Doug's Effect: The Impact of Influencer Marketing on Community-Driven Online Auctions

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Abstract

The pandemic restrictions imposed during 2020 contributed to a significant shift of economic activity in online automotive auction markets. Yet, with vehicle sales going down in the post-pandemic period, online auction platforms are struggling to keep their communities engaged and active. One such platform (Cars & Bids) leverages Doug DeMuro, founder and social media influencer, to bolster user engagement and auction performance on the platform. To explain the effect of their "endogenous to the platform" influencer, we rely on the theoretical principles of resource mobilization and relational herding. We collected a panel dataset of N = 1300 vehicles auctioned from 2020 to 2024 and leverage difference-in-differences and coarsened exact matching to conduct our analyses. Our findings suggest that an endogenous influencer effect can significantly increase user engagement (i.e., viewership and commenting), as well as increase auction performance with a higher number of bids and higher final auction price.

Keywords: influencer, platform, auction, herding

1. Introduction

The pandemic restrictions imposed in many countries during the first half of 2020 contributed to the significant shift of economic activity in online automotive auction markets.[1] For example, Cars & Bids (C&B), one of the biggest and well-known digital car auction platforms, has completed over 17,000 auctions and sold over $230 million worth of cars since its launch in 2020.[2] Traditionally, the drivers behind higher premiums in online auction markets (in addition to the product characteristics, rarity, condition, etc.) have been attributed to the institution-based trust or the buyer's perception that effective third-party institutional (or platform in our case) mechanisms in place facilitate the transaction success (Bockstedt and Goh 2011). However, what differentiates C&B from other car auction platforms is not the platform infrastructure and features alone, but its unique community of car enthusiasts, which is a novel approach in online automotive auction markets. In 2023, C&B reported nearly half a million registered members[3] who, in addition to having economic interest, are genuinely committed to voicing their opinions and contributing their knowledge and expertise to the transaction process. Yet, with vehicle sales going down in the post pandemic period (by about 6.7% and in North America)[4], auction platforms are struggling to keep their communities engaged and active. Accordingly, we seek to answer the following research question: *"How can online auction platforms leverage influencers to enhance community engagement and improve performance?"*

Community engagement is the central driver of active participation in online networks, which, in turn, directly influences the performance of increasingly digitized businesses (Ray et al. 2014). Today, with the rise of social media platforms with global reach, a robust and growing research stream on the influencer marketing has showed that who creates and shares content around a brand or product is oftentimes just as important as what is being shared. For example, product endorsements from known or trusted platform members (Brass 2015), explicit sponsorship disclosures (Cao and Belo 2023), and the use of seeded marketing campaigns (Chae et al. 2017) have been shown to positively impact user engagement. At the same time however, influencers' excessive characteristics can decrease rather than boost engagement due to diminishing credibility and trustworthiness (Cascio Rizzo et al. 2023; Wies et al.

[1] https://www.nytimes.com/2022/01/17/business/classic-car-auctions-online.html
[2] https://www.autoevolution.com/news/doug-demuros-auction-site-cars-bid-website-receives-37-million-investment-209579.html
[3] https://getultimateauction.com/blog/cars-and-bids-vs-bring-a-trailer/
[4] https://www.linkedin.com/pulse/current-state-automotive-industry-future-revolution

URI: https://hdl.handle.net/10125/109179
978-0-9981331-8-8

2023). These findings underscore the importance of distinguishing between different influencer categories.

While IS research has traditionally focused on external influencers who are exogenous to the organization, emerging research in other areas highlights the unique role of internal influencers. For example, Mero et al. (2023) find that internal influencers are uniquely positioned to create social bonds with target audiences and other stakeholders, which is indispensable for building interpersonal trust with community members. Similarly, Huang et al. (2022) found that internal influencers improved new technology acceptance rates due to their stronger social bonds with core audiences. Despite the strong indication of internal influencers' ability to shape user behavior, there is a dearth of research examining the impact of internal influencers on engagement and performance of community-based online auction platforms. We seek to fill this gap by analyzing a unique natural experiment which allows us to compare the performance of products that have been promoted by a trusted internal influencer to the performance of similar products that lack this type of representation.

