tokyo and the University of Wisconsin-Maddison. We also assess centrality through *PageRank* (see Table 2) which allows us a better understanding of the influential position of the universities. The *PageRank* values in Table 2 show that the most influential university according to this measure is Yale University (YALEUNI).

[INSERT TABLE 2 ABOUT HERE]

4.2. Determinants of Granger causation

In Table 3 we provide the results of the Logit estimation of the model (a Probit specification gives qualitatively similar results).

[INSERT TABLE 3 ABOUT HERE]

Online video impact difference, ID, is the only determinant which remains significant after controlling for fixed effects of each university. The positive coefficients in (1) and (2) indicate that it is more likely that the audience dynamics of university *y* influences university *x* the more video impact university *y* has with respect to *x*, even taking into account each university's propensity to be influential or susceptible. In the specification without fixed effects (1), we find that the more different university *x* and *y* are with respect to their specialization areas, the less likely it is that one influences the other, given the negative and significant co-efficient of *Knowledge field distance, KD*. We also find in specification (1) that it is more likely that audience dynamics of university *y* influences *x* the higher the prestige of *y* with respect to *x* is (see the positive and significant coefficient of *Prestige difference, PD*. However, neither the effect of *KD* nor of *PD* remains significant in specification (2) when we control for idiosyncratic characteristics of each university when acting as susceptible or influential. Finally, *Geographical distance*, *GD*, seems to have no relation with Granger causality of one audience dynamic on the other.

Result 2: Hypothesis 2 stated that online video impact and institutional characteristics could affect audience dynamics. However, these findings suggest that such an influence is driven by online video characteristics and not by the institutional characteristics of universities. The audience dynamics of university *y* influences audience dynamics of university *x* the higher the online video impact of *y* with respect to *x* is. Institutional characteristics between each pair of universities are not clearly associated with causality in the Granger sense. Thus, we answer our RQ2 and partially accept H2.

4.3. Prestige of universities and centrality in the Audience Dynamics Network

Once the structure of the Audience Dynamics Network has been described, we next focus on the relation between centrality in such a network and university prestige. In Table 4 we report the Pearson correlation among our three centrality measures (i.e., *Out-degree, In-degree, PageRank*), the prestige score according to ARWU (2018) and the total number of views of the university on YouTube at the beginning of the period we study (*Initial impact*).

[INSERT TABLE 4 ABOUT HERE]

Out-degree is relatively highly correlated with *PageRank, Prestige* and *Initial impact*. The significant correlation between *Out-degree* and *Initial impact* suggests that the more prestigious the university, the more influential in the Audience Dynamics Network, in line with our hypothesis 2. The significant correlation of *Out-degree* and *PageRank* is expected, since both measure influence in the network. The significant correlation of *Prestige* with *Initial impact* is in line with previous evidence (Meseguer-Martinez et al. 2019a). With respect to *In-degree,* there is a weakly significant negative correlation only with *Prestige*. It may suggest that the more prestigious the university, the less susceptible in the Audience Dynamics Network is. However, this is very weak evidence. *PageRank,* finally, seems to be weakly correlated with *In-degree* or *Prestige*, and the correlation with *Initial impact* is slightly elevated but not significant.

[INSERT TABLE 5 ABOUT HERE]

To clarify the relation between *Prestige* and centrality, we conducted a regression analysis on our centrality measures with respect to *Prestige*, and then we controlled for *Initial impact* (see Table 5). Neither *In-degree* nor *PageRank* are significantly associated with *Prestige*, once we consider our control variable. In the case of *Out-degree*, the significant relation when we do univariate regression disappears when controlling for *Initial impact*. Specifically, *Initial impact* is significant in this case, while the significant effect of *Prestige* on *Out-degree* disappears. This suggests that the relation between *Out-degree* and *Prestige* is explained by their relation to *Initial impact*. Therefore, we follow Baron and Kenny (1986) to test the mediating effect of the online video impact on this relationship (see Figure 2).