To tackle the challenges of low community engagement and decline in enthusiast contributions, C&B harnesses its substantial social media following (728k on YouTube, 132k on Instagram, 107k on TikTok, and 42k on Facebook). In a strategic move to draw users to the auction website and facilitate their interactions, the platform leverages the influence of Doug DeMuro, a prominent social media figure in the car enthusiast community. Influencer marketing typically involves endorsements by individuals who are not directly associated with the company. However, in the case of Doug DeMuro and C&B, a unique situation arises where DeMuro is not only an influencer but also the founder of the C&B car auction platform (i.e., he is endogenous to the platform). This distinction is significant because it allows C&B to leverage not just an influencer's reach but also the credibility and authority of its own founder within its community engagement strategy. We argue that leveraging such influencer persona has the capacity to address community engagement concerns and ultimately improve auction performance.

To explain the mechanism underlying endogenous influencer effect on user engagement and auction performance, we rely on the theoretical foundations of resource mobilization (McCarthy and Zald 1977) and relational herding (Brass 2015). The principles of resource mobilization suggest that certain individuals within a social group may hold informational resources capable of shaping attitudes, beliefs, and behaviors of others due to their perceived knowledge, trustworthiness, and credibility. Similarly, figures like Doug DeMuro exemplify opinion leaders within the broader car enthusiast community. Relational herding principles suggest that when such influential figures actively participate in and promote auction platforms, their behaviors can trigger a cascade of engagement and involvement among other group members. This occurs as enthusiasts emulate the actions of these opinion leaders, contributing to a domino effect of increased participation and interest within the community.

To test the proposed hypotheses, we collected a panel dataset including a total of N = 1,300 vehicles auctioned from 2020 to 2024. To identify the focal effect of endogenous influencer marketing, we leverage the difference-in-differences approach to compare user engagement and listing performance between treated (featured by Doug DeMuro) and control (regular) listings before and after the start of Doug's featured car series on the Instagram social media platform. To address the issue of non-random sample selection (Doug's choice is beyond our control), we rely on a combination of sample matching techniques. First, we seek car expert opinion on the cars comparable to those featured by the focal influencer in our study. Second, we use coarsened exact matching (CEM) to ensure appropriate comparability of treatment and control groups.

The contributions of our study are threefold. First, we contribute to the IS literature by clarifying the distinct roles played by influencer personas in facilitating community engagement. Second, we contribute to theory by explaining the mechanism underlying the link between internal influencers and organizational performance. Finally, we contribute to practice by offering platform managers an efficient solution to the problem of low user engagement and contribution.

2. Context

Over the past years the C&B platform has attracted a variety of vehicles (cars, vans, trucks, motorcycles, SUVs, etc.) across a wide range of prices ($1,800-1,450,000+) and age (1980s to the 2020s). What differentiates C&B from other auction platforms is its knowledgeable community with more than 500,000 registered users that vets each listing, so potential buyers can bid with confidence. In contrast to most other online car auctions that generally preclude user interaction, C&B offers an interactive online environment that is rich in engagement features and user roles.

Website visitors can freely browse listings, however, cannot comment or bid. Registered users have the benefit of commenting on the listings (only text is allowed). Users that connect their credit card to the account get the privilege of bidding (bidders). Direct communication between users and bidders (and sellers) is only possible in the form of public comments on a given listing's page. The platform also pre-screens comments posted by users with a low reputation. Comments can also be flagged by community members as non-constructive if perceived so by other users.

All of the submitted listings have a standardized representation that generally includes a detailed description complemented by select photos, listing of car features, CARFAX information, photo gallery, videos, and discussion board in the form of public comments. Each individual comment contains a timestamp, user nickname (users are anonymous), measure of user reputation, and measure of comment helpfulness. The typical auction runs for 7 days. There are two types of auctions, with and without reserve. Listings that do not require a reserve price have a "No Reserve:" note in front of the listing title.

During the auction, the seller is encouraged to be an active participant of the communication process with users and bidders. Generally, many platform participants engage by voicing their opinions and engaging in conversations with seller or others. The range of topics revolving around the listing can include various aspects associated with history, condition, service records, maintenance issues, color, specifications, price, ownership, technical details, questions and clarifications about listing, etc. The sellers are allowed to show the car to the interested bidders in person; however, the transaction must occur on the platform. In instances when a car is examined in-person, usually, the user shares their experience with others in comments.

3. Literature review

Our survey of the literature lies at the intersection of online auction behavior, community design considerations, and online influencer marketing strategies. To facilitate comprehension of the corresponding streams of literature, we organize our analysis into the three IS research streams most central to the study of community engagement and platform performance: platform design, online influencer research, and digital auction bidding behavior.