[INSERT FIGURE 2 ABOUT HERE]

First, university prestige (predictor) was regressed on centrality (outcome), obtaining *path c* (β=0.149; $p<0.05$). Next, university prestige was regressed to the online video impact (hypothesized mediator), which is called *path a* (β=1236825; $p<0.05$). Finally, to test whether the online video impact was related to centrality, we regressed centrality simultaneously on both university prestige and online video impact. Online video impact was also associated with centrality controlling for university prestige, which is represented by *path b* (β=1.000e-07; $p<0.05$). This regression also provides the estimate for the *path c'* (β=0.025; p=0.70), which represents the relationship between university prestige and centrality controlling for online video impact. Since the effect in *path c'* is very close to zero, there is evidence of full mediation. To test the significance of this mediated effect (defined as the difference in *paths c* and *c'* or as the product of *paths a* and *b*), we draw on the standard error term, $\sqrt{b^2 \cdot sa^2 + a^2 \cdot sb^2 + sa^2 \cdot sb^2}$, where a and b are unstandardized regression coefficients and *sa* and *sb* are their standard errors. Then, by dividing the mediated effect by its standard error term, the z-score is obtained. The z-score is 2.838, greater than 1.96, and thus significant at 95%. Therefore, 83% of the total effect of university prestige on centrality is mediated by the online video impact.

Result 3: Hypothesis 3 stated that university prestige should be associated with a central position in the Audience Dynamics Network. However, and in line with previous results, centrality is affected by online video behaviour rather than by university prestige. *Out-degree* in the Audience Dynamics Network is associated with *Prestige* because online video impact is related to both of them. Other centrality measures, as *In-degree* and *PageRank*, have no relation with *Prestige*. Thus, we answer RQ3 and reject H3.

5. Discussion and conclusion

We describe the audience system of content providers through the Audience Dynamics Network. We show the existence of such a network for the YouTube channels of 26 of the most prestigious universities. Among them, 17 form a strongly connected component. It implies the existence of a path of influence between any of the universities in such a group in line with the literature on interdependencies between agents in social media (Ver Steeg and Galstyan, 2012) and, in particular, among content creators (Susarla et al., 2016). Thus, any change in one of them is able to affect any other, although some of these changes affect directly (through connections, between connected universities) and some others indirectly (through paths).

Regarding centrality, both *Out-degree* and *PageRank* can be considered as measures of the influence of the Audience Dynamics of one university. With respect to *Out-degree*, Stanford University and MIT influence 14 other universities. We can imagine that fluctuations in the audience dynamics of these two universities are later replicated in the audience dynamics of their group of susceptibles, as found by Susarla et al. (2016). *PageRank* assigns a value to the out-links of each university weighted by the relevance (*PageRank*) of the influenced university. Its implications can be easily interpreted in the case of University College London (UCLTV) and the case of North-Western University (NORTHWE). Both have the same *Out-degree* equal to 1, meaning that their audience dynamics only influences the audience dynamics of one university, and therefore both have the same *Out-degree*. However, UCLTV has a four times higher *PageRank*. This is because UCLTV is the only university whose audience dynamics causes the audience dynamics of Harvard University, which is itself an influential university that creates cause in another 6 different universities. On the other hand, the influence of NORTHWE is limited to one of the 4 universities that influence UC Berkeley (UCBERKE), which, moreover, has no special influence since it has a null *Out-degree*. The *PageRank* values in Table 1 show that the most influential university according to this measure is Yale University (YALEUNI), although it is fifth in *Out-degree* ranking. This is because, although audience dynamics of YALEUNI is not the one that most influences other audience dynamics, it influences some of the most influential universities in the Audience Dynamics Network i.e., it is the only one that influences MIT and one of the four universities influencing Stanford University (STANFOR), the two universities with the highest *Out-degree* in our sample. This result is in line with the literature as high popularity does not necessarily imply high influence (Ver Steeg and Galstyan, 2012).