When it comes to the study of platform design, the IS literature has suggested several affordance dimensions to address the problems of user engagement and performance, including the implementation of monetary and non-monetary participation incentives (Wang et al. 2023), the use of interactive user and content features such as identity disclosure (Pu et al. 2020) and "Like" buttons (Liang et al. 2023), as well as direct brand communication to signal credibility and trustworthiness (Bapna et al. 2019; Kumar et al. 2022). Trust is particularly important in markets with information asymmetry and adverse selection problems (Akerlof 1970; Spence 2002). Moreover, it has been shown that when assessment of product quality or seller credibility is difficult, one-quarter to one half of all U.S. purchases of goods are made through personal networks (Granovetter 2018). The rise of digital auction platforms exemplifies these challenges: although classic forms of auction bidding represent an inherently social process with multiple actors, the online marketplaces digital technologies have enabled embody both the advantages and disadvantages of online communication vis-à-vis offline interactions.

Digital auctions are convenient, decentralized, more inclusive, and can take place over a longer time period; however, they do not offer the same level of access to social cues and product evaluation opportunities their in-person counterparts afford. It has thus been noted that trust is of an even greater importance in these settings (Bagozzi and Dholakia 2002), and that bidders, both actual and potential, actively seek, and are passively exposed to, signals from their digital auction environment (Cui et al. 2017) which shape their bidding behavior and thus – the performance of the auction platform in general. Lack of trust, particularly in the online market structure, has been associated with reluctance to bid, which is especially pronounced among inexperienced bidders (Stern and Stafford 2006). However, even when institutional trust has been established, highly experienced bidders tend to bid at lower levels than moderately experienced bidders, likely because they develop additional skills that allow them to find better deals with a more parsimonious bidding approach (Stern and Stafford 2006). Thus, credibility and trust extend beyond the digital auction platform itself: all participating actors and their actions present potential opportunities for evaluation. Relatedly, indicators of the virtual presence of bidders (e.g., their photos, instant messaging, and auction proxy, etc.) have been found to significantly affect both bidding strategy and market outcomes in online auctions (Rafaeli and Noy 2005).

The proliferation and ubiquity of social networks have further strengthened virtual presence and have given rise to a new category of engagement and performance levers through online influencer marketing strategies. Product endorsements from known or trusted platform members (Brass 2015), explicit sponsorship disclosures (Cao and Belo 2023), the emotional tone of online influencer content

(Mallipeddi et al. 2017), and the use of seeded marketing campaigns (Chae et al. 2017) have been found to play a positive role in this relationship. At the same time however, influencers' excessive characteristics can decrease rather than boost engagement due to diminishing credibility and trustworthiness (Cascio Rizzo et al. 2023; Wies et al. 2023). It is thus important to distinguish between different influencer categories.

While the main focus of extant IS research has traditionally been on external influencers who are external, or exogenous, to the organization, emerging research in other areas highlights the unique role of internal influencers. For example, Mero et al. (2023) find that internal influencers are uniquely positioned to create social bonds with target audiences and other stakeholders, which is indispensable for building interpersonal trust with community members. Similarly, Huang et al. (2022) found that internal influencers improved new technology acceptance rates due to their stronger social bonds with core audiences. The authors highlight that persuasions originating from internal influencers generally have longer lasting impact due to stronger bonds compared to those of external influencers. Moreover, while external influencers are mostly concerned about facilitating product sales, internal influencers offer high-level domain expertise and fact-checking through discourse and interactions with target audiences.

4. Hypothesis development

The extant literature on internal influencers offers valuable insights into why this type of influencers is positively perceived by community members, including due to the stronger interpersonal trust (Mero et al. 2023) and social bonds (Huang et al. 2022) that they can establish. These explanations, however, cannot readily explain the mechanism at work in the relationship between internal influencers on one hand, and platform performance and community engagement on the other. Therefore, to elucidate this complex connection, we employ the so-called resource mobilization theory (RMT) (McCarthy and Zald 1977). RMT posits that consumers draw upon their existing knowledge and other resources to guide their behaviors, and when the new resources become available, or an existing resource migrates from one practice to another, a change in behavior can occur (Angelopoulos et al. 2023). At the core of RMT is the idea of resource mobility which can transcend boundaries, particularly group boundaries. With respect to digital auction platforms, internal influencers, in their role as experts and boundary spanners, can open up pathways for resource mobilization among community members (Angelopoulos et al. 2023) by making available to the customer community information or knowledge which was hitherto inaccessible to them. This example of resource mobilization is in turn expected to change community member behavior. Extending RMT's concept of resource mobilization to the context of C&B, it can be expected that insider knowledge, along with Doug's trusted endorsement as examples of newly mobilized resources, has the capacity to spark interest among community members to consider car models that had hitherto been neglected. On digital auction websites, this interest is reflected in the number of interactions with a given car listing, including the number of views and comments associated with it. We therefore hypothesize:

Hypothesis 1: Internal influencer featuring will have a positive effect on user engagement with listing.