We have found a relation between *Out-degree* in this network and prestige, which at first glance suggests that influential universities in the Audience Dynamics Network are the more prestigious ones. However, the result disappears if we control for the online video impact, which had been found to be associated with prestige in previous studies (Meseguer-Martinez et al., 2019a). Therefore, universities are influential not because of prestige itself but because of their video impact. From this point of view, influential audiences are those of the universities with a higher online video impact. This is an intuitive result that makes sense as the audience dynamics of the most successful universities on YouTube anticipates the dynamics of the others, in line with the results of the literature on Granger causality relations which has uncovered such type of relations in a plethora of different settings (Billio et al, 2012; Papaioannou et al., 2020; Park et al., 2020). However, this is not so clear with respect to *PageRank*, the other measure of influence. In any case, this suggests that influence in this network is not as greatly associated with university prestige as with success in the provision of online video.

These results have implications for academics and university managers. Firstly, given that current research on the online video impact on YouTube focuses on the direct effects of agents' characteristics on their own channels, we draw attention to the need for further research on the effects of factors external to the channel owner as potentially significant drivers of online video impact. For university managers, these results have important practical implications for the management of their institutional YouTube channels. This study unveils a pattern of interdependences among the audiences of universities on YouTube. The university impact on YouTube is subject not only to its own activities, but also to the audience and decisions of other universities on which it depends in terms of YouTube. It is, therefore, advisable for university managers in general, and marketing managers in particular, to identify the interdependences of their audience on YouTube and keep track of these channels to anticipate changes in their own audience and tap the potential of such changes. The strategies and outreach of their channels can be significantly determined by the relations of influence and dependence with other universities in a context of increasing competition. Knowing the interconnections, university managers can anticipate how video impact will evolve and, thus, adapt advertising timing and other aspects related to online video management.

The theoretical literature explaining how competition occurs in broadcasting markets (Mangàni 2003; González-Maestre and Martínez-Sanchez, 2015; Battaggion and Drufuca, 2019) typically focuses on duopoly cases, analysing the optimal strategy of one producer with respect to others, when they try to capture attention of viewers. Our study illustrates the importance of audience behaviour in this new environment, and calls for an extension of these models to an environment where competition is stronger, and probably new studies based on monopolistic competition could be developed.

Some limitations to this study are worth mentioning. Firstly, the sample is limited in size, so the generalization of findings should be taken with caution. Further research should replicate the analysis on a broader sample of universities. Secondly, the data for the time series was gathered for a specific time interval. It remains unknown whether these results would remain along different time intervals. Research could consider broader time spans in order to overcome this limitation. In addition, the study draws on a single metric, namely view-count. Despite being the most utilised metric of online video impact (Xiao et al., 2015), future research should consider expanding the study to other metrics such as comments or likes. Furthermore, this article does not distinguish between the audiences of the different types of videos that universities produce (teaching or other). Hence, the generalization of the results is limited and content analysis could be performed to address this issue in future studies. While the study finds university prestige to be related to interdependence among channel audiences, further research should determine the mechanisms that connect university prestige and the influence among channels. In the same vein, the only institutional variable taken into account in the study is university prestige. Additional factors underlying the relations between university channels may yet be found. Finally, the network analysis identified isolated channels. Whether this is due to missing channels to which the isolated universities relate, or because these channel audiences are not interconnected, the reasons for channels to be independent from the rest of universities is to be analysed.

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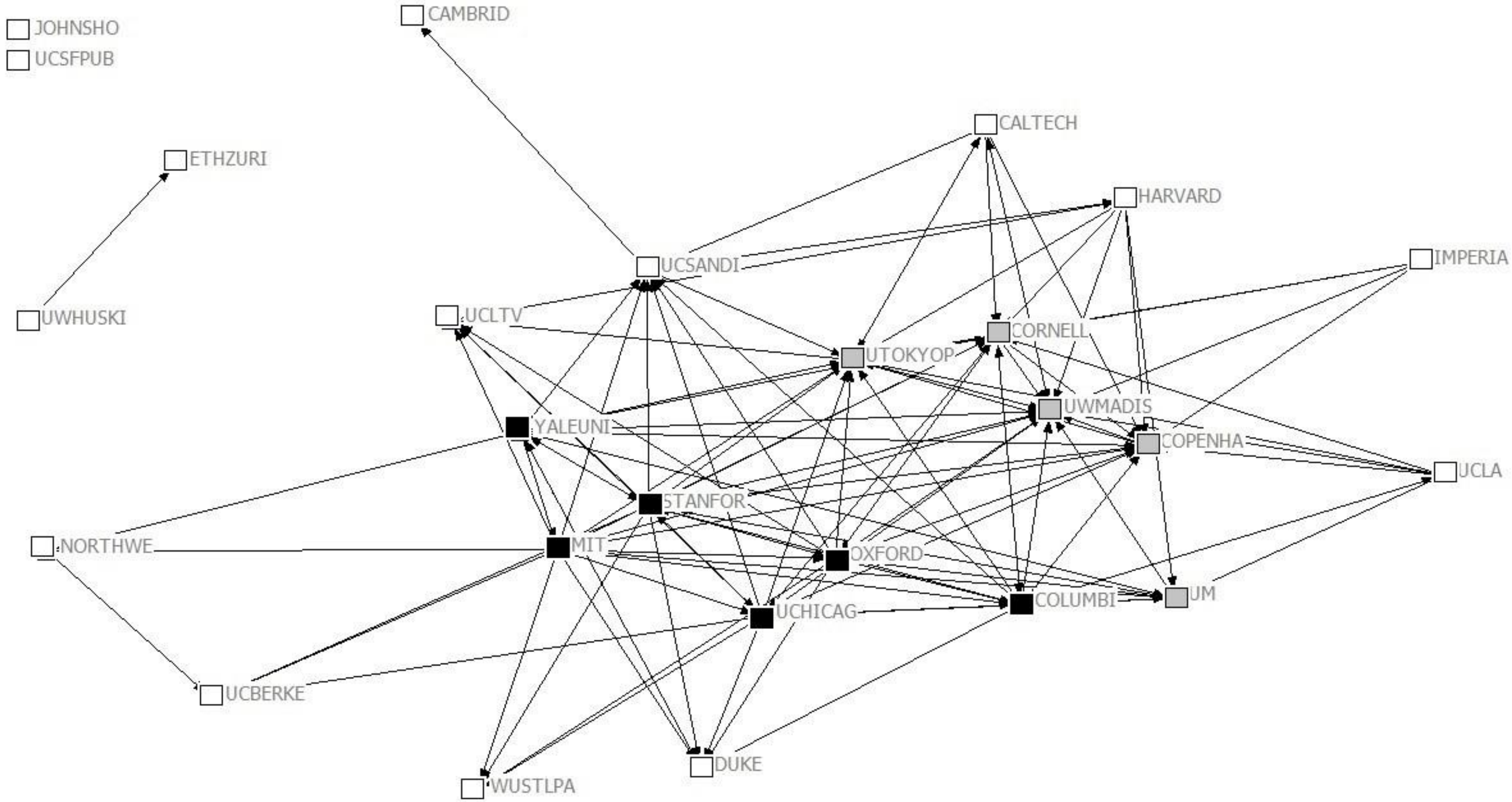
Table 1. Summary of variables

Type	Source	Name	Description
Online video impact	Social Blade	Total views	Total acc. views reported by Social Blade for the period 26/12/16 to 02/10/18
	Total views	Audience Dynamics	Daily difference of Total views
	Total views	Initial impact	Total views per 26/12/16
	Total views	Online video impact difference, ID	Difference of initial views between pairs of universities
Network centrality	Audience Dynamics Network	Out-degree	Number of susceptible content providers of a given content provider
		In-degree	Number of influential content providers of a given content provider
		PageRank	Number of audience dynamics caused by a content provider weighted by the PageRank of those in a recursive way
Institutional characteristics	ARWU 2018	University Prestige	Total score ARWU 2018
	ARWU Fields 16	Knowledge specialization	Vectors of scores in each knowledge field reported in ARWU Field 2016
Pairwise comparison of institutional characteristics	University Prestige	Prestige difference, PD	Difference of prestige score between pairs of universities
	Geographical distance	Geographical distance, GD	Difference of geographical distance between pairs of universities
	Knowledge specialization	Knowledge field distance, KD	Euclidean distance of the addition of the differences between the vectors of scores of a pair of universities

Source: own work.