Community engagement on online auction websites is, however, not necessarily the same as actual bidding required for the success of the platform transaction. Auction research shows that bidders are more likely to follow the "wisdom of crowds" with respect to placing bids—a phenomenon known as "herding"—and that this likelihood increases when those crowds include acquaintances rather than strangers (Brass 2015). And yet, early online auction research has argued that while the individuals participating in an auction are present at the same place, have a similar goal, and are influenced by one another, this collection of people has a limited life span and is more properly understood as a group as opposed to a community (Rafaeli and Noy 2005). This is likely why the field has focused on the manifestation of bidder *behaviors* such as number of bids, likes, and comments, but not on questions of *relationality*, especially when it comes to the influence of familiar community members. The integration of auction platforms with social media sites and auction platform community features as is the case with C&B, has made possible the emergence of a more consistent community with valued opinion leaders, embodied by the internal influence of Doug. In this novel informational environment, the theory of relational herding (Brass 2015) predict that the social influence of familiar community members such as Doug would have a positive impact on bidder behavior that ultimately results in improved auction listing performance. We therefore hypothesize:

Hypothesis 2: Internal influencer featuring will have a positive effect on auction listing performance.

5. Methods

To collect our dataset, we executed the following approach. First, from the C&B account on Instagram, we identified a list of individual cars that were featured by Doug DeMuro. Second, for each of the featured cars (i.e., their year, make and model combination), we identified a corresponding car make and model that could be considered as a comparable alternative from the perspective of potential buyers. For example, we matched a featured Ford Focus RS to its competitor Honda Civic Type R, which was not featured. To execute such matching, we relied on the expertise of a recognized car expert and auctioneer, the founder and CEO of Opposite Stock (https://www.oppositestock.co.uk). It is important to note that matching was done with respect to each model's generation (i.e., year of manufacture) of the featured car. Finally, after compiling the list of featured cars and their corresponding competitors, we conducted searches on the C&B platform for every combination of car make, model, and generation to identify all auction listings spanning from 2020 to 2024. The final sample included a total of N=1,300 listings, of which 621 (48%) were featured by Doug (in some cases, the expert identified more than one comparable alternative for featured listings). The descriptive statistics and operationalization of the variables are presented in Table 1.

Table 1. Descriptive Statistics (*N* = 1,300)

Variable	Description	Mean	SD	Min	Max
win_bid	Winning or highest bid	40635.27	59740.40	2600	710000
sold	Indicator is car was sold or not (for instances when reserve was not met)	0.76	0.42	0	1
bids	Total number of bids submitted by bidders	28.11	14.22	0	151
views	Total number of listing views by users	14927.17	10443.96	3362	138835
comments	Total number of comments by users	53.13	42.31	0	528
photos	Total number of photos submitted by seller	123.62	50.84	37	485
one_owner	Indicator if car has only one owner	0.13	0.34	0	1
manual	Indicator if car has manual transmission	0.51	0.50	0	1
no_reserve	Indicator if auction is with reserve or not	0.32	0.47	0	1
inspected	Indicator if car was inspected by third party	0.03	0.17	0	1
low_miles	Indicator if car is listed with "low miles"	0.39	0.49	0	1
doug_review	Indicator if listing description was written by Doug	0.02	0.15	0	1
car_year	Year of car manufacture	2006	8.28	1982	2023

5.1. Model-free analysis

We begin our analysis by presenting model-free evidence of the "Doug's effect" on the outcome variables of interest, i.e., highest bid value, number of bids, numbers of listings views, number of comments, indicator if the listing was sold, and number of images included in the listing.