Figure 1. Audience Dynamics Network / Core-Periphery representation



Source: own work. Nodes in the core are displayed in black (highly influential) or grey (highly influenced) and nodes in the periphery are displayed in white.

Table 2. Audience Dynamics Network, Online Video Impact and Prestige

		Audience Dynamics Network							Online Video Impact	Prestige
University	**Channel**	Out-degree	In-degree	Bidirectional Connections	PageRank	Strongly Connected Component	Weakly Connected Components	Core-Periphery structure	Initial Views	ARWU 18 Score
Stanford University	STANFOR	14	4	4	0.063	1	1	Core-Out	109589425	75.6
Massachusetts Institute of Tech.	MIT	14	1	0	0.061	1	1	Core-Out	98743187	69.9
University of Chicago	UCHICAG	12	4	3	0.070	1	1	Core-Out	5154776	55.5
University of Oxford	OXFORD	11	3	2	0.058	1	1	Core-Out	7431253	60
Yale University	YALEUNI	10	2	2	0.127	1	1	Core-Out	9908981	50.7
Columbia University	COLUMBI	9	6	2	0.044	1	1	Core-Out	6851665	58.8
University of California, Los Angeles	UCLA	6	1	0	0.045	1	1	Periphery	18983171	51.2
Cornell University	CORNELL	6	10	3	0.034	1	1	Core-In	10164297	50.7
Harvard University	HARVARD	6	1	0	0.028	1	1	Periphery	47987858	100
California Institute of Technology	CALTECH	5	2	2	0.023	1	1	Periphery	6456619	57.4
Imperial College London	IMPERIA	4	0	0	0.021	0	1	Periphery	6870576	40.1
The University of Tokyo	UTOKYOP	3	14	2	0.049	1	1	Core-In	291224	41.5
University of Wisconsin - Madison	UWMADIS	2	14	2	0.049	1	1	Core-In	2364910	38.9
University of California. San Diego	UCSANDI	2	8	0	0.036	1	1	Periphery	1046459	47.8
University of Michigan - Ann Arbor	UM	2	8	1	0.035	1	1	Core-In	4633713	39.4
University of Copenhagen	COPENHA	2	11	0	0.017	1	1	Core-In	500009	38.7
University College London	UCLTV	1	5	0	0.049	1	1	Periphery	2562824	46.1
University of Washington	UWHUSKI	1	0	0	0.046	0	2	Periphery	2271407	50
Duke University	DUKE	1	6	1	0.018	1	1	Periphery	2733729	39.7
Northwestern University	NORTHWE	1	2	0	0.012	0	1	Periphery	3032162	39.9
Washington University in St. Louis	WUSTLPA	0	4	0	0.036	0	1	Periphery	1519622	42.1
University of California, S Francisco	UCSFPUB	0	0	0	0.025	0	0	Periphery	1249699	41.9
University of California, Berkeley	UCBERKE	0	4	0	0.022	0	1	Periphery	8377940	68.3
Swiss Fed Institute of Techn Zurich	ETHZURI	0	1	0	0.011	0	2	Periphery	943439	43.9
Johns Hopkins University	JOHNSHO	0	0	0	0.011	0	0	Periphery	2532186	45.4
University of Cambridge	CAMBRID	0	1	0	0.009	0	1	Periphery	15180057	71.8

Source: own work, except Prestige variable (ARWU 2018). Universities are ordered according to their *Out-degree* and *PageRank*.

Table 3. Logit estimation of existence of links between audience dynamics of two universities

	Model 1	Model 2
Geographical distance, GD	0.027	-0.071
	(0.036)	(0.081)
Knowledge field distance, KD	-0.011***	0.006
	(0.003)	(0.006)
Online video impact difference, ID	0.016***	0.623***
	(0.004)	(0.186)
Prestige difference, PD	0.022***	-0.139
	(0.007)	(0.132)
Constant	-1.138***	-1.631
	0.287	1.117
LR - Chi2 (P-value)	0.000	0.000
Pseudo R2	0.119	0.478
N	650	422

N=26. Significance is indicated as ***1%, **5% or *10%. In Model 2 we control by fixed effects of each university as influential or susceptible.

Table 4. Pearson correlation for centrality, prestige and video impact measures

	Out-degree	**In-degree**	**PageRank**	**Prestige**	**Initial impact**
Out-degree	1				
In-degree	-0.078	1			
PageRank	0.674***	0.073	1		
Prestige	0.474**	-0.338*	0.117	1	
Initial impact	0.661***	-0.210	0.266	0.647***	1

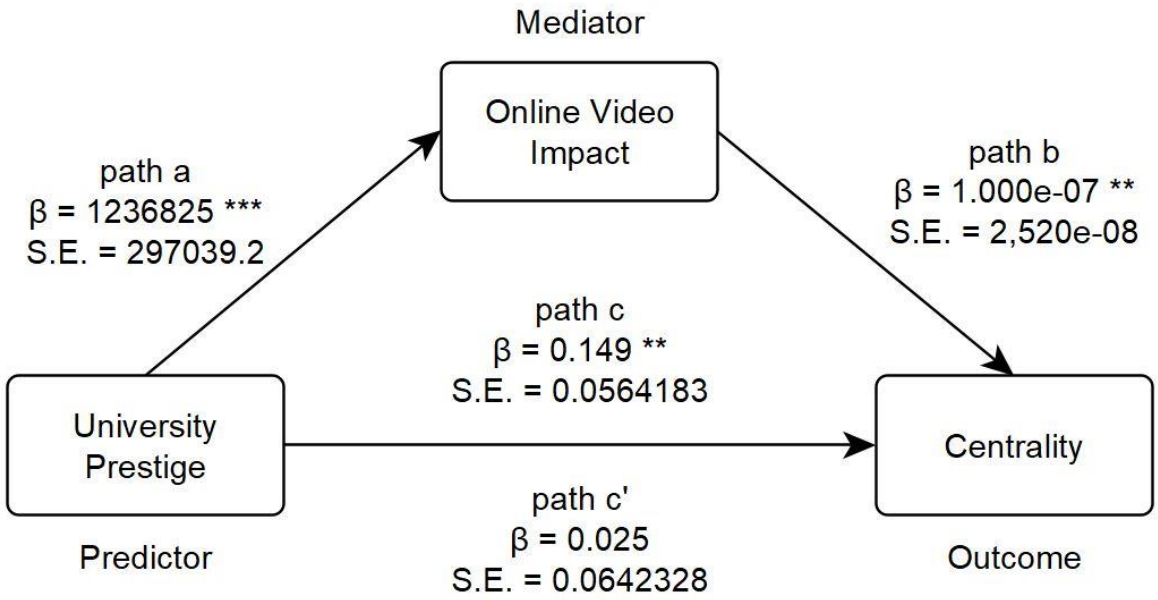
N=26. Significance is indicated as ***1%, **5% or *10%.

Table 5. Multiple regression for centrality measures

	Out-degree		**In-degree**		**PageRank**	
Prestige	0.149**	0.025	-0.097*	-0.099	0.000202	-0.000161
	(0.056)	*(0.064)*	*(0.055)*	*(0.073)*	*(0.000)*	*(0.000)*
Initial impact		1.00e-7**		2.22e-9		2.94e-10
		(3.36e-08)		*(3.87e-8)*		*(2.36e-10)*
Constant	-3.520	1.537	9.404***	9.515**	0.027	0.402*
	(3.072)	*(3.159)*	*(3.002)*	*(3.634)*	*(0.018)*	*(0.022)*
F-statistic (P-value)	0.014	0.001	0.091	0.247	0.566	0.402
Adj. R^2	0.193	0.392	0.077	0.037	-0.027	-0.004

Ordinary Least Squares regression. N=26. Significance is indicated as ***1%, **5% or *10%. Estimated coefficients in regular font, standard deviation between parentheses.

Figure 2. Mediation analysis



Significance is indicated as ***1%, **5% or *10%.