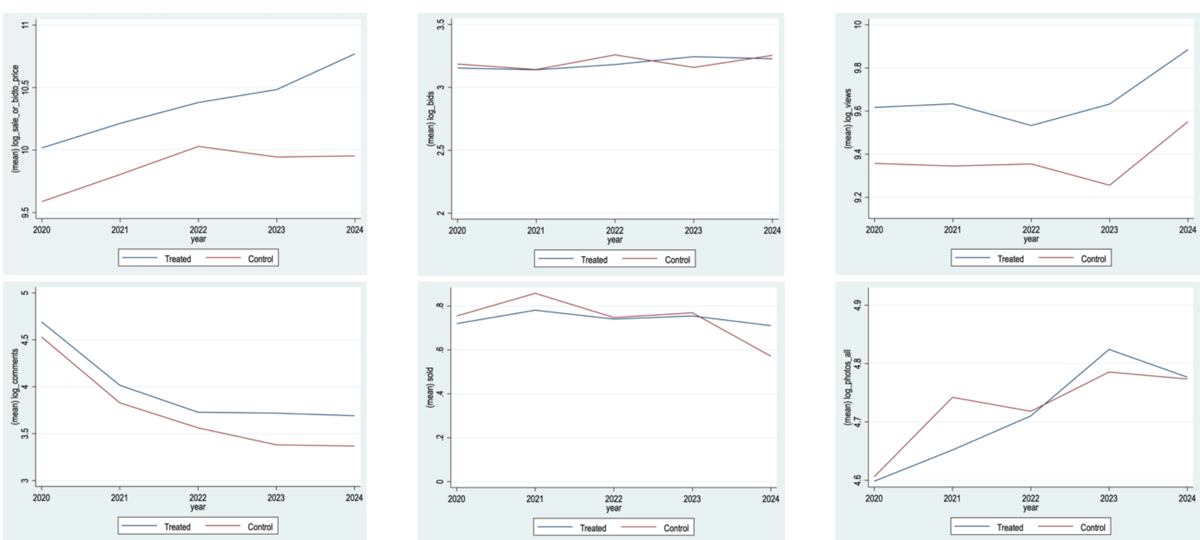

Figure 1. Outcomes of interest by treated and control groups (intervention is March 2023 onwards)

Based on the data, we can make the following preliminary conclusions. First, we observe a notable difference between the winning (or highest) bids of the treated and control groups. That is, while the prices of the listings in the control group flatten from 2022 onwards (which is consistent with decline in automotive sales nationwide), there is an evident increase in the price of the cars in the treated group. The notion of enhanced performance is further supported by the notably slower rate of sales decline observed in the treated group compared to the control group, which has been adversely affected since 2023. Next, we can see a substantial increase in the number of listing views in the treated group starting in 2022 compared to control whose engagement picked up later in 2023. Finally, we can see that while the number of comments has been steadily declining for both groups since 2020, the rate of decline has been slower for listings in the treated group. We do not observe other differences in the number of submitted bids or the number of photos included by sellers in the listings (we are using the latter variable to gauge the extent of effort that sellers put in the presentation of their cars).

5.2. Difference-in-differences analysis

To capture "Doug's effect" on engagement and performance outcomes, we use a DID approach. To this end, we estimate the following equation:

$$Y_i = \alpha + \sigma Post_i + \gamma Treated_i + \beta(Post_i \times Treated_i) + \phi Controls_i + Brand_i + Year_t + \epsilon_i \quad (1)$$

In the above equation, Y_i represents one of the dependent variables of interest (i.e., winning bid amount in U.S. dollars, indicator if vehicle was sold or not, number of bids submitted users, number of listing views, number of listing comments, number of listing photos submitted by seller). The treatment group dummy $Treated_i$ equals 1 if the listing (i.e., the associated car make and model combination) was featured by Doug DeMuro, or 0 otherwise. $Post_i$ represents the time dummy for the period after Doug's featuring of the cars in the treatment group, which is equal to 0 for the time intervals before featuring, and 1 otherwise. We interact the treatment and time indicators to capture the effect of the intervention. The interaction coefficient β captures the difference in the engagement and performance of the listings after Doug's featuring. The positive sign of the interaction would capture the hypothesized positive effect. $Controls_i$ is the vector of observed confounders, including one owner vehicle indicator, transmission type indicator, auction with no reserve indicator, third-party inspection indicator, low-miles indicator, description written by Doug indicator (different from featuring on social media), and vehicle's year of manufacturing. We also control for the car brand fixed effects and year fixed effects. Finally, α is a constant and ϵ_i is the idiosyncratic error term. Table 2 presents estimation results.

Table 2. DID estimation results (SE in parenthesis)

Model Outcome	(1) log_win_bid	(2) sold	(3) log_bids	(4) log_views	(5) log_comments	(6) log_photos
one_owner	-0.11* (0.05)	0.08* (0.03)	-0.01 (0.05)	-0.02 (0.03)	0.04 (0.05)	0.03 (0.03)
manual	0.04 (0.04)	-0.02 (0.02)	0.06* (0.03)	-0.03 (0.03)	-0.03 (0.04)	0.015 (0.02)
no_reserve	-0.87*** (0.04)	0.35*** (0.02)	0.01 (0.04)	-0.20*** (0.03)	-0.14** (0.04)	0.03 (0.02)
inspected	-0.10 (0.10)	0.11 (0.06)	-0.03 (0.08)	-0.09 (0.07)	-0.16 (0.09)	-0.13 (0.07)
low_miles	0.35*** (0.04)	-0.03 (0.02)	0.05 (0.03)	-0.04 (0.03)	0.02 (0.04)	-0.03 (0.02)
doug_review	0.44* (0.18)	-0.02 (0.07)	0.05 (0.11)	0.93*** (0.09)	0.51*** (0.10)	0.22** (0.07)
car_year	0.019*** (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.01*** (0.01)	-0.01*** (0.01)	-0.01*** (0.00)
treated	0.22*** (0.05)	0.01 (0.03)	-0.04 (0.04)	0.21*** (0.03)	0.17*** (0.05)	-0.01 (0.03)
post	0.01 (0.05)	-0.09** (0.03)	-0.08 (0.05)	-0.10** (0.04)	-0.43*** (0.06)	0.12*** (0.03)
treated×post	0.31*** (0.08)	0.04 (0.05)	0.13# (0.07)	0.12* (0.05)	0.15* (0.08)	0.01 (0.04)
Constant	*-26.98**** *(6.06)*	*-1.38* *(3.19)*	*6.55* *(4.07)*	*29.21**** *(3.41)*	*22.93**** *(4.80)*	*24.33**** *(2.63)*
Car brand FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	*0.45*	*0.15*	*0.01*	*0.22*	*0.12*	*0.09*

Significance levels: #p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Hypothesis 1. Supporting H1, our results provide evidence that, on average, Doug's Effect has a statistically significant positive effect on the *user engagement* with the auction listing resulting in 12% increase in the number of views ($\beta = 0.12$, $p < 0.05$) and 15% increase in the number of comments ($\beta = 0.15$, $p < 0.05$). In addition to that, we also observe a statistically positive increase of 12% on the seller engagement with their listing ($\beta = 0.12$, $p < 0.001$).

Hypothesis 2. Supporting H2, our results provide evidence that, in general, Doug's Effect has a statistically significant positive effect on the auction listing *performance* resulting in a 31% increase in the winning bid amount ($\beta = 0.31$, $p < 0.001$), as well as marginal 13% increase in the number of bids ($\beta = 0.13$, $p < 0.1$). In contrast, we do not observe any statistically significant effect on the likelihood of the car being sold.

Next, we turn to the visual examination of the statistically significant interaction effects (Figure 2). First, the results offer evidence that treated listing featured Doug experience a significantly higher amount of the winning bids. Second, the treated listings also attract significantly higher number of views and, in contrast to listings in control group, indicate a positive trend overall. Finally, our results provide evidence that the rate of decline in the number of comments for treated group is substantially slower than that for control group.

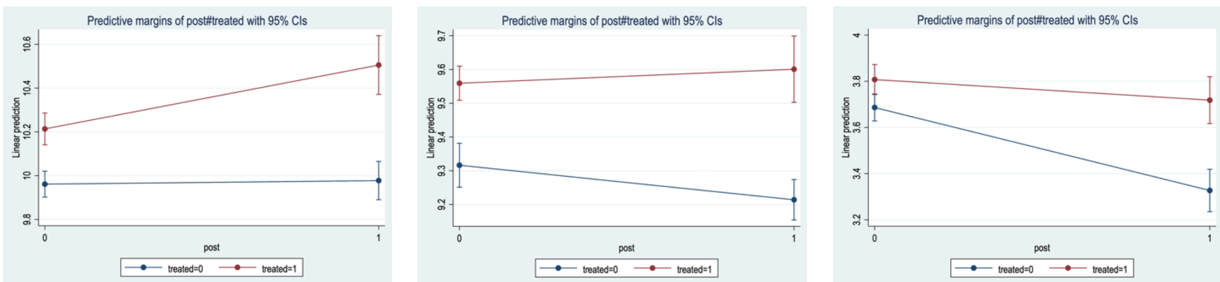

Figure 2. Interaction plots

5.3. Coarsened exact matching

We note that Doug DeMuro is not randomly deciding on which cars should be featured. Therefore, self-selection bias could possibly pose a challenge for the identification of the focal effects. To mitigate this bias, we use CEM to improve the estimation of causal effects by reducing imbalance in covariates between treated and control groups (Blackwell et al. 2009). To do so, we match the listings in our sample based on the two primary characteristics: car price and year of manufacturing. We note that the addition of other characteristics does not influence the estimated coefficients, which remain qualitatively consistent. The estimates of Equation 1 on the matched sample are presented in Table 3. The results provide compelling evidence of the consistency of our estimates reported in Table 2 as part of the main estimation procedure. Moreover, in case of the number of bids, the model fit has improved by 2% and the estimated coefficient of the interaction term has become statistically significant at the $p<0.05$ level suggesting a 16% increase behind Doug's Effect.

Table 3. CEM estimation results (SE in parenthesis)

Model	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	log_win_bid	sold	log_bids	log_views	log_comments	log_photos
one_owner	-0.10	0.08*	-0.02	-0.01	0.08	0.01
	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)	(0.03)
manual	0.08	-0.02	0.078*	0.01	0.08	0.02
	(0.04)	(0.01)	(0.04)	(0.03)	(0.04)	(0.02)
no_reserve	-0.81***	0.33***	0.02	-0.17***	-0.12*	0.05
	(0.05)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)
inspected	-0.02	0.13*	-0.05	-0.06	-0.11	-0.15*
	(0.09)	(0.06)	(0.09)	(0.067)	(0.10)	(0.06)
low_miles	0.38***	-0.01	0.07	-0.03	0.05	-0.03
	(0.05)	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)
doug_review	0.31	0.10	0.23	0.91***	0.57***	0.08
	(0.16)	(0.09)	(0.14)	(0.09)	(0.12)	(0.09)
car_year	0.013***	0.01	0.01	-0.01***	-0.01***	-0.01***

	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treated	0.07	0.01	-0.08	0.11**	0.05	-0.01
	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)
post	-0.13	-0.10	-0.18*	-0.32***	-0.35***	0.15*
	(0.12)	(0.07)	(0.09)	(0.07)	(0.10)	(0.06)
treated×post	0.22**	0.05	0.16*	0.12*	0.19*	0.01
	(0.08)	(0.05)	(0.07)	(0.06)	(0.08)	(0.05)
Constant	-16.05**	-0.59	2.66	38.19***	25.22***	23.84***
	(5.602)	(4.01)	(4.69)	(3.78)	(4.92)	(2.91)
Car brand FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.45	0.15	0.03	0.22	0.25	0.09

Significance levels: #p<0.1, * p<0.05, ** p<0.01, *** p<0.001

6. Discussion

In this study, we have attempted to elucidate the internal influencer effect on platform performance and community engagement in the context of a digital auction website. Previously, such analyses have been performed on the level of community engagement. However, to the best of our knowledge, ours is the first attempt to shed light on the impact of internal influencers on community engagement and platform performance in the context of online automotive marketplaces. The intersection of these two digital dimensions is important because extant research mostly regards community engagement as a driver of performance (Ray et al. 2014). Our study extends the IS literature by demonstrating that both engagement and performance can be actively shaped by the actions of internal influencers. These findings are consistent with resource mobilization theory which postulates that the resource mobilization of information or knowledge transferred from one group to another can enable individuals to introduce novel resources and practices into their group, gaining an advantage from the ensuing innovations (Murray et al. 2020). In the context of C&B, the Doug Effect offers indications of resource mobilization, as expert knowledge migrates from the insider's mind to the public. Moreover, the Doug Effect can also be said to spur the transition of C&B members from a disparate group of individuals to an engaged community. According to the principles of resource mobilization theory, potential access to the vital resource of an authentic expert endorsement can facilitate the emergence of a community around car listing on the website (Angelopoulos et al. 2023). Our findings offer compelling evidence that the endogenous influencer effect can significantly impact both user engagement, manifested in increased viewership and commenting on auction listings, as well as auction performance, reflected in the higher number of submitted bids and the final price achieved. While the use of internal influencers requires thoughtful consideration by practitioners, we show that this strategy is readily available for platform managers to address the issue of low engagement and performance.

References

Akerlof, G. A. 1970. "The Market for Lemons: Quality and the Market Mechanism. Quarterly," *Journal Economics* (84), pp. 488-500.

Angelopoulos, S., Canhilal, K. S., and Hawkins, M. A. 2023. "From Groups to Communities: A Resource Mobilization Theory Perspective on the Emergence of Communities," *Information Systems Frontiers* (25:6), pp. 2457-2474.

Bagozzi, R. P., and Dholakia, U. M. 2002. "Intentional Social Action in Virtual Communities," *Journal of interactive marketing* (16:2), pp. 2-21.

Bapna, S., Benner, M. J., and Qiu, L. 2019. "Nurturing Online Communities: An Empirical Investigation," *MIS quarterly* (43:2).

Blackwell, M., Iacus, S., King, G., and Porro, G. 2009. "Cem: Coarsened Exact Matching in Stata," *The Stata Journal* (9:4), pp. 524-546.

Bockstedt, J., and Goh, K. H. 2011. "Seller Strategies for Differentiation in Highly Competitive Online Auction Markets," *Journal of Management Information Systems* (28:3), pp. 235-268.

Brass, D. J. 2015. "Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding," *MIS Quarterly* (39:3).

Cao, Z., and Belo, R. 2023. "Effects of Explicit Sponsorship Disclosure on User Engagement in Social Media Influencer Marketing," *Forthcoming, MIS Quarterly*).

Cascio Rizzo, G. L., Villarroel Ordenes, F., Pozharliev, R., De Angelis, M., and Costabile, M. 2023. "How High-Arousal Language Shapes Micro-Versus Macro-Influencers' Impact," *Journal of Marketing*), p. 00222429231207636.

Chae, I., Stephen, A. T., Bart, Y., and Yao, D. 2017. "Spillover Effects in Seeded Word-of-Mouth Marketing Campaigns," *Marketing Science* (36:1), pp. 89-104.

Cui, X., Zhang, N., and Lowry, P. B. 2017. "The Agent Bidding Habit and Use Model (Abhum) and Its Validation in the Taobao Online Auction Context," *Information & Management* (54:3), pp. 281-291.

Dabiran, E., Farivar, S., Wang, F., & Grant, G. (2024). Virtually human: anthropomorphism in virtual influencer marketing. *Journal of Retailing and Consumer Services*, 79, 103797.

Granovetter, M. 2018. "The Impact of Social Structure on Economic Outcomes," in *The Sociology of Economic Life*. Routledge, pp. 46-61.

Huang, Z., Guo, H., Lim, H. Y.-F., Ho, K. N., Tay, E., and Chow, A. 2022. "The Value of Social Interactions and Incentives on the Use of a Digital Contact Tracing Tool Post Covid-19 Lockdown in Singapore," *Scientific Reports* (12:1), p. 12416.

Kumar, N., Qiu, L., and Kumar, S. 2022. "A Hashtag Is Worth a Thousand Words: An Empirical Investigation of Social Media Strategies in Trademarking Hashtags," *Information Systems Research* (33:4), pp. 1403-1427.

Liang, C., Wu, J., and Li, X. 2023. "Do "Likes" in a Brand Community Always Make You Buy More?," *Information Systems Research*).

Mallipeddi, R., Janakiraman, R., Kumar, S., and Gupta, S. 2017. "The Effects of Social Media Tone on Engagement: Evidence from Indian General Election 2014," *Information Systems Research, Forthcoming*).

McCarthy, J. D., and Zald, M. N. 1977. "Resource Mobilization and Social Movements: A Partial Theory," *American journal of sociology* (82:6), pp. 1212-1241.

Mero, J., Vanninen, H., and Keränen, J. 2023. "B2b Influencer Marketing: Conceptualization and Four Managerial Strategies," *Industrial Marketing Management* (108), pp. 79-93.

Murray, A., Kotha, S., and Fisher, G. 2020. "Community-Based Resource Mobilization: How Entrepreneurs Acquire Resources from Distributed Non-Professionals Via Crowdfunding," *Organization Science* (31:4), pp. 960-989.

Pu, J., Chen, Y., Qiu, L., and Cheng, H. K. 2020. "Does Identity Disclosure Help or Hurt User Content Generation? Social Presence, Inhibition, and Displacement Effects," *Information Systems Research* (31:2), pp. 297-322.

Rafaeli, S., and Noy, A. 2005. "Social Presence: Influence on Bidders in Internet Auctions," *Electronic markets* (15:2), pp. 158-175.

Ray, S., Kim, S. S., and Morris, J. G. 2014. "The Central Role of Engagement in Online Communities," *Information Systems Research* (25:3), pp. 528-546.

Spence, M. 2002. "Signaling in Retrospect and the Informational Structure of Markets," *American economic review* (92:3), pp. 434-459.

Stern, B. B., and Stafford, M. R. 2006. "Individual and Social Determinants of Winning Bids in Online Auctions," *Journal of Consumer Behaviour: An International Research Review* (5:1), pp. 43-55.

Wang, Q., Qiu, L., and Xu, W. 2023. "Informal Payments and Doctor Engagement in an Online Health Community: An Empirical Investigation Using Generalized Synthetic Control," *Information Systems Research*).

Wies, S., Bleier, A., and Edeling, A. 2023. "Finding Goldilocks Influencers: How Follower Count Drives Social Media Engagement," *Journal of Marketing* (87:3), pp. 383-405